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Abstract

This dissertation is composed of two related parts. The first part corresponds to chapter 1; the second part is developed in chapters 2 and 3. The common thread is the focus on academic choices, both in students' everyday life and at the moment of an important investment. Both situations have consequences on the human capital accumulation process.

The first chapter explores the relationship between constant smartphone distractions and academic outcomes. In this setting, I concentrate on an every-day choice about efficient time allocation that may have an impact on performance at the university level. To investigate how technological distractions affect concentration and learning, I assign first-year university students to the use of an app that helps them disconnect from distractions on their smartphones. The treatment lasts for four weeks up to the midterm exams. Through the combination of administrative data with survey responses collected before and after the intervention, I first document potential selection mechanisms into the treatment, and I then balance treated and control individuals using propensity score matching. I find that there is a positive effect on the midterm performance of particular kinds of courses, namely the most qualitative ones like Management and Law but not Math or Computer Science. I do not find significant differences in terms of expected percent chance of passing the exams, expected grades, course evaluations, anxiety levels, and study time.

The second part of the dissertation focuses on the high school choice and uses survey data to uncover some important factors in shaping the decision. Chapter 2 deals with the influence of peers on an academic decision. I use expectations about friends' future high school choices to detect an influence on own choice. I use multiple waves of a survey to collect beliefs about expected high school characteristics and future outcomes and gather information about friends' network structure. I solve for the reflection problem by exploiting the architecture of the reconstructed network. I instrument the expectations about friends' future choices using excluded peers (friends of friends) and I estimate a multinomial logit model of high school track choice. Expectations about friends' future choices matter more for the choice than expectations related to school-specific outcomes, such as the probability of liking the subjects taught at a certain school and the expected effort.

Chapter 3 looks at the decision-making process within the family and aims to uncover the relevant actors and their interactions. In the choice of high school, the family is not

a unitary decision maker, but rather it is composed by different agents: the child and the parents. Moreover, models of school choice usually assume complete choice sets. However, informational constraints, heterogeneous preferences within family and the parenting style may lead to heterogeneous choice sets in terms of both size and composition. In this chapter I use survey data to document how family dynamics affect size and composition of choice sets in facing the high school choice. I find substantial evidence of limited agency and limited consideration at the time of choice, but no limited awareness. During the decision-making process agents tend to expand their choice sets over time, with students' sets smaller than their parents' ones. More research is needed to establish a clear link between choice set dynamics and parenting styles.

Contents

Chapter 1

Studying without distractions? The effect of a digital blackout on academic performance

Francesca Garbin

Abstract

Rising awareness about the effects of technological distractions on concentration raises many questions related to tasks that require deep levels of focus. I study an educational setting and I evaluate the impact of reducing disruptions on students' performance and related outcomes. To investigate this issue, I assign first-year university students to the use of an app that helps them disconnect from distractions on their smartphones. The app blocks notifications and access to any other app during a pre-set time window; the treatment lasts for four weeks up to the midterm exams. Through the combination of administrative data with survey responses collected before and after the intervention, I first document potential selection mechanisms into the treatment; I find that students who are willing to participate are those who indeed report being aware of their problematic smartphone usage. I balance treated and control students using propensity score matching, and I find that the intervention has a positive effect on the midterm performance of specific courses, namely the most qualitative ones like Management and Law but not Math or Computer Science. Using survey measures I do not find a significant effect of the intervention on expected percent chance of passing the exams, expected grades, course evaluations, anxiety levels, and self-reported study time.

[*Field codes (JEL)*: I23, O33, D91, C93.]

[*Key words*: Technological Distractions, Education, Time Allocation, Propensity Score Matching.]

1.1 Introduction

Taming our wandering minds when we have an infinite source of distractions in our pockets has become more and more challenging. Before the rise of smartphones, Mark, Gudith, and Klocke (2008) showed that generic outside distractions while working affect our ability to gain back a deep level of concentration afterward. Considering that we pick up our phone more than 100 times per day[1], what is the impact of this constant checking on our ability to carry out activities that require a deep level of focus?

I address this question within an educational setting. The goal of this paper is to assess whether distractions coming from smartphones are detrimental to academic performance. Motivated by the evidence that incessant mobile distractions affect attention (Junco and Cotten (2012), Ward et al. (2017), End et al. (2010)) and that leisure smartphone usage is a substitute for productive activities like sleep (Billari, Giuntella, and Stella (2018)), I question whether these factors can affect learning too. I design and implement an intervention that provides students with an aid to limit the exposure to the most distracting tools on their smartphones when studying or attending classes, such as social media or games, through an app that can prevent the use of other apps and the display of notifications. The distraction block needs to run for four weeks in order to allow people to experience the situation for a prolonged period of time so that they may form a new habit. A set of surveys aimed at uncovering relevant factors, such as habits and expectations, is also administered throughout the study.

For this intervention I target first-year university students in multiple economics bachelors attending different courses that have partial (midterm) exams. After running an online baseline survey I assign to the intervention students who are willing to participate; students who engage with the questionnaire but don't express their intention to participate in the study are used as control group in my matching exercise. The treatment consists of activating an app that prevents the use of distracting apps on the smartphone in a relevant time window, i.e. during four hours in the afternoon from Monday to Friday, when students may be either studying or attending lectures. Students are asked to do this for the four weeks that precede the first partial examination(s) of the semester. On the app I label this intervention as a "Distraction Blackout". At the end of the four weeks I survey the students after the midterms and again at the end of the semester. I repeat the

[1] Among others, Asurion in November 2019 reported an average of 96 times per day for American users (refer to www.asurion.com), while SlickText in January 2021 reported 63 checks on average per day but smartphone owners unlocked them on average 150 times per day (refer to www.slicktext.com).

implementation in both Fall 2020 and Spring 2021 with the same target group.

I combine the following three data sources. The first one is represented by the intervention itself; the software providers gave me data on the students' actual minute-by-minute usage of the app. The second is my surveys, distinguishing a baseline (pre-intervention) wave, a post-midterms one and a final end-of-semester one; I design the questions with the objective of uncovering potentially relevant drivers in intervention takeup and heterogeneous effects. Third, I rely on the university administration for students' grades and backgrounds.

In order to quantify a causal effect on academic performance, I first investigate potential self-selection mechanisms into the intervention assignment. Using my survey measures related to academic motivation, habits and distractions, and personality traits, I document how untreated and treated strudents are mostly balanced, and I repeat the same analysis by comparing the Fall and the Spring samples. The discrepancies between the untreated and treated groups can be reconciled with the fact that participating students are those who seem to be aware of their problematic smartphone behavior and for whom participation is costly (in line with other papers such as Allcott, Gentzkow, and Song (2021), and Hoong (2021)). Second, I use administrative and survey variables to construct a propensity score and match observations for causal analysis. I construct the main specification of the score relying on administrative information and on the survey variables that showed some unbalancedness, but I also refine the analysis using only administrative variables with the objective of increasing the sample size.

I find that in both semesters there is a positive effect on the Management and Law exams, i.e. the most qualitative among the economics-related courses, while there is no detectable effect on more quantitative courses like Math or Computer Science. As for the Economics Principles exams, I find a positive effect on the Macroeconomics performance but not on the Microeconomics one. Statistically significant results are of a magnitude between 0.22 and 0.54 standard deviations, therefore above the standard 0.2 threshold "of policy interest" (Kraft (2018)). These results suggest that distractions from smartphones can hinder differentially the study of subjects requiring varying levels of concentration. I do not find relevant patterns in terms of expected percent chances of passing the exams, expected grades, course evaluations, anxiety levels, and self-reported study hours. Motivated by the economic and psychological literature I also conduct an heterogeneity analysis (in the Appendix) in terms of gender, network dimension, technological history and habits, and family background using the survey information I gathered throughout the semesters. Finally I perform some robustness checks estimating Lee bounds (Lee (2009)) for my results and exploiting the random allocation of students to classes as an instrumental variable[2].

The peculiar situation in the a.y. 2020/21 dictated by the global pandemic crisis of COVID-19 led to some modifications in the teaching methodologies. Some of these changes proved beneficial for the intervention, mostly for two reasons. First of all, students attended classes on a rotating basis, resulting in less frequent contacts with a halved classroom; reduced exposure to classmates decreased the size of social networks, thus diminishing the possibility of spillovers. Second, the stronger salience of smartphones for communication purposes (refer to Sañudo, Fennell, and Sanchez-Oliver (2020)) increased the need for tools that help students create better study habits. Students who participated in my surveys indeed reported an increased smartphone usage and an intensified desire to act to improve their habits, thus supporting the idea that these sophisticated agents are aware of their bad behaviors and want to take actions.

The standpoint of this work is not that smartphones are bad *per se*; they are tools, and as such they are as valuable as the use we make of them. Smartphones are empowering devices that give us an important window on the world, through constant streams of information and contacts with others at virtually no cost. The rapid technological change of the last decades has not given us enough time to assess its consequences and react, but rather we face a situation of basic ignorance when it comes to a deeper understanding of how the digital world works[3]. To use fully the instruments we have, we need to understand how they work on us.

With this work I contribute to the growing number of studies that assess the impact of constant exposure to technological distractions. I refer mostly to two strands of the literature. The first one is related to the educational impacts of digital tools, from the introduction of laptops in the classroom (Payne-Carter, Greenberg, and Walker (2017), Ravizza, Uitvlugt, and Fenn (2017), Sana, Weston, and Cepeda (2013)) to correlational evidence on the negative effects of smartphone usage (Katz and Lambert (2016), Whittington (2019)), to the application of school bans on smartphones (Beland and Murphy (2015),

[2]Some highly attended bachelor programs randomly split students in multiple classes. Each of these classes has its own course schedule. This means that students attending the same bachelor were exposed at random to different class schedules, with some courses that potentially were never taught in the afternoon (i.e. when students were asked to activate the block). This creates random variation in treatment exposure for some students attending specific courses in one class *versus* students attending the same bachelor and the same courses in another class.

[3]See for example the discussion of Micheal Bess, historian of science at Vanderbilt University, about the role of technology in our future on vox.com.

Kessel, Hardardottir, and Tyrefors (2020)) and more in general studying how broadband connection affects average students' achievements (Felisoni and Godoi (2018)). I contribute to these studies by implementing a month-long intervention without restriction to the classroom environment, but rather allowing students to block distractions both when attending classes and while studying. By design, I let the subjects choose their own actions in a real-life setting. The second strand is represented by studies on digital distractions in general. I relate to works that show how smartphones are distracting tools (Campbell (2006), End et al. (2010), Ward et al. (2017)) and how limiting some of their features may affect important individual dimensions (Patterson (2015), Marotta and Acquisti (2017), Mosquera et al. (2018), Allcott, Braghieri, et al. (2019), Allcott, Gentzkow, and Song (2021)). My contribution to this field is to quantify the impact of digital distractions on academic performance, while targeting all smartphone disruptions without restricting to specific apps or notifications.

In this paper I focus on a particular target population doing a specific task, university students while pursuing their academic learning through both studying and attending classes. On the one hand, understanding the potentially disruptive effects on education may have important implications for the human capital accumulation and the resulting labor market prospects of the next generations. On the other hand, this application suggests the need to investigate the more general consequences of digital distractions on work productivity. Two implications can therefore be drawn from my results. The first one is related to the effect on labor market outcomes. By estimating the change in a student's GPA, keeping into account the bachelor-specific share of qualitative *versus* quantitative subjects, it could be possible to calculate the modified chances of obtaining a job within the first year of graduation, or those of obtaining a more stable contract, or the starting salary. Unfortunately there is no availability of data about this university's students' labor market outcomes matched with their past performances, so such an estimation would be made using another sample as proxy. The second implication is related to the habit component driving app usage. Behavioral patterns influence both constant checking (without the intervention) and distraction blackout activation (during the intervention). By understanding when the first is disruptive, it could be possible to incentivise the latter and improve the performances of tasks harmed by erratic focus. In this case, the observed tasks may not be purely academic but might consider also workplace-related activities. It is undeniable that smartphones are pervasive tools in our everyday life: how much do we know about the overall effect they have on our behaviors and habits?

The paper is structured as follows. Section (1.2) presents the relevant literature on the effects of smartphones and new technologies. Section (1.3) presents the setup of the intervention; first I describe the institutional setting of the university where it takes place, then I detail its design, how the distraction-blocking app works, and the survey structures and questions. Section (1.4) describes the survey respondents and the app users, providing insights about these students using the survey measures on habits, expectations, demographics, and personality traits. Section (1.5) analyses the different layers of potential selection in the sample, distinguishing students on the basis of their engagement intensity and of their participation timing. Section (1.6) presents the empirical results for all the relevant outcomes, namely midterm grades, expected performance, anxiety levels, course evaluations, and study time. Section (1.7) outlines the robustness checks, i.e. first the estimation of Lee bounds and then the use of the random allocation of students to classes as an IV. Section (1.8) concludes.

1.2 Literature Review

In this section I focus on the economic literature that has studied the effect of new technologies on educational achievements and digital distractions in general. Section (A.1) in the Appendix expands this review also by giving an overview of the current Internet and screen-use diffusion among younger generations, of the medical and psychological research on technology use, and of other fields more broadly related to this project, i.e. task-based goal setting, peer effects, and family role in defining smartphone use.

In this work I mostly refer to two strands of the literature. The first one is related to the educational impacts of digital tools. Amez and Baert (2020) review many studies that focus on the relationship between smartphones and educational achievements, detecting a predominance of negative effects but mostly in observational studies. Some works assess the negative impacts of technologies on academic outcomes through the introduction of laptops in the classroom (Payne-Carter, Greenberg, and Walker (2017), Sana, Weston, and Cepeda (2013)), monitoring their academic *versus* non academic Internet usage (Ravizza, Uitvlugt, and Fenn (2017)) and the related Internet usage to assess negative academic impacts (Felisoni and Godoi (2018)); some focus on the introduction of Internet (Belo, Ferreira, and Telang (2014)); others present evidence of the negative correlation between using smartphones in the classroom and performance (Katz and Lambert (2016), Whittington (2019)). Many schools have reacted by introducing bans on smartphones, but there is mixed evidence that this policy really works (Beland and Murphy (2015), Kessel, Hardardottir, and Tyrefors (2020), Abrahamsson (2020)). Although still not backed by sound reseach, these sort of bans seem to be a salient policy intervention as smartphones are perceived not as a study tool but as a source of entertainment for the students (Lepp et al. (2013)), with many distractions coming from notifications (Junco and Cotten (2012)), a lack of focus deriving from FOMO (Chen and Yan (2016)), and the possibility to find a fast source of amusement (Hawi and Samaha (2016)). My contribution to this literature is to quantify the impact of a reduction in smartphone distractions on academic performance in a month-long intervention. I do not focus only on the classroom environment but by setting a fixed schedule I allow for an heterogeneous allocation of intervention time to both classes and personal studying. Moreover, by design I do not force students to participate but I let them freely decide to first enroll in the project and then on a daily basis, thus letting the agents choose their actions in a real-life setting.

A second strand of the literature is related more broadly to digital distractions. This line of research has seen an increase in contributions over the last years. Some studies focus on the effect of Internet distractions on computer-based tasks and courses (Marotta and Acquisti (2017), Patterson (2015)). Starting from the evidence that mobile phones are distracting tools (Campbell (2006), End et al. (2010), Ward et al. (2017)), other works have tried to experimentally evaluate the effects of some social media features on aspects such as subjective well-being (Mosquera et al. (2018), Vanman, Baker, and Tobin (2018)) and information diffusion (Allcott, Braghieri, et al. (2019)), also providing commitment devices to try to restrain self-control problems (Hoong (2021), Allcott, Gentzkow, and Song (2021)). Differently from other works which focus on specific social media, in this paper I target all smartphone distractions in terms of any app and any notification; moreover, I examine the outcome of a non-repetitive and heterogeneous task conducted over a prolonged period of time.

1.3 The Setup: Design and Institutional Setting

1.3.1 The Institutional Setting

The intervention takes place at Bocconi University, an Italian private institution of tertiary education located in the center of Milan. Its educational offer is concentrated on Economics, Management, Social Sciences and Law, both at the undergraduate and graduate level.

The focus of this analysis is on students entering Bocconi in the 2020/2021 academic year at the undergraduate level. Bachelor programs last 3 years, and Bocconi offers them both in Italian and in English. Table 1.1 presents an overview of the 3 programs in Italian and the 6 programs offered in English by field of study. These programs offered in the a.y. 2020/2021 are those on which my analysis is focused, including the newly offered course in Artificial Intelligence. I exclude the class belonging to the degree in Law, offered in Italian.

Table 1.1: Analysed bachelor programs at Bocconi, a.y. 2020/2021.

Field	**Acronym**
Econonimcs & Management	CLEAM (Ita)
	BIEM (Eng)
Economics & Finance	CLEF (Ita)
	BIEF (Eng)
Economics for Arts, Culture and Communication	CLEACC (Ita)
Economics, Management & Computer Science	BEMACS (Eng)
Economics & Governments	BIG (Eng)
Economics & Social Sciences	BESS (Eng)
Mathematical & Computing Sciences for Artificial Intelligence	BAI (Eng)

All the students in these programs take a fixed sequence of compulsory courses, spanning over the first year and over most of the second and third, when electives can also be chosen. Tables A.1 and A.2 in the Appendix present the total number of courses and credits allocated to the Fall and Spring semesters of the first year.

Some bachelor programs have more than one class. At the beginning of the first year, students attending these multi-class bachelors are randomly assigned to a class made up by approximately 100 students, and they follow all their courses within this class. First-year courses are mandatory and usually taught by different professors across classes, even if the same course has a central coordinator that defines the syllabus, the material, and prepares the exams. This means that exam questions and formats are the same for all the students within the same degree program (and sometimes across degree programs), independently of their class and their lecturer. Grading is delegated to the class lecturer and/or the teaching assistant. The coordinator checks distribution of grades and usually makes sure that they are similar across classes before approving the publication of results to students. Grading is on a scale from 0 to 30, where the passing grade is set at 18.

During each semester, after six weeks of lectures there is a break in which most courses activate midterm (partial) examinations. Students have different options in terms of how to face their exam. The first option is to take the first partial examination, and then if students like the awarded grade they can take the second partial examination that will take place at the end of the course, and if the average of the two examinations is a passing grade this grade ends up in their academic career. Second, students can take the first partial examination and then disregard it (in particular if the grade is below their expectations) and take the general exam at the end of the course. Third, take only the complete exam at the end of the semester or afterwards[4]. Students have high incentives to participate in midterm examinations, because this allows them to split their course load and to eventually reject a non-pleasing grade, while at the same time obtaining a signal about their preparation (and about the difficulty of the exam) without paying any cost in terms of GPA. If a student gets a passing grade in a final exam, they cannot repeat it and the grade will show up in their career.

Table 1.2 presents some descriptive statistics about first-year students of the cohort considered in this paper. The biggest sample is represented by students in the Italian degree in Economics and Management (CLEAM, 40% of the total first-year students), while the second largest is the same program offered in English (BIEM, 18%). Female students account for 40% of the total student body; the lowest share of female students is in the programs in Math&Artificial Intelligence (24%) and Economics and Finance in Italian (24%), while they are the majority in the Arts and Communication degree (75%). The programs in English attract many foreign students, who make up from 33% to 47% of these classes.

The a.y. 2020/21 presents some peculiarities with respect to the other years because of the COVID-19 pandemic crisis. I am now listing some of them, starting from the student body, to the teaching methods, to examinations.

First, randomization into classes. In July 2020 a small fraction of the whole student

[4] Some courses may have different exam structures. First of all, not all courses have partial examinations. Second, some courses may not assign a 50%-50% weight on the midterm and final exams, as they may require students to complete other assignments or group works. In this context I use as an outcome the grade obtained in the midterms and registered as so by the Bocconi administration in each student's career.

Table 1.2: ENROLLED FRESHMEN BY PROGRAM, A.Y. 2020/2021.

Program	Num. classes	Total first-year	% female	% foreign
CLEAM *of which virtual: 1*	8	1047	35	3
CLEF	2	257	24	5
CLEACC	2	259	75	24
BIEM *of which virtual: 1*	4	470	43	47
BIEF	2	227	30	43
BEMACS	1	104	30	44
BIG	1	103	41	37
BESS	1	118	44	33
BAI	1	45	24	33
Total	22	2585	40	21

The total number of students refers to data updated in November 2020.

body at Bocconi (around 10%) opted for an online-only academic experience for the a.y. 2020/21, due to travel restrictions and other health issues. This creates a group of "virtual only" students that have specific needs. Bachelor programs who have more than three classes (see Table 1.2) activated a "virtual only" class; in this case, there is one virtual-only class in the Economics and Management Italian (CLEAM) and English (BIEM) programs. All other classes were formed following the usual criteria of random allocation.

Second, the course structure. Lectures needed to be carried out in compliance with safety measures to guarantee social distancing. There are two main organizational structures: the "basic" model, and the "blended" one. The basic model allows teachers to carry out all their lectures in class for on-campus students, with live streaming for off-campus students; if classrooms are too small or on-campus classes are too big, then the class is divided into two groups that alternate physical attendance every other week on the basis of the last digit of their ID number (even or odd). The blended model instead foresees only part of the lectures to be scheduled in presence or live; in fact, 40% to 60% of the classes are carried out exclusively online (either live or through asynchronous videos), and the rest of the classes need to be in presence for students on-campus. If the on-campus students in the blended model are too many, then there is no rotation but rather a duplication of in-presence lectures in order to allow all the students to be physically in class. Off-campus students in blended courses can follow the live-streaming of the physical lectures; this is true both for virtual-only classes and for the fraction of virtual students in the bachelor programs without virtual-only classes. All the live classes are recorded and uploaded to the course e-learning page until the end of the semester. Table 1.3 summarizes the teaching models adopted by each course in both semesters. For the first six weeks of courses in Fall, i.e. for the relevant time window of the intervention until midterm examinations in mid October 2020, courses were carried out according to this setup without further interruptions due to the COVID-19 pandemic. Starting from end of October, the second part of the Fall semester resumed through remote learning only, due to the worsening of the pandemic situation in the North of Italy. Similarly in the Spring semester courses were carried out according to this setup without further interruptions due to the COVID-19 pandemic until the end of week 5 in the first half of the semester. After some weeks of online-only teaching, the second half of the second semester after the Easter break was conducted according to the outlined teaching models.

Third, exams. All exams were carried out online, drawing on the experience gained during the Spring semester of a.y. 2019/20. Most of the first-year courses offer also midterm exams (online). Refer to Tables A.1 and A.2 in the Appendix to see which ones do.

Of particular importance for the setup of this intervention is the second change outlined, i.e. the new teaching methodologies dictated by the need to decrease classrooms sizes to comply with social distancing rules. These constraints imposed by COVID-19 on peer interaction affected the network structure for the students in my sample, who started university during this academic year and had almost no previous connections to their classmates. As highlighted during the cognitive interviews I conducted in Spring 2020 (see section (A.9) in the Appendix), in normal times students meet mostly during classes, in particular in the very first weeks, but given the fact that students were allowed to attend classes in person only every other week[5] and in smaller groups this reduced the opportunities to be exposed to more peers and have a wider network[6]. The same holds for other places where social distancing was monitored, such as canteens and study rooms, where seats needed to be booked in advance. As will be described in section (1.4.6) most of the students in my sample report living in Milan (73%) and could thus potentially attend classes and hang around campus when possible, following the prescribed rules about social distancing. On the other hand 39% of the students report living with their families, meaning that the remaining group lives potentially with other students[7]. In this setting

[5]Most of the courses adopted the basic model, as seen in Table 1.3; even with the blended model first-year classes include more than 100 students in almost all the programs (see Table 1.2), and given classroom capacities these classes had to be split into two alternating groups.

[6]In section (A.3.9) I show that when I ask students to name their friends the average number of answers increases by less than one individual from Fall to Spring, from 3.83 to 4.32 names mentioned on average.

[7]In the Fall Baseline survey only I asked about how many people students were living with, if not living with their families. Out of 286 respondents, 27% reported living alone, 32% with one person,

Table 1.3: Fall and Spring semester first-year courses by program, with teaching model adopted for a.y. 2020/21.

	Fall semester		Spring semester	
Program	**Course**	**Teaching Model**	**Course**	**Teaching Model**
CLEAM	Microeconomics	Basic	Macroeconomics	Basic[b]
	Mathematics	Blended	Mathematics	Basic[b]
	Management	Basic	Computer Science	
	Critical Thinking (seminar)[a]	Online	Private Law	Basic[b]
CLEF	Microeconomics	Basic	Macroeconomics	Basic
	Mathematics	Blended	Mathematics	Basic
	Management	Basic	Computer Science	
	Critical Thinking (seminar)[a]	Online	Private Law	Basic
CLEACC	Mathematics	Blended	Microeconomics	Basic
	Management	Basic	Computer Science	
	Private Law[a]	Basic	Methods&Research[a]	Basic
	Aesthetic theory[a]	Basic/blended	Economic History[a]	Basic
BIEM	Microeconomics	Basic	Macroeconomics	Basic[b]
	Mathematics	Blended	Mathematics	Basic[b]
	Management	Basic	Computer Science	
	Critical Thinking (seminar)[a]	Online	Private Law	Basic[b]
BIEF	Microeconomics	Basic	Macroeconomics	Basic
	Mathematics	Blended	Mathematics	Basic
	Management	Basic	Computer Science	
	Critical Thinking (seminar)[a]	Online	Private Law	Basic
BEMACS	Microeconomics	Basic	Computer Science	Blended
	Mathematics	Basic	Mathematics and Statistics	Basic
	Management	Basic	Accounting[a]	Basic
			IT Law	Basic
BIG	Microeconomics	Basic	Macroeconomics	Blended
	Mathematics	Basic	Computer Science	
	Public Law[a]	Basic	Political Philosophy[a]	Basic
	Political Science[a]	Basic	Quantitative Methods	Basic
			Marketing Research Skills[a]	Basic
BESS	Microeconomics	Basic	Macroeconomics	Basic
	Mathematics	Basic	Mathematics	Basic
	Management	Basic	Computer Science	
	Logic[a]	Basic	Statistics	Basic
BAI	Microeconomics	Basic	Computer Science	Basic
	Mathematics	Basic	Mathematics	Basic
	Algebra&Geometry	Basic	Probability	Basic
	Computer Science[a]	Blended	Physics[a]	Basic

[a]: in the analysis these courses fall into the "Other" category.
[b]: these courses also have a completely virtual class.

potential spillovers may stem from treated and control first-year students living together; I do not have this information available.

1.3.2 Intervention Design

In the first two weeks of the semester I ask students whether they want to participate in a project[8]. In the Fall semester I only ask their willingness to participate in "an experiment", only specifying that they would not need to go to the lab or to subtract time from their study, and that they would only need their smartphones. In the Spring semester I ask students their willingness to participate in "a challenge to help them improve their study habits", still specifying that they would not need to go to the lab or to subtract time from their study, and that they would only need their smartphones[9]. All the students who declared their willingness to participate were assigned to the intervention.

I ask students to use a smartphone app in order to block all other distracting apps. This smartphone application is available on the market for both Android and iOS, and was designed to promote classroom engagement and attendance. Its premium version costs around $7.99 USD per semester, and I offer it for free to the students.

This is how the intervention works. Students download the app and thanks to a five-digit code they obtain access to the premium features and can join a "class" on the app. This class was scheduled every weekday from 2pm to 6pm for the four weeks of the intervention, and it was called "Distraction Blackout". Every day before the class starts students get a reminder that reads "Distraction Blackout is happening now. Join the class"

16% with two, 16% with three, and 10% with four or more.

[8]The intervention was registered on the AEA RCT Registry (RCT ID: AEARCTR-0006378) as a randomized experiment in August 2020, although the design changed before the implementation. The project also obtained the approval of the Bocconi Ethics Committee (ECR ID: FA000028).

[9]From Fall to Spring there were two main changes in the recruitment of students. The first one was the fact that in Fall I first surveyed respondents and then at the end of the survey I asked them about willingness to participate, while in Spring I asked them directly about their willingness to participate. I adopted this change because I wanted to reduce potential frictions in participation due to first taking a survey, and I wanted to reach the maximum potential audience directly with the question about participation. I could not contact students repeatedly as the first communication in each semester was sent to all students by the administration and not by me as I did not have access to students' mailing lists. Therefore the administration sent in Fall an email with a link to the baseline survey, with the participation question at the end, while in Spring an email with a link to a participation survey. The second change was the recruitment question. In the first semester I asked students their willingness to participate in "an experiment", while in the second semester I mentioned "a challenge to help them improve their study habits". I decided to be more explicit about the intervention for two reasons. First, I wanted to maximise participation and take-up rate by being more upfront about what the intervention was about. Second, there was the possibility that some students already knew my project from the previous semester and therefore knew what it was going to be about; there was the chance that these students also shared the information with others. If the latter was the case, then by making the content of the intervention more explicit I wanted to minimise potential heterogeneity in the information that students (connected to past participants, or not) might have.

and on which they can tap to activate the block. Alternatively, they can just tap on the app's icon in their home screen. Students can see that the block is active because there is a timer running on their screen. During the distraction blackout, students make the conscious and intentional choice to remain off their phones. They can take breaks from the app if needed, but this behavior is monitored. While the timer is running, students cannot open other apps and do not receive notifications. Whenever they leave the timer screen or tap on the "Start a break" button they are pausing the class. If they take a break they can rejoin the class by re-opening the app. At the end of the class, students get a report telling them the number of minutes and the percentage of completion of the session.

The treatment runs from weeks 3 to 6 of each semester, ending right before the ten-day break in which students take midterm exams. This allows me to use midterm grades as a direct outcome affected by my intervention.

To incentivise participation on a daily basis and to minimise the breaks, I offered students Amazon gift cards of the value of €70 through a lottery. In each semester 8 to 10 Amazon gift cards were randomly assigned to eligible students, i.e. those who activated the block on at least 80% of the days (i.e. 16 out of 20) on at least 80% of the time (i.e. 192 minutes out of 240).

On top of my scheduled classes, students can use the app for their own blackout sessions. While the intervention lasts for four weeks, students have access to the premium version of the app for the whole semester and can possibly keep using it also after the incentivised period is over.

If a student uninstalls the app, their usage will no longer be tracked. However, the information collected up to that date remains accessible, and the student can reinstall the app and join the class again at any time.

In the app it is possible to create polls and send messages in the form of notifications through the app. I sent some multiple-answer quizzes at the beginning or end of each week in order to ask students about their experience.

Spillovers. One potential issue related to this implementation comes from potential spillover effects. There are many channels through which they could contaminate the control group: for example, treated students in class may be more likely to look for in-person distractions and bother their colleagues; treated students in the library may represent a virtuous example of smartphone abstention; control students may be inspired by their peers' committment and may look for similar solutions; treated students who use their smartphones less often may send less messages to control students, who in turn experience a reduction in notification exposure. The best way to address this issue at the design stage was to plan a cluster randomization of the intervention on the basis of the reported network of friendships, elicited in the surveys; unfortunately, this kind of design required many more participants and a complete knowledge of the network. Although the intervention was not randomized (neither at the cluster nor at the individual level) spillovers in this context should not be a big concern because of the peculiar situation dictated in a.y. 2020/21 by COVID-19. I target the intervention to first-year bachelor students knowing that the network of new-comers is potentially smaller; moreover, because of the pandemic crisis students attended classes on a rotating basis, resulting in less frequent contacts with a halved classroom. Reduced exposure to classmates decreased the size of social networks, thus diminishing the possibility of spillovers.

1.3.3 Survey Design and Questions

Figure 1.1: Timeline of the intervention in the Fall and Spring semesters.

Timeline of implementation

Start of Semester	**Fall 2020**	**Spring 2021**
Weeks 1-2		
Recruitment	Early September	Early February
Baseline survey	(with Recruitment)	Mid February
Assignment	September 10	February 11
Weeks 3-6		
Treatment	Sept 14 - Oct 9	Feb 15 - Mar 12
Midterm exams		
Postmidterm survey	End October	End March
Weeks 7-12		
End-of-semester survey	December	May

Figure 1.1 presents the timeline of the intervention in the two semesters.

At the start of the semester I contact all first-year students by email through the administrative direction of each bachelor program or through professors in charge of one curricular course of that semester. In the Fall semester I ask students to take the baseline survey and then to state their willingness to participate in the intervention. In the Spring semester I directly ask the students if they want to participate in the challenge, and then I send the baseline survey to all the students participating over the academic year, i.e. treated and controls stemming from the first survey of the Fall semester and the new treated of the Spring semester.

The first survey aims to elicit some traits and habits of the students. In particular I focus on demographics, study and technological habits, and network. Students who took the baseline in the Fall, when re-invited to take it in Spring did not have to answer to the full set of questions about their background, but rather only to those about habits and expectations.

In the first survey I use some measures taken from the economic and psychological literature. For personality traits, I use three questions, each addressing in turn discounting, risk-taking, and competitiveness, and an eight-item "grit" measure as introduced by Duckworth and Quinn (2009) and Duckworth, Peterson, et al. (2007), assessing the ability to maintain focus and interest, and the perseverance for pursuing long-term goals. Questions related to Coronavirus and COVID-19 were designed following the guidance of WHO and some questions were taken from their "Survey tool and guidance" document[10]. PISA questionnaires provided some questions about socio-economic background (e.g. the number of books or other objects in the house), parenting supervision (e.g. activities carried out together during childhood) and reading attitude (e.g. whether enjoying it and on which supports)[11]. For smartphone usage I exploit some items from van Deursen et al. (2015).

After six weeks of classes, midterm exams are offered by most of the compulsory first-year courses during a ten-day break. Students have the option to take them if they want, and there is a strong incentive to do so as explained in the previous section. Administrative data about midterm exam grades represents the most important outcome in the intervention evaluation. After the midterms, the semester resumes for its second half.

The post-midterm wave, administered right after the exams, focused on assessing the

[10] See www.euro.who.int/survey-tool.
[11] See www.oecd.org/pisa.

ex-post expectations about exam performance, and it asks treated individual about the intervention experience and the use of the app. Students also report attendance, study time, and course evaluations mimicking Bocconi's official set of questions[12]. To assess exam anxiety I exploit the State Trait Anxiety Inventory (STAI) as introduced by Spielberger (1983), addressing both "state anxiety" and "trait anxiety" in order to distinguish the daily experience of stress from the more general perception of the individual. I also use some items from Thong, Hong, and Tam (2006) and their Expectation-Confirmation Model (ECM), a paradigm that hypotheses how a consumer's satisfaction determines re-purchase intention based on the Technology Acceptance Model (TAM2) by Venkatesh and Davis (2000). I exploit a set of questions in order to assess the experience with the app in terms of perceived usefulness and ease of use, enjoyability, satisfaction.

As a followup, at the end of the semester all the students are asked to fill in a last survey assessing their study and technology habits, mostly following the lines of the first survey. This has the objective of gathering information on how some behaviors may have changed or some outcomes may have realized.

I conclude each questionnaire with three survey evaluation questions following Bruine de Bruin and Carman (2018).

Taking surveys was incentivised through a lottery. The first survey awarded one Amazon gift card per class, while in the other cases a fixed number of cards (up to 10) was made available. Values ranged from €25 to €40.

1.3.4 Intervention Outcomes

In this paper I am going to use both administrative data and survey measures to estimate an effect of the intervention on potentially relevant variables. First, I use as main outcome the midterm grades as reported by the administration. Second, I use survey measures to detect an impact on expected midterm performance, in terms of both expected percent chances of passing and expected grade (conditional on passing the exam, i.e. obtaining a grade of at least 18/30). Third, given that the intervention operates both during study time and lectures, I use as outcomes the course evaluations as reported by students in my post-midterms surveys. Fourth, I rely on my measure of anxiety to detect a potential treatment effect also on students' well-being. Last, I investigate potential effects on study time.

[12]In the Fall semester I administer an additional pre-midterms wave in which I gather some information about habits and pre-exam expectations, but I do not exploit that information in my analysis.

1.4 The Sample Description

During the Spring semester 2020, when COVID-19 first interrupted the normal course of lectures and distance learning was activated, I conducted some cognitive interviews with third-year Bocconi bachelor students in order to understand their smartphone habits, their network formation mechanism, their family attitude towards technology, and their online learning experience. This process was useful to determine leading habits and how students would value my intervention. I used some of the collected information in order to address some concerns about potential mechanisms and also COVID-19-related academic changes. A summary of the interviews can be found in the Appendix, section (A.9).

The target sample of this study is composed by nineteen and twenty-year old students, thus a population that grew up tech-savvy but that is also aware of their intensive smartphone use. They are a mixture of what Morace (2017) called ExpoTeens and ExperTeens, i.e. the digital natives of Generation Z that first experienced the disruption of tradition, and the sharing of the same experience, i.e. the Internet, beyond social and geographical differences. They are individuals who experience their identity through exposition, communicate through storytelling, and intervention diversified uses of media looking for inspiration. On the one hand, having grown up exposed to digital technologies may have made them more able to manage different constant streams of information (Wolf (2018)), but on the other hand their learning may be more superficial and distracted[13]. As long as studying is built on more traditional learning approaches, it is important to understand who today's learners are and how mobile technologies are redefining our attention.

In the next paragraphs I describe questionnaire and intervention participation, and then using survey measures I describe the students in my sample providing details about their study and technological habits, their demographics and family background, their friends, and some personality traits.

1.4.1 Response Rates and Participation

Table 1.4 summarizes participation in all the survey waves across both semesters. In Fall the response rate to the baseline survey was 23% out of whole first-year cohort; among respondents, 36% of them (218 students) declared to be willing to participate in "an experiment", and were invited to download the app and join the "distraction blackout" class for four weeks up to the midterm exams. In Spring the whole first-year cohort was

[13]See the literature review on the medical research in section (1.2).

invited to participate in "a challenge", with a number of volunteers similar to the Fall (225 students), while the baseline survey was sent to the pool of students who had answered to at least a survey or expressed their willingness to participate in the intervention in at least one semester.

Response rates of the Post-Midterms and the End-of-Semester surveys were similar in both semesters.

Table 1.4: PARTICIPATION TO SURVEYS – FALL VS SPRING.

	Fall, N		**Spring, N**	
Baseline				
Respondents	597		128	
Assigned to intervention	218		225	
Post-Midterms				
Respondents	132		148	
of which assigned to the intervention	*59*	*27% of 218*	*84*	*37% of 225*
End of Semester				
Respondents	122		121	

Table 1.5 breaks down survey participation comparing the beginning and final survey wave of each semester by bachelor program, versus total cohort enrollment.

Table 1.6 presents more in detail information about the intervention participants. Take-up rate was 38% in Fall (42% in Spring), as out of the 218 (225) students who declared their willingness to participate only 83 (94) actually downloaded the app and entered the "Distraction Blackout" class. Among them, 19 students downloaded the app in both semesters. I define students as "participants" if they volunteer for the challenge, and "active" if they activate the app for at least one minute of class time. The total number of active participants over the academic year was 158 (as seen in Table A.3 in the Appendix). More details about intervention participation and students' feedback is presented in sec-

Table 1.5: SURVEY PARTICIPATION AT THE BEGINNING AND END OF EACH SEMESTER VS ENROLLMENT, BY BACHELOR PROGRAM.

Bachelor	**Enrolled, %**	**Fall**		**Spring**	
		Baseline, %	**End Sem., %**	**Baseline, %**	**End Sem., %**
	Nov 2020	*Sept 2020*	*Dec 2020*	*Feb 2021*	*May 2021*
CLEAM	40.5	36.74	29.51	23.44	27.27
CLEF	9.94	6.88	9.84	16.41	14.05
CLEACC	10.02	15.6	15.57	11.72	9.09
BIEM	18.18	15.6	11.48	14.84	14.05
BIEF	8.78	6.38	8.2	9.38	9.92
BESS	4.56	5.37	8.2	8.59	10.74
BEMACS	4.02	4.7	4.92	4.69	4.96
BIG	3.98	4.87	9.84	7.03	4.13
BAI	1.74	3.86	2.46	3.91	5.79
N	2585	597	122	128	121

Table 1.6: PARTICIPATION TO THE INTERVENTION – FALL VS SPRING.

Intervention *Use of the app*	**Fall** **N**	**Spring** **N**
Invited to experiment	218	225
Downloaded app and entered class	83	94
of which, participating both in Fall & Spring:	*19*	*19*
Active (number of minutes> 0)	72	80
Active, but minutes<100 (including 0)	17	18
Active, but minutes<240 (one afternoon)	23	28
Avg num. minutes, if minutes> 240 (one afternoon)	2179	2871
Active >80% of the time, at least 80% of the days[a]	24	41
Avg num. minutes, if >80% at least 80% of the days	3972	4076
Active outside of class time	37	50
Avg num. minutes outside class	227	183
Maximum num. minutes outside class	1501	5471
Pop quizzes		
Number of quizzes	6	9
Average answer rate	25%	22%

[a]: Lottery eligibility. 80% of the time: 192/240 min., 80% of the days: 16/20.

tion (1.4.2).

1.4.2 The Intervention: App Usage

Figures A.1 and A.2 in the Appenddix present information about app behavior of active users, i.e. students who on each day activated the app for at least one minute during class time, using data obtained directly from the app providers. The number of daily active users is higher in Spring (orange bars, left axis), with also a higher average number of minutes per afternoon (blue line, right axis)[14]. Figures A.3 and A.4 in the Appendix present the average daily number of minutes spent on the app by all users, i.e. considering the total number of students who at least downloaded the app in that semester.

Considering all active users (83 in Fall, 94 in Spring), Figures 1.2 and 1.3 present the session participation patterns in each semester. In both cases the percentage of people who never participate and those who participate in all the sessions is very similar, around 13% in Fall and 15% in Spring. However, students who comply with the minimum lottery eligibility requirement of attending at least 80% of the sessions for already 80% of the time is different: in Fall only 31% of the users participate at least 16 days, in Spring 44%. In Fall more students attend less than 5 classes (37% versus 32%), but in Spring 83% of these not-very-active users try only during the first week, compared to 71% in Fall. This suggests that there is a habit component related to the use of the app: the more you stick to it in the first week, the more likely you are to keep using it.

[14] The last Spring session on March 12 was affected by technical problems due to the app.

Figure 1.2: Frequency of individual patterns in session participation (total sessions: 20) – Fall.

	Example of pattern	%
Always		12.05
18-19 sessions		13.25
16-17 sessions		6.02
11-15 sessions		7.23
6-10 sessions		10.84
1-5 sessions		37.35
[of which, in the first week only]		*26.51 [71]*
Never		13.25
	N 83	100%

Figure 1.3: Frequency of individual patterns in session participation (total sessions: 20) – Spring.

	Example of pattern	%
Always		14.89
17-19 sessions		28.72
16 sessions		0
11-15 sessions		2.13
6-10 sessions		7.45
1-5 sessions		31.91
[of which, in the first week only]		*26.6 [83]*
Never		14.89
	N 94	100%

Looking deeper into session behavior, Table 1.7 presents information about the daily distribution of minutes. In Spring students are more active than in Fall, and moreover the students who participate in both semesters (those presented in column (3) as "Persistent Participants") appear since the beginning to be on average more engaged than their peers. Table A.4 in the Appendix summarises information about overall number of minutes spent on the app during the whole intervention (measured in hours).

The next set of tables and figures relies on self-reported information from the Post-Midterms survey in both Fall and Spring, with aggregated answers.

First, it is interesting to see that students do not have a clear recall of how much they used the app, probably because of the possibility to take breaks. Table A.5 in the Appendix contrasts students' reports versus actual usage for both Fall and Spring.

Table 1.8 presents the students' percent chance of keeping using the app after the end of the intervention, until the end of the semester. Students do not foresee to keep using it, as they report only a 37 percent chance on average. Figure A.5 in the Appendix contrasts reports from Fall and Spring, while Figure A.6 in the Appendix presents the distribution of the reported percent chance for both those who did not keep using it after the intervention and the students who indeed continued. Moreover, most students say that they would use the app only if they had it for free (70% of respondents), versus a 4% that would be willing to pay for the service[15]. This is at odds with what students report in terms of perceived usefulness (Thong, Hong, and Tam (2006)) as seen in Figure 1.4: most students tend to agree with the fact that the app is useful, helps them accomplish things more quickly, and increases their productivity.

One way to try to increase app usage is to inform students about the potential benefits stemming from its use; not only they perceive that it is useful in their everyday life, but also according to the results of this paper it may be beneficial for their academic performance. In fact Ersoy (2020) shows that the use of an online learning platform is driven by beliefs about its returns and the effectiveness of hard work. By assimilating the distraction-blocking app to a support tool for studying, and thus a complement to the study effort, it may be possible to induce students to use it more, presenting evidence about its returns in terms of increased performance.

Students may not want to use the app not because it does not help them but rather because they feel like it is too costly for them in terms of behavioral change. Figure

[15]In Fall I ask students about their general willingness to pay for an app on the basis of usage frequency (Figure A.7) and substitutability (Figure A.8).

Table 1.7: Summary statistics at the session level (in minutes) – Fall vs Spring.

Per Session, Minutes	**Fall 2020**	**Spring 2021**	**Persistent Participants**
Average minutes Fall	79		141
Min	0		0
Max	237		237
N	83		19
Average minutes Fall, if > 0	91		149
Min	1		3
Max	237		237
N	72		18
Average minutes Spring		103	142
Min		0	0
Max		240	240
N		94	19
Average minutes Spring, if > 0		121	159
Min		1	3
Max		240	240
N		80	17

Table 1.8: Reported percent chance of keeping using the app after the end of the intervention and Willingness to Pay – Post-Midterms, Fall & Spring.

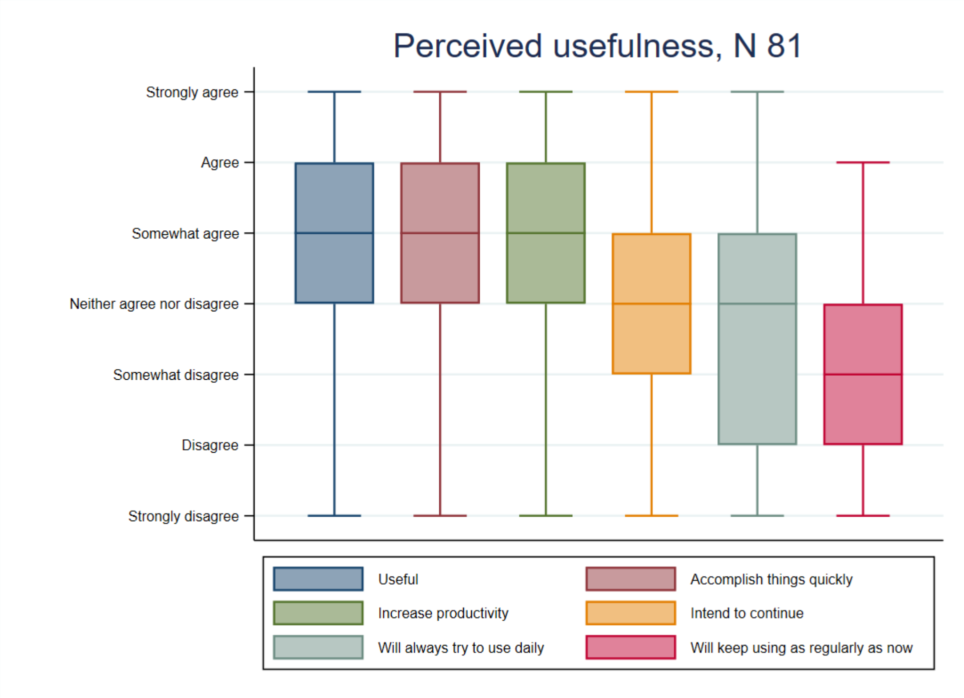
Percent chance that you will keep using the app?
(until the end of the semester = still for free)

Mean	*Std. Dev.*	*Min*	*Median*	*Max*
37.10	30.71	0	36.5	100

Would you pay to keep using this app?

	% Respondents
No, I would use it only if I had it for free	69.88
No, I would not use it even if it was for free	16.87
Not this app, but I would pay for a similar service	9.64
Yes	3.61
N	83

Figure 1.4: Perceived usefulness of the app – Post-Midterms, Fall & Spring.



In this and all following box-and-whiskers plots presented in the paper, the box spans from the 25th percentile (lower hinge) to the 75th percentile (upper hinge), reporting also the median with an inside-box line. The whiskers extend until the upper and lower adjacent values, which are the most extreme values within 1.5 times the interquartile range. Potential outliers are usually represented as round outside values.

A.9 in the Appendix presents the average perceived difficulty of various aspects related to the intervention, for example not receiving notifications or not checking the news. These features were evaluated on a slider from 0 to 100 to measure intensity. The average reported difficulty of not being able to check social media is higher, but none of these values are significantly higher than the others. The values attached to the inability of checking notifications in general, emails, social media, and news are statistically different from zero. Similarly Figure A.10 in the Appendix displays the reported difficulty of the intervention by week; the average perceived difficulty decreases, but values are not statically different. They are all statistically different from zero. Moreover, Figures A.11 and A.12 in the Appendix present the same information of, respectively, Figures A.9 and A.10 but separate the Fall and Spring samples.

Trying to monitor cheating behaviors I also asked students to report how they felt during the intervention. Table 1.9 reports their answers. More than 40% of respondents took breaks for “productive” reasons (e.g. checking Wikipedia), felt bored, and felt the need to check notifications. Some students cheated at times by activating the block when

Table 1.9: Reported feeling and reactions with the block active – Post-Midterms, Fall & Spring.

	% Respondents
If I took breaks, it was mostly for "productive" distractions	45
I was bored and felt I wanted to use my smartphone	45
I sometimes felt the need to check my notifications	42
I mostly forgot about my smartphone and carried out my activities	33
I sometimes cheated by using another device	20
I took a lot of breaks from the block	9
I sometimes cheated by activating the block when not studying	7
N	83

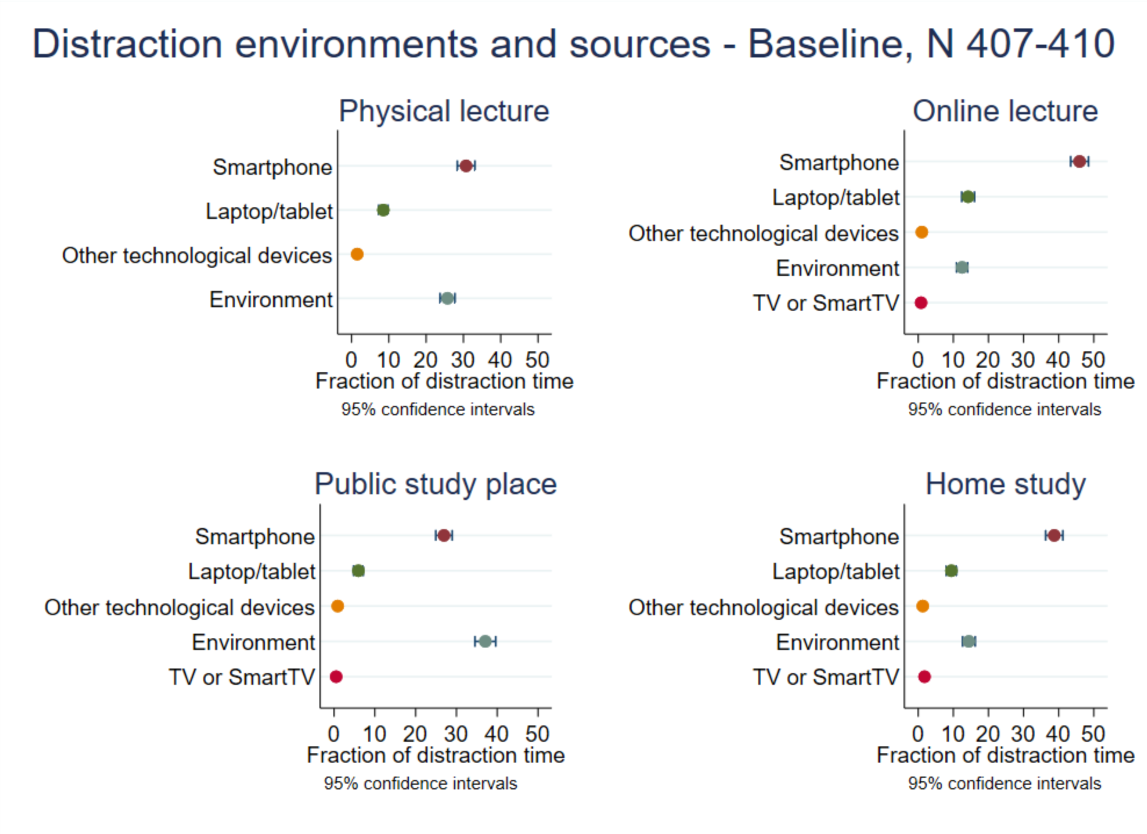
not studying (7%) or by using another device (20%).

1.4.3 Students' Study Habits

Which is the impact of study places on students' concentration? How do students react in different situations? I ask them to rank the sources of distractions, or rather how they seek distractions when they want them, considering different situations. In particular, I ask students to distinguish how distraction sources change in physical *versus* online classes, and in public spaces *versus* own home; respondents had to think about the percentage of times in which each situation happens. Figure 1.5 presents the results in terms of average fraction of times in which a certain tool is responsible for distractions. Overall, the smartphone is the primary source of distractions, together with the environment. While in the physical lectures these two factors are not statistically different, the smartphone is the primary distraction source in online lectures and when studying at home, while the environment gains the first place in public study spaces. Students in the a.y. 2020/21 experienced social distancing and faced many restrictions in terms of crowded gatherings and study/lecture spaces. These students mostly experienced online lectures and studying at home, thus situations in which the smartphone is the most distracting tool available. Moreover, the laptop or tablet does not seem to be important in these situations, probably because it is mostly used for attending classes and studying, while the smartphone is usually perceived as a source of entertainment and not as a study tool (Lepp et al. (2013)).

In Appendices A.3.3 and A.3.4 I present additional figures about other study-related behaviors and study time.

Figure 1.5: Average distraction factors when attending a physical lecture in class, when attending an online class, when studying in a public space, when studying at home – Baseline, Fall & Spring.



1.4.4 Students' Expectations

In the Post-Midterms survey I ask students about their grade expectations before knowing the results of the midterms. I ask them first the expected percent chance of passing each exam, and then the expected distribution of their possible grade, i.e. assigning a probability that their final grade will be in one of the six possible grade bins from 18 (passing grade) to 31 (where 30 is the maximum and 31 signals the attribution of *cum laude*); from this distribution I compute each subject's expected grade.

Table 1.10: Expected percent chance of passing each exam, conditional on having taken the exam – Post-Midterms, Fall & Spring.

	Mean	**Std. Dev.**	**Min**	**25^{th} perc.**	**Median**	**75^{th} perc.**	**Max**	**N**
Fall semester								
Management	77.09	16.18	30	70	76.5	90	100	116
Mathematics	72.43	21.86	0	61	75	90	100	130
Microeconomics	75.76	17.25	30	63	79	90	100	104
Other subjects	72.32	19.88	20	60.5	73	89	100	117
Spring semester								
Macroeconomics	78.6	20.94	5	70	83	96.5	100	112
Mathematics	87.43	20.97	12	80	100	100	100	115
Computer Science	87.7	17.11	0	80	93	100	100	140
Law	92.25	8.69	70	86.5	95	100	100	24
Other	79.19	20.48	13	68	79.25	100	100	34

Table 1.10 presents the expected percent chance of passing each exam by subject in the two semesters. Figures A.23 and A.24 in the Appendix present graphically the distributions of these expected percent chances. From the comparison of Fall and Spring it looks like students become more confident in the second semester, as the distributions seem to be shifted up (from the 25^{th} percentile upward). This may be due to the nature of the subjects, or to a better comprehension of the university experience and what is required by different examinations, or to having already received a signal from the first semester about own performance and ability to compete with classmates.

Figures A.25 and A.26 in the Appendix present graphically the distributions of the expected grades.

In my surveys I also ask students to state what they think the fraction of passing students will be in their class, and the average class grade. In Table 1.11 I present the comparison of own percent chance and expected grade, and the class expected fraction to pass and expected grade. While in Fall both percent chances to pass and expected grades tend to be lower than the expected class performance, in Spring in most of the cases more than half of the respondents expects to perform better under both accounts.

Table 1.11: EXPECTED PERFORMANCE (PERCENT CHANCE OF PASSING EACH EXAM, EXPECTED GRADE), OWN AND WITH RESPECT TO THE EXPECTED CLASS PERFORMANCE – POST-MIDTERMS, FALL & SPRING.

	Mean	Compared to the expected class performance, own is... lower than class average, (%)	equal to class average, (%)	higher than class average, (%)	N
Percent chance of passing					
Fall semester					
Management	77.09	69	8	23	116
Mathematics	72.43	54	8	38	130
Microeconomics	75.76	61	7	32	104
Other subjects	72.32	72	4	24	117
Spring semester					
Macroeconomics	78.6	40	6	54	112
Mathematics	87.43	26	3	71	115
Computer Science	87.7	34	11	55	140
Law	92.25	29	12	59	24
Other	79.19	47	9	44	34
(Derived) Expected grade					
Fall semester					
Management	25.02	63	2	35	116
Mathematics	24.47	46	4	50	131
Microeconomics	24.92	57	4	39	104
Other subjects	25.34	59	11	30	121
Spring semester					
Macroeconomics	25.05	50	2	48	110
Mathematics	25.12	41	5	54	112
Computer Science	26.38	43	2	55	133
Law	26.17	50	0	50	24
Other	24.87	41	0	59	32

In Fall I ask these same expectation questions in an additional survey wave, Pre-Midterms. In that questionnaire I also elicit the students' network of friends, asking them to report the friends' names, and I therefore introduce an additional set of friend-specific expected performance questions. Table A.8 in the Appendix summarises this information by computing the average friends' percent chance of passing each exam and the average friends' expected grade, and I then compare own performance with expected friends' performance. In Fall students expect to perform worse than their friends in most of the cases, both in terms of percent chances of passing (with 66% to 79% of the respondents reporting an own percent chance lower that their friends' average) and expected grade (with 72% to 85% of the respondents reporting an own expected grade lower that their friends' average), in line with expected performance with respect to the class but with even a more negative outlook.

Given that the Fall midterm exams are the first university examinations that these students take, it is understandable that they may have a distorted perception of both what is required in order to pass the exams and their own abilities. The fact that many students tend to report an expected performance lower than their actual one (as is the case in my data[16]) may be good for boosting their effort; in fact Beattie et al. (2016) find that students who perform below their own expectations also self-report greater tendency to procrastinate and being less gritty than their peers. The fact that the students in my sample do the opposite, i.e. perform above own expectations, may be an incentive for putting more energy into studying if they see that their effort is rewarded.

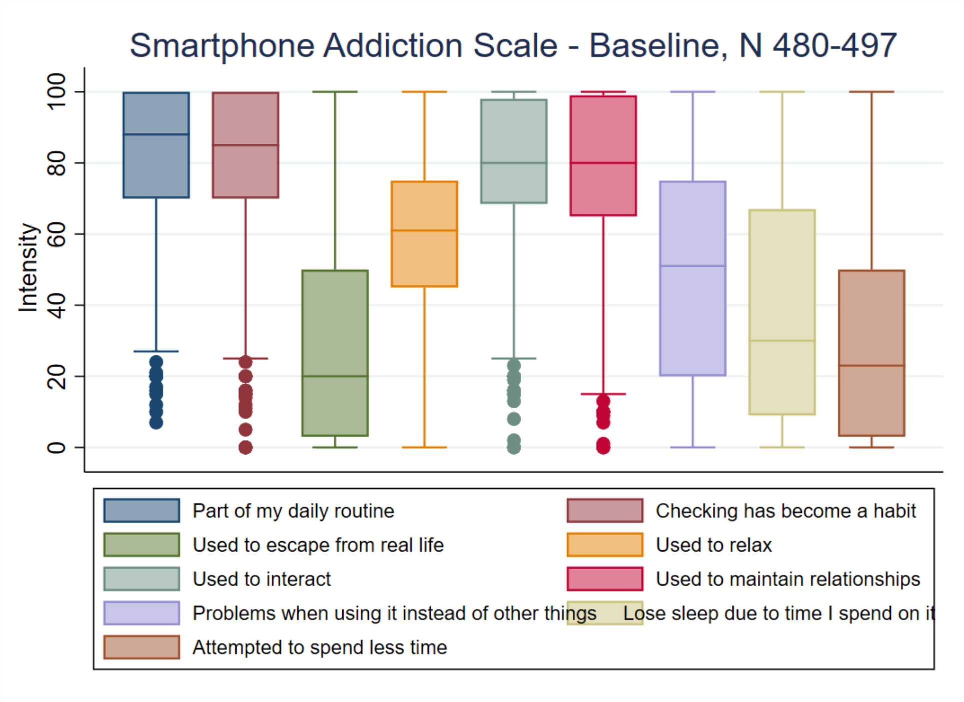
1.4.5 Students' Smartphone Habits

I exploit some items from van Deursen et al. (2015) in order to determine which is the perception that students have of their relationship with their smartphone. Differently from the authors' setting, I do not rely on Likert scales but rather on sliders, i.e. horizontal bars that appear on screen and indicate at the two extremes two opposed behaviors, e.g. agreeing and disagreeing with a statement. By clicking on the bar in the desired range a pointer and a value appear, thus indicating how close the individual feels to one of the two extremes. Questions have been designed such that the horizontal bar spans from 0 to 100, where 0 is associated with the most negative perception (i.e. strong disagreement or dislike). I use this visual device instead of eliciting subjective probabilities because the latter are usually biased by the use of reference numbers (0%, 50%, and 100%). Bruine de Bruin and Carman (2018) compare the distributions of open-ended and visual-scale responses, and report that indeed using a linear scale reduces the use of focal responses.

Students were presented some statements and had to move a slider from a value of 0 to 100 according to how relatable the sentences were for them; an increasing value means that the statement represents them more. Figures 1.6, 1.7, and 1.8 present the distribution of the answers to the statements across the three survey waves: Baseline, Post-Midterms, End of Semester (Fall and Spring answers aggregated). In most cases the average value significantly increases over time from the Baseline survey at the beginning of the term to the Post-Midterm period (e.g. for "I use my smartphone to escape from real life", "... to relax", "... to interact with people", "... to maintain relationships") or to the End-of-Semester survey ("Checking has become a habit") or both ("Checking my smartphone is part of my daily routine", "I lose sleep due to the amount of time I spend on it", "I have attempted to spend less time using it, but I am unable to", "I experience problems when

[16] I do not show this analysis here. In the Fall semester, where I gather both pre-midterms expectations and post-midterms expectations, it is interesting to see how not only students expect *ex ante* a performance worse than the actual one, but their *ex post* expectations are even lower, thus indicating that the perceived difficulty of the exam is not a self-explanatory signal of own ability to pass it: students need to see their grades.

Figure 1.6: Distribution of the Smartphone Addiction Scale items – Baseline, Fall & Spring.



I find myself using my phone instead of doing other things"). The statistical significance of differences is reported in Table A.9 in the Appendix.

Table 1.12 presents some information about the intensity of smartphone usage. Students report being registered to an average of 8 to 10 social media platforms, and 74-78% of them report posting stories[17] on a regular basis. Students use a selection of apps, concentrating regular use of 5 to 20 apps (82-88% of respondents).

In the Appendix Figures A.27 and A.28 report the frequency of reported reasons why students use their smartphones, at the beginning and end of the semester (Fall and Spring, aggregated answers). The most common reasons are: messaging, listening to music, social media and blogs, phone calls. Figure A.29 in the Appendix contrasts the answers given in Fall and Spring (matched respondents).

On the other hand, students reported some different reasons for usage during high school. Figure A.30 in the Appendix shows that most students used their smartphones for messaging and internet banking; less for listening to music and taking videos and pictures.

As for self-reported usage in terms of time, Figure 1.9 presents aggregated data at baseline and at the end of the semester. Over time students declare using their smartphones increasingly more, with a percentage of respondents that use it less than 2 hours per day

[17] On social media platforms like Instagram, Facebook, or WhatsApp, stories are short video content that stays online 24 hours.

Figure 1.7: Distribution of the Smartphone Addiction Scale items – Post-Midterms, Fall & Spring.

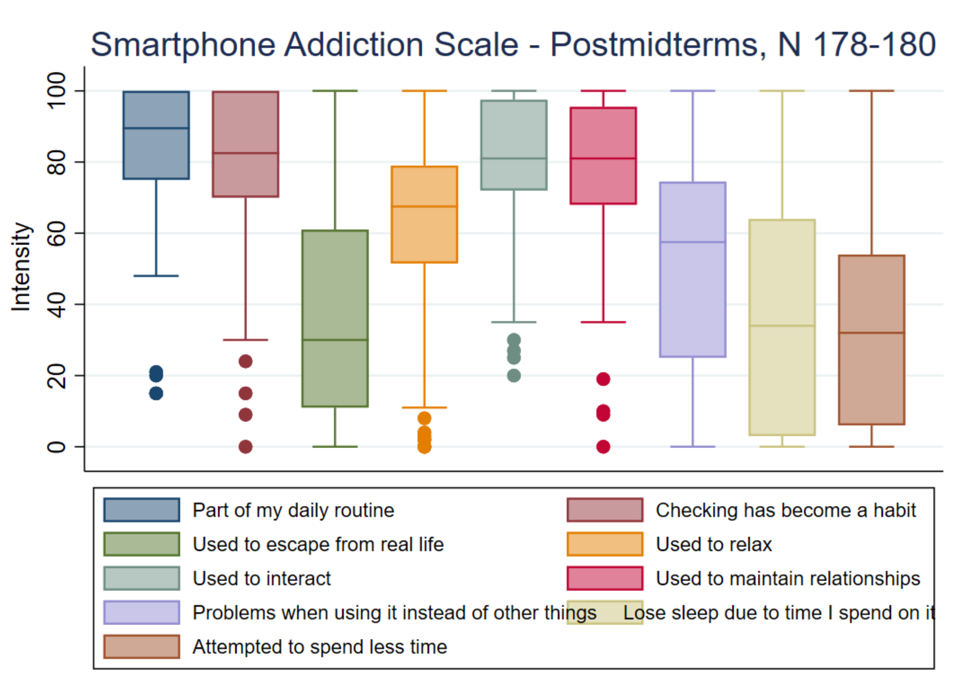


Figure 1.8: Distribution of the Smartphone Addiction Scale items – End of Semester, Fall & Spring.

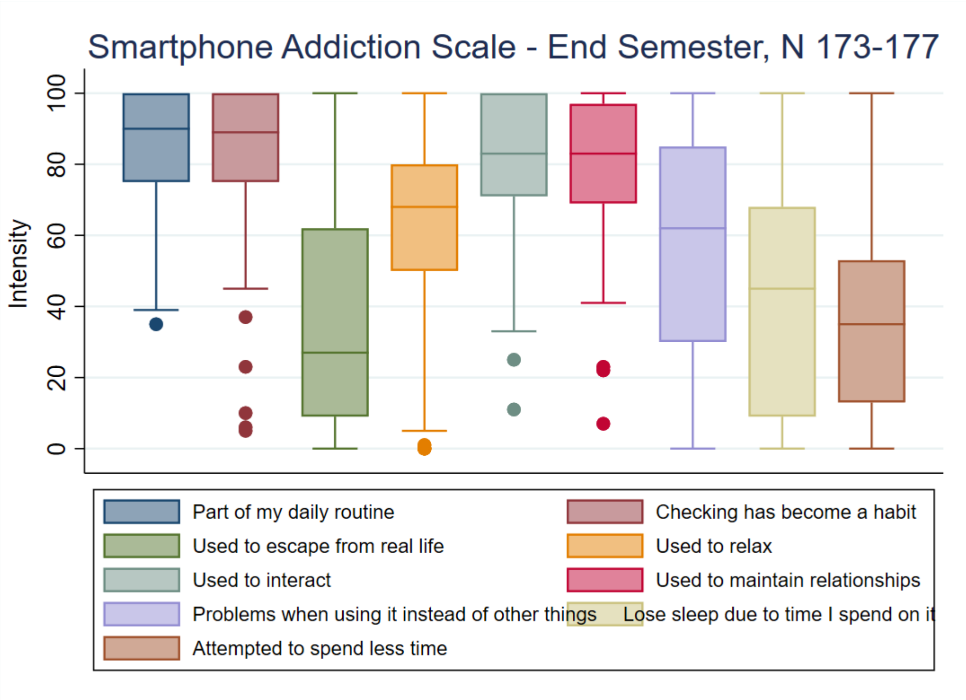


Table 1.12: Descriptive statistics of social media and app use – Fall vs Spring.

Social media and smartphone apps

Number of social media (as registered user)	**Mean**	**Std Dev**	**Min**	**Max**	**N**
Baseline, Fall	7.71	3.57	0	19	483
Baseline, Spring	9.99	4.60	0	23	128

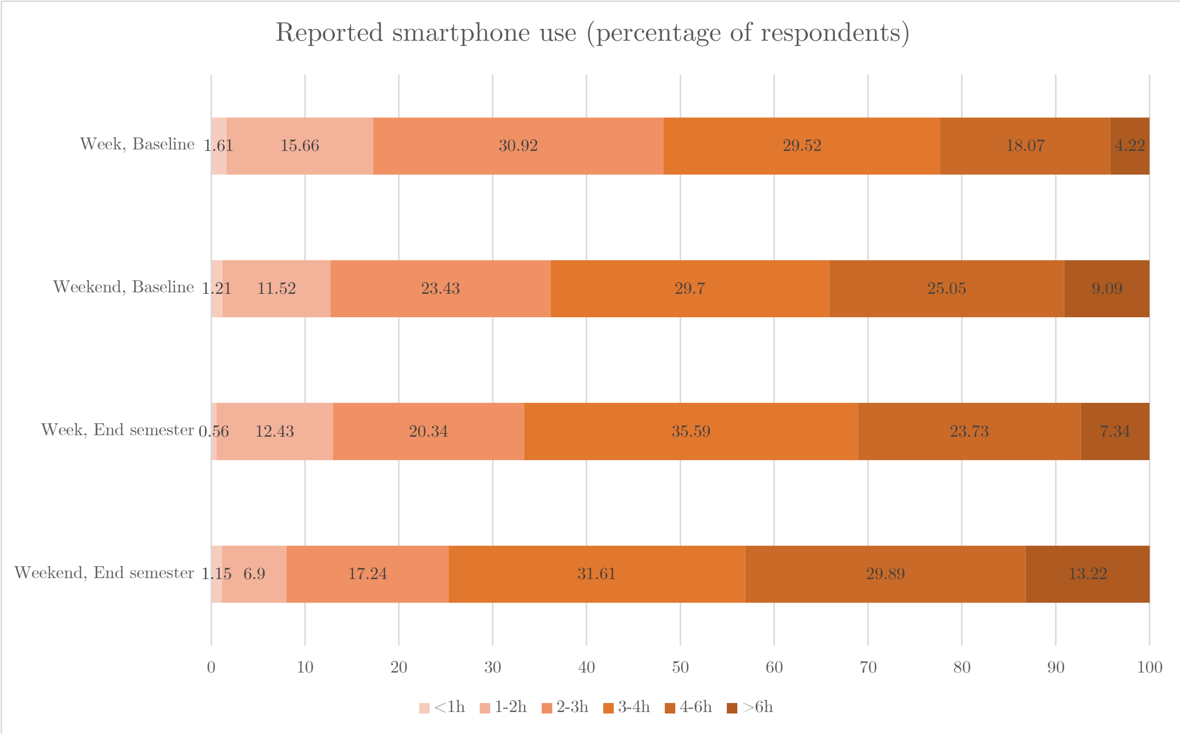
Do you post stories on social media?	**% Yes**	**Std Dev**	**N**
Baseline, Fall	77.73	0.42	458
Baseline, Spring	74.38	0.44	121

Number of apps used weekly (%)	**Baseline, Fall**	**End semester, Fall**	**Baseline, Spring**
Less than 5	8.87	5.04	8.2
Between 5 and 10	41.13	36.13	45.9
Between 10 and 15	27.06	30.25	28.69
Between 15 and 20	14.5	15.97	13.11
Between 20 and 30	5.84	10.92	3.28
More than 30	2.6	1.68	0.82
N	462	119	122

falling from 17% to 13% during the week (13% to 8% on weekend days), and those who use it more then 4 hours a day shifting from 22% to 31% (34% to 43% on weekend days).

In the Appendix Figure A.31 and Table A.10 present the same information distinguishing Fall and Spring.

Figure 1.9: FREQUENCY OF REPORTED SMARTPHONE USE ON A DAILY BASIS – BASELINE, FALL & SPRING.



1.4.6 Demographics and Family Background

Table 1.13 shows that survey respondents are mostly male (55%) and born in Italy (78%), not far from the overall Bocconi first-year cohort average (respectively, 60% and 79%). Sixty-four percent of respondents declare to live within 4km from the Bocconi campus, and an additional 9% lives in Milan but a bit further away, with a 39% that reports living with their families.

Inference on the socio-economic background can be made by looking at some indicators. Fathers are mostly either self-employed (49%) or full-time employees (49%), compared to only 32% and 46% for mothers. Fifty-one percent of the respondents report having had more than 200 books in the home where they grew up, thus giving us an idea of the value placed on education and reading in the family[18]. Almost 80% of the students have siblings. Table 1.14 presents the educational achievements of older family members, showing how the majority has at least some university education (65% of fathers, 70% of mothers, 52% of older siblings) while some of the 45% of older siblings that achieved a high school diploma may be still in the process of obtaining a higher degree.

[18] This question was borrowed from the PISA students' questionnaire of 2015. OECD provided evidence that the number of books in the home correlates with engagement and reading literacy.

Table 1.13: Demographics and family indicators for survey respondents – Baseline, Fall & Spring.

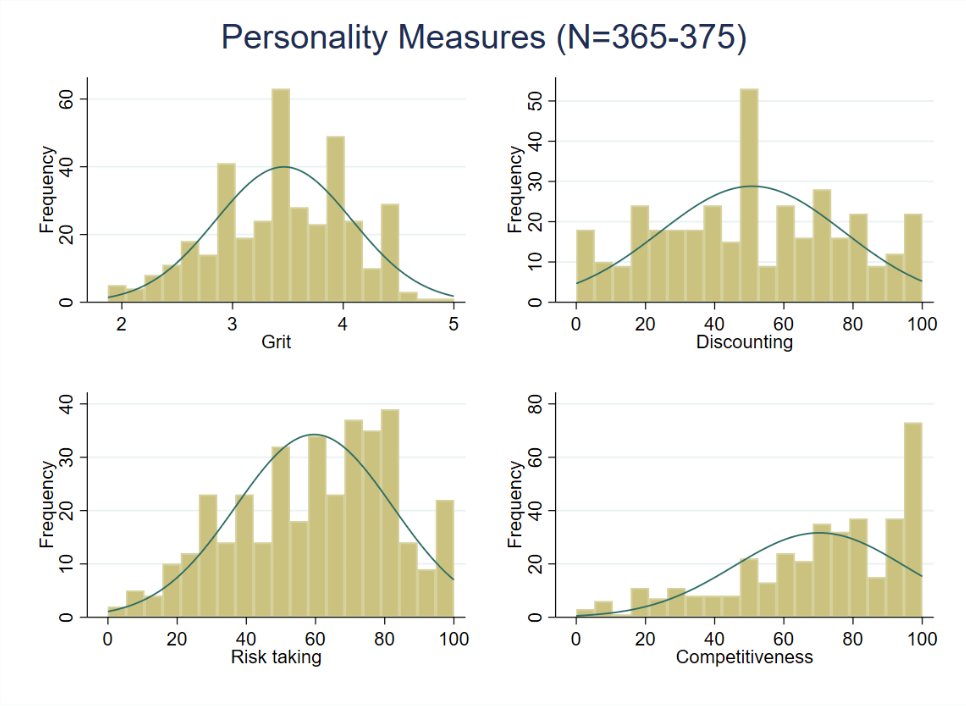
	Mean, %	**N**		
Demographics				
Female	.45	625		
Born in Italy	.78	519		
Father born in Italy	.74	519		
Mother born in Italy	.72	519		
At least one parent born in Italy	.77	519		
Both parents born in Italy	.69	519		
Residence				
Living with family	.39	518		
	Mean	**Min**	**Max**	**N**
If not with family, living with n. people[a]	1.54	0	5+	286
Distance from campus				
	Mean, %	**N=518**		
Below 4km (in Milan)	.64			
Above 4km (in Milan)	.09			
Another city in Italy	.22			
Living abroad	.05			
Number of books at home				
	Mean, %	**N=380**		
0-10 books	.01			
11-25 books	.03			
26-100 books	.19			
101-200 books	.25			
More than 200 books	.51			
Family				
	Mean, %			
Self-employed father	.49	**N=481**		
Full-time employee father	.49			
Part-time employee father	.02			
Self-employed mother	.32	**N=479**		
Full-time employee mother	.46			
Part-time employee mother	.14			
Having siblings	.79	518		
	Mean	**Min**	**Max**	**N**
Number of older siblings	1.28	1	4	195

[a]: Fall only.

Table 1.14: Highest educational achievements of parents and older siblings – Baseline, Fall & Spring.

	Mean, %	**N**
Older siblings		
Lower secondary	.02	264
Upper secondary	.45	
Bachelor	.28	
Master	.22	
PhD	.02	
Father		
Lower secondary	.04	512
Upper secondary	.31	
Bachelor	.12	
Master	.43	
PhD	.10	
Mother		
Lower secondary	.03	508
Upper secondary	.27	
Bachelor	.16	
Master	.43	
PhD	.11	

Figure 1.10: Distribution of personality measures – Fall & Spring.



1.4.7 Personality and Anxiety

In the surveys I ask baseline questions about personality traits and some repeated observations of items related to anxiety.

As for personality I use three questions addressing in turn discounting, risk-taking, and competitiveness, all on a 0-100 slider, and an eight-item "grit" measure as introduced by Duckworth and Quinn (2009) and Duckworth, Peterson, et al. (2007), assessing the ability to maintain focus and interest, and the perseverance for pursuing long-term goals. Figure 1.10 presents graphically the distributions of the four variables.

In the Appendix, Figure A.32 presents the distribution of the answers to the three questions, while Table A.11 presents summary statistics for the value of grit, both for the overall sample and by gender.

For anxiety I rely on the State Trait Anxiety Inventory (STAI-Y) introduced by Spielberger (1983), a validated self-assessment device. The first 20 items aim to elicit the "trait anxiety", i.e. the general attitude of the individual, while the next 20 items focus on the "state" component, i.e. how anxious the individual is on that day or in that period. I used both the original English version and the validated Italian translation (Spielberg (1989)), as the survey could be taken in both languages. Questions are in the form of short sentences ("I feel calm") and they need to be rated according to a four-point Likert scale, thus allowing for the computation of a score: higher scores are positively correlated with

Table 1.15: Summary statistics of STAI scores, both Trait and State – Fall & Spring.

	Mean	Std. Dev.	Min	Median	Max	N
STAI-Y Score, Trait	46.63	10.76	26	45	71	191
By gender						
Male students	44.65	11.12	26	43	71	81
Female students	48.62	10.09	28	49	71	86
STAI-Y Score, State						
Post-Midterms	52.99	11.59	29	54	78	182
End Semester	50.97	12.33	20	51	77	173
By gender						
Post-Midterms, male students	49.45	11.60	29	47	78	83
Post-Midterms, female students	56.08	10.75	31	57	78	98
End Semester, male students	47.27	11.06	25	46	76	83
End Semester, female students	54.52	12.45	20	56	77	87

higher levels of anxiety. Scores can range from 20 to 80. Administration of this test was not carried out in a controlled lab setting, and therefore no conclusions about pathological conditions can be made.

Table 1.15 presents the summary statistics of STAI scores, both for the overall sample and according to gender, aggregating answers from Fall and Spring.

1.4.8 Further Descriptives

In the Appendix I also introduce some information about the use of technologies in the families (section (A.3.8)) and the network at Bocconi (section (A.3.9)). I alsp elicit COVID-19 perceptions and expectations (section (A.3.10)); I do not report it here as this set of questions was asked only at the very beginning of the academic year, in September 2020 (within the Fall Baseline), and I do not exploit this information in my analysis.

1.5 Dealing with Potential Selection Threats

Selection in my sample may happen at different levels, as shown in Figure 1.11:

1. the first layer is represented by the the potential pool of students (i.e. the first year cohort, ca. 2500 students as seen in Table 1.2) *versus* the actual survey respondents and/or participants[19]. To address this layer I would need information about all the first-year students who decided never to take any survey or participate in the intervention, but I do not have this information;

2. the second layer is thus represented by the students who only participated in the surveys *versus* those who at least in one semester expressed their willingness to be involved in the challenge[20]. This is the most important layer of selection in my following analysis;

3. the third layer of selection is represented by students who volunteered but never took any action *versus* those that at least downloaded the app;

4. the fourth layer is represented by students who at least downloaded the app and may have used it a little *versus* the students who actively complied with the minimum requirements for participating in the lottery (i.e. activating the app on at least 80% of the required days for at least 80% of the time on each of them).

In this analysis my results are in terms of intention to treat, therefore I compare students assigned *versus* not assigned to the treatment; the most important layer of selection operating here is the second one. The last two layers mentioned are of secondary importance as they do not impact my results, but they are still addressed in the next sections.

Formally selection can be defined as

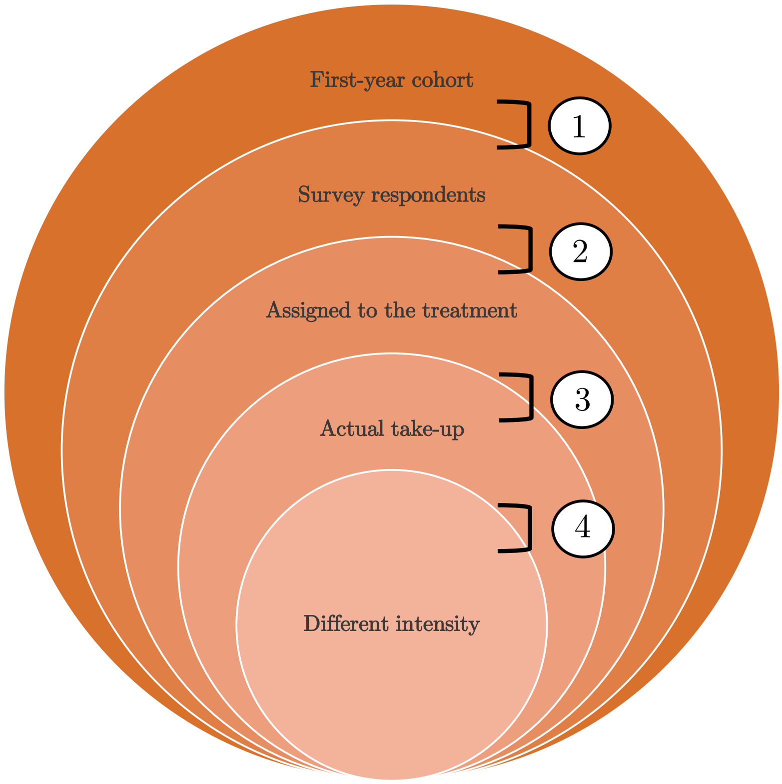
$$D = \mathbb{1}[\mathbf{Z}\boldsymbol{\delta} + \nu > 0]$$

[19]In the Fall I first asked students to respond to a survey, and then I asked their willingness to participate to the intervention. I used as control students those who answered to the Fall baseline survey but did not volunteer. In Spring I directly ask for the students' willingness to participate in the intervention. Then I use as control for the surveys those students that participated (to the surveys and/or the intervention) in Fall but who did not volunteer in Spring.

[20]Participation in the intervention was offered to all the students willing to participate "in an experiment" (Fall)/"in a challenge" (Spring). Those who only answered to the surveys but never volunteered for the project are my controls.

where, in the case of our layer 2, indicator $D = \{0, 1\}$ is participation in the intervention, the multidimensional vector $\mathbf{Z}$ represents the exogenous characteristics and includes at least one factor that affects selection[21], and ν is the error term.

Figure 1.11: Graphical depiction of all the possible layers of selection in the intervention.



One additional friction layer in my dataset is given by the fact that I implemented the intervention both in Fall and Spring of a.y. 2020/21. When invited to participate in the Fall semester students did not not know what the intervention was about, and this led to a compliance rate of 38%, as most of the students who volunteered to participate then did not take any action (not even download the app). Moreover, the non-explicit recruitment may have caused the potential exclusion of students interested in the distraction blackout initiative but who refused to participate blindly. In the Spring semester the recruitment more explicitly referred to "a challenge to help you improve your study habits", and this may have differently selected the students on the basis of their behavioral traits and problems. Take-up in Spring was 42%.

In order to deal with potential selection in my sample, I approach it in two different ways.

[21] Once we assume that our observable measures capture all the relevant factors that drive selection, then $\mathbf{Z} = \mathbf{X}$.

First, I use survey measures to assess whether there are imbalances between any two layers. I explore differences in observed characteristics across four dimensions elicited at baseline: academic motivation; sources of distractions in class or while studying; personality traits; smartphone habits. I check for imbalances in the following groups: students ever assigned to the treatment *versus* students not willing to participate (layer 2 in Figure 1.11, analysed in section (1.5.1)); among the students assigned to the treatment, students who never take any action *versus* students who at least download the app and enter the class (layer 3 in Figure 1.11, section (1.5.2)); among the students who at least download the app, students who may have just downloaded it and used a little *versus* students who actively comply with the minimum requirements to be eligible for the lottery (layer 4 in Figure 1.11, section (1.5.3)); Fall *versus* Spring students assigned to the intervention (section (1.5.4)). The analysis on the layers 2 to 4 is conducted by pooling respondents from the two semesters.

Second, when detecting the ATT I use propensity score matching to identify a suitable control group. To build the propensity score I rely on administrative measures to ensure comparability and increase the sample size (see section (1.6.3) for the balance checks).

While selection represents a potential threat to the identification of a causal relationship, in this context it is appropriately dealt with through the use of the propensity score. As for the external validity of this work, the fact that students accepted to participate in the intervention without knowing exactly the required tasks to perform on the app ensures that there is no Hawthorne effect. Results can be generalized to other situations where there is awareness about potentially harmful habits that individuals want to change.

1.5.1 Layer 2: Assigned to the Treatment *versus* Not Assigned

In this section I evaluate the potential selection between students who at least participated in one survey but never expressed their willingness to participate in the intervention (*Never Treated*) *versus* students who were assigned to the treatment in at least one semester (*Treated*). Tables from 1.16 to 1.19 explore potential imbalances across smartphone habits, sources of distractions in class or while studying, academic motivation measured as expected GPA under different attendance scenarios, and personality traits. All these measures have been elicited at baseline before the intervention.

Table 1.16 shows that there are some differences in terms of smartphone behavior, in particular with reference to the items of the Smartphone Addiction Scale (van Deursen et al. (2015)), measured on a slider from 0 to 100. Students who participated in the intervention display a closer relationship with their smartphones, as they report significantly higher intensities for both positive (e.g. "I use my smartphone to maintain relationships") and negative items (e.g. "I experience problems when I find myself using my mobile phone when I should be doing other things"). Moreover, students assigned to the intervention are also those who potentially use more social media (they are registered users in more platforms) and feel more pressure in having to answer quickly in digital interactions. This means that students who volunteer to participate are those that may be indeed interested in the project and could potentially benefit more. If the assigned students were those with lower values for these categories, then this would mean that their participation would be costless or requiring less effort. Instead, students who decide to accept the challenge are those for which activating the block is actually relevant as they are more likely to be more dependent on their smartphones according to these measures.

Table 1.16: Smartphone Addiction Scale Items at Baseline, Never Assigned vs Assigned.

	Never Treated		Treated		Difference	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Part of my daily routine	80.911	21.603	86.752	17.113	-5.842**	2.182
Checking has become a habit	78.821	22.954	82.889	19.873	-4.068	2.355
Used to escape from real life	26.476	26.499	35.817	30.030	-9.341**	2.918
Used to relax	57.077	24.749	59.724	26.405	-2.647	2.669
Used to interact	77.412	21.660	80.410	20.896	-2.999	2.272
Used to maintain relationships	75.346	23.455	81.162	19.792	-5.817*	2.395
Have problems when using it instead of doing other things	46.281	31.215	58.897	31.592	-12.616***	3.320
Lose sleep due to time I spend on it	36.631	31.994	44.835	33.389	-8.203*	3.453
Attempted to spend less time, but unable to	26.962	26.691	38.353	30.865	-11.392***	2.959
Number of social media *(registered user)*	7.662	3.750	9.463	4.113	-1.801***	0.397
Posting stories? *(dummy)*	0.785	0.411	0.767	0.424	0.018	0.044
Pressure to answer quickly *(slider: 0-100)*	36.316	25.613	46.564	28.771	-10.248***	2.794
Multiple Hypotheses Testing						F(12,454)=3.41 Prob> F = 0.0001
Observations	408		121		529	

Students do not differ in terms of academic motivation (Table 1.18) or personality traits (Table 1.19).

Ultimately these imbalances do not threat the causality of my estimates. Students who volunteer to participate are those who both need to decrease their smartphone consumption and are aware of it. Other studies that find positive effects of commitment devices on reduced use also report that results are driven by individuals who indeed wished for a change in their habits or reported higher addiction measures before the interventions (Hoong (2021), Allcott, Gentzkow, and Song (2021)). The students who participate in my challenge are indeed sophisticated people who foresee that they might have self-control

Table 1.17: Distractions Factors at Baseline, Never Assigned vs Assigned.

	Never Treated		Treated		Difference	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Physical lecture						
Smartphone	29.886	23.638	32.711	26.079	-2.825	2.640
Laptop/tablet	8.377	13.411	8.876	11.300	-0.499	1.389
Other technological devices	1.536	6.748	1.496	5.720	0.040	0.700
Environment	26.841	21.460	23.074	18.019	3.766	2.221
I don't get/seek distractions	32.242	32.350	32.702	33.091	-0.460	3.527
Other	1.118	6.208	1.140	7.531	-0.023	0.717
Online lecture						
Smartphone	44.524	26.261	49.383	25.749	-4.859	2.837
Laptop/tablet	13.830	19.271	15.150	17.387	-1.320	2.036
Other technological devices	0.979	4.661	1.200	5.954	-0.221	0.551
Environment	13.104	16.434	11.033	15.969	2.071	1.771
I don't get/seek distractions	24.802	28.812	22.075	26.120	2.727	3.048
Other	1.729	10.451	0.875	5.749	0.854	1.013
Studying in a public space						
Smartphone	26.111	20.489	28.967	20.891	-2.856	2.239
Laptop/tablet	5.899	12.742	6.167	10.483	-0.267	1.317
Other technological devices	0.906	3.741	0.917	4.727	-0.010	0.441
Environment	37.865	26.401	35.225	25.252	2.640	2.833
I don't get/seek distractions	26.771	29.358	27.050	28.269	-0.279	3.156
Other	1.733	11.222	1.617	10.436	0.116	1.195
Studying at home						
Smartphone	37.502	25.050	41.717	25.372	-4.215	2.734
Laptop/tablet	8.422	14.540	11.842	15.560	-3.420*	1.614
Other technological devices	1.118	4.770	1.742	7.018	-0.623	0.601
Environment	15.265	18.470	12.417	18.410	2.848	2.006
I don't get/seek distractions	34.446	33.062	30.208	30.385	4.238	3.511
Other	1.077	6.829	1.158	8.082	-0.082	0.785
Multiple Hypotheses Testing						F(23,383)=0.93 Prob> F = 0.5584
Observations	289		121		410	

Table 1.18: Expected GPA at Baseline under Different Scenarios, Never Assigned vs Assigned.

	Never Treated		Treated		Difference	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Fully on campus	27.080	3.240	26.596	4.326	0.484	0.406
Half on campus, half online	26.379	2.689	26.404	2.240	-0.025	0.286
Fully online	24.599	3.772	24.748	4.161	-0.149	0.442
Not attending	21.127	4.364	21.811	4.752	-0.684	0.520
Multiple Hypotheses Testing						F(4,332)=1.40 Prob> F = 0.2348
Observations	270		115		385	

Table 1.19: Personality Measures at Baseline, Never Assigned vs Assigned.

	Never Treated		Treated		Difference	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Discounting *(slider: 0-100)*	51.451	26.281	49.287	27.379	2.164	3.051
Risk taking *(slider: 0-100)*	60.596	22.045	57.282	24.023	3.314	2.576
Competitiveness *(slider: 0-100)*	70.565	25.100	69.609	23.738	0.956	2.807
Grit *(scale: 0-8)*	3.474	0.604	3.440	0.645	0.034	0.070
Multiple Hypotheses Testing						F(4,356)= 0.57 Prob> F = 0.6861
Observations	267		110		377	

problems in the future and may have present-biased tendencies (O'Donoghue and Rabin (1999)). As Bianchi and Phillips (2005) state, problematic behaviors associated with mobile phones are due to lack of self-control and/or societal control, and with this intervention I supply a commitment device to these sophisticated students who need it and are aware of needing it.

The unbalanced survey measures from Table 1.16 will be used, together with administrative variables, to construct the propensity score.

1.5.2 Layer 3: Assigned to the Treatment *versus* Participating Users

In this section I address the potential selection between students assigned to the treatment but who do not even enter the distraction blackout class in the app (*Assigned, Never*) *versus* students who at least download the app and enter the class, regardless of their degree of participation (*Assigned, Participating*).

Table A.17 in the Appendix shows that some imbalances across the Smartphone Addiction Scale items remain, mostly due to social interactions ("I use my smartphone to interact with people", students are more likely to post stories regularly on social media) and entertainment ("I use my smartphone in order to relax", "I use my smartphone in order to escape from real life").

Table A.18 in the Appendix highlights the fact that actively participating students are more likely to be distracted by the environment when studying in a public space. Tables A.19 and A.20 in the Appendix show that the samples are balanced in terms of expected GPA at Baseline and personality traits.

Again, this is in line with the results commented in the previous section. Students who actively participate, instead of only volunteering, are those who need a commitment device even more. They use their smartphones more to communicate, potentially receiving more notifications from social media and messaging apps, and are the individuals who primarily benefit from a distraction-blocking software.

1.5.3 Layer 4: Participating *versus* Compliers

Another relevant degree of selection is in terms of intensity of the treatment. In fact students are asked to download the app and join the distraction blackout class voluntarily for four hours each afternoon during the week, for a total of four weeks. To incentivise students to participate and not to take too many breaks from the app on each afternoon, at the end of the intervention I randomly assign Amazon gift cards to eligible students. Eligibility is based on activating the app on at least 80% of the days (i.e. 16/20 days) and on each of these days for at least 80% of the time (i.e. 192/240 minutes).

It is then natural to compare students who participated by at least downloading the app and entering the class (*Participating*) *versus* students who actively comply with the minimum requirements laid out to be eligible for the lottery (*Compliers*).

Table A.22in the Appendix shows that the two groups are balanced in terms of smartphone habits. Table A.23in the Appendix shows that students who do not comply with the minimum requirements are those more distracted by their environment during online classes, and Table A.24in the Appendix indicates that these students would also expect a lower GPA in case they attended Bocconi as non-attending students. Table A.25in the Appendix displays no imbalances in terms of personality traits.

1.5.4 Across Semesters: Assigned to the Treatment, Fall *versus* Spring

In sections (1.5.1), (1.5.2), and (1.5.3) I pooled together the samples from the two semesters. In this section I explore potential differences between the students assigned to the intervention in Fall *versus* Spring. As detailed in section 1.3.2, recruitment from Fall to Spring was slightly changed with the objective of increasing the take-up rate, and this may have impacted the selection of the sample.

Table 1.20 presents only one difference, namely the fact that students in the Spring sample report having had more troubles with the time they spent on their smartphones ("I have attempted to spend less time on my mobile phone but am unable to"). This is in line with the different recruitment carried out in the Spring semester: these students are those motivated to challenge and improve their study habits because they are those that struggled more with them. Also Table 1.21 tells a similar story, as Spring students are more likely to be distracted by their laptops compared to Fall participants. Both these traits may however be a natural outcome of social distancing and the teaching models adopted during the a.y. 2020/21 due to the COVID-19 pandemic: students were forced to reduce social engagements and to spend more time in front of their laptops; this may have led to a general increase in problematic smartphone usage and laptop distractions in the whole cohort over the academic year. Tables A.27 and A.28 in the Appendix show

Table 1.20: Smartphone Addiction Scale Items at Baseline, Fall vs Spring.

	Fall		Spring		Difference	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Part of my daily routine	82.904	20.080	89.212	13.716	-5.803	3.759
Checking has become a habit	81.942	20.945	81.909	20.590	-0.740	3.492
Used to escape from real life	27.569	29.608	38.200	29.067	-7.246	6.616
Used to relax	56.471	27.702	60.667	27.153	-0.059	5.754
Used to interact	77.346	23.605	80.712	22.171	-2.414	4.204
Used to maintain relationships	78.654	22.911	81.636	19.613	-2.786	4.042
Have problems when using it instead of doing other things	45.392	34.839	61.576	31.282	-9.905	6.131
Lose sleep due to time I spend on it	33.098	34.132	47.109	32.216	-10.192	7.056
Attempted to spend less time, unable to	20.800	24.361	44.606	29.882	-27.063***	6.115
Number of social media (registered user)	8.731	3.144	9.899	4.226	-0.562	0.885
Posting stories? *(dummy)*	0.788	0.412	0.754	0.434	0.026	0.091
Pressure to answer quickly *(slider: 0-100)*	40.288	29.457	48.091	26.548	-8.358	6.200
Multiple Hypotheses Testing						$F(12,375) = 4.23$ $Prob > F = 0.000$
Observations	52		69		100	

that the samples are balanced in terms of academic expectations and personality traits.

Table 1.21: Distractions Factors at Baseline, Fall vs Spring.

	Fall		Spring		Difference	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Physical lecture						
Smartphone	27.862	22.911	35.435	25.570	-7.250	5.344
Laptop/tablet	5.845	8.776	11.043	12.897	-5.136*	2.325
Other tech devices	0.569	1.748	2.000	7.304	-0.632	0.863
Environment	27.931	20.815	20.986	15.620	5.175	3.923
Online lecture						
Smartphone	46.638	24.902	55.632	25.988	-6.144	5.163
Laptop/tablet	10.569	12.982	17.529	19.958	-5.823	3.719
Other tech devices	0.086	0.657	1.794	7.589	-1.478	1.098
Environment	13.741	16.288	6.706	9.408	2.829	3.462
Studying in a public space						
Smartphone	29.017	20.714	25.912	18.679	2.494	4.466
Laptop/tablet	4.810	8.949	7.456	11.585	-3.141	2.273
Other tech devices	0.983	4.854	0.779	4.438	0.948	0.818
Environment	39.000	25.211	37.824	25.459	3.323	5.242
Studying at home						
Smartphone	38.569	25.589	44.603	26.970	-3.076	5.334
Laptop/tablet	7.310	12.644	13.691	16.681	-4.980	3.324
Other tech devices	1.190	6.080	2.059	7.479	-0.185	1.449
Environment	16.483	21.343	9.500	13.650	3.337	3.969
Multiple Hypotheses Testing						F(23,291)=0.90 Prob> F = 0.6011
Observations	58		69		100	

1.5.5 Predictors of Assignment to and Intensity of the Intervention

To check which baseline measures predict treatment participation, I use all the variables considered until now in a regression framework. I use all the measures related to smartphone habits, sources of distractions in class or while studying, academic motivation, and personality traits. I regress them all on five different dummies, corresponding to the five columns of Tables 1.22 and 1.23: first, whether the students has ever been assigned to the intervention or not (*Never Treated/Assigned* vs *Treated/Assigned*, as defined before); second, conditional on having been assigned, whether the student has at least downloaded the app (*Assigned* vs *Participating*, as defined before); third, conditional on having been assigned, whether the student has at least used the app; fourth, conditional on having been assigned, whether the student has complied with the minimum requirements to be eligible for the lottery; fifth, conditional on having been assigned, whether the student has ever used the app after the end of the four weeks of the intervention.

Table 1.22 shows that none of the smartphone addiction scale items predict any engagement, as is true for all the distraction factors when attending classes both in person and online and for studying in a public space. Being a registered user in a higher number of social media platforms, being more distracted by their laptop and other technological

Table 1.22: PREDICTORS OF ASSIGNMENT TO AND INTENSITY OF THE INTERVENTION.

	Ever treated?	Ever downloaded?	Ever used?	Ever complied?	Ever used beyond?
Smartphone Addiction Scale Items					
Part of my daily routine	-2.13e-05	0.00395	0.00377	0.00311	0.0170
	(0.00305)	(0.00574)	(0.00655)	(0)	(0.0102)
Checking has become a habit	-0.00406	-0.00136	-0.00548	-0.00904	-0.00925
	(0.00285)	(0.00427)	(0.00486)	(0)	(0.0104)
Used to escape from real life	0.00149	0.00254	0.00417	-0.00224	0.00467
	(0.00159)	(0.00245)	(0.00280)	(0)	(0.00527)
Used to relax	0.000909	0.00345	0.00239	0.00688	-0.00126
	(0.00166)	(0.00256)	(0.00292)	(0)	(0.00611)
Used to interact	-0.00189	0.000661	0.00618	0.00807	-0.0113
	(0.00242)	(0.00410)	(0.00467)	(0)	(0.0124)
Used to maintain relationships	0.00237	-0.00187	-0.00252	0.00233	0.00921
	(0.00232)	(0.00385)	(0.00439)	(0)	(0.00755)
Have problems when using it instead of doing other things	0.00155	-0.00125	-0.00129	-0.00424	0.000532
	(0.00155)	(0.00266)	(0.00304)	(0)	(0.00613)
Lose sleep due to time I spend on it	-0.000693	0.00140	-0.000157	0.00547	-0.000399
	(0.00142)	(0.00219)	(0.00250)	(0)	(0.00434)
Attempted to spend less time, but unable to	0.000245	0.00133	-6.08e-05	0.00573	-0.00321
	(0.00152)	(0.00236)	(0.00269)	(0)	(0.00484)
Number of social media *(registered user)*	0.0203*	-0.00450	0.00419	0.0245	0.0302
	(0.0119)	(0.0169)	(0.0192)	(0)	(0.0444)
Posting stories? *(dummy)*	-0.127	0.329**	0.255		-0.157
	(0.0890)	(0.134)	(0.153)		(0.455)
Pressure to answer quickly *(slider: 0-100)*	0.00194	-0.00360	-0.00282	0.00928	-6.00e-05
	(0.00146)	(0.00244)	(0.00279)	(0)	(0.00437)
Distractions: Physical lecture					
Smartphone	-0.000161	0.0117	0.0111		0.0454
	(0.00891)	(0.00711)	(0.00811)		(0.0719)
Laptop/tablet	-0.00188			-0.00452	0.0537
	(0.00952)			(0)	(0.0697)
Other technological devices	0.00151	-0.0315	-0.0230		
	(0.0140)	(0.0282)	(0.0322)		
Environment	-0.00320	0.00416	0.00625	-0.0184	0.0298
	(0.00895)	(0.00713)	(0.00813)	(0)	(0.0709)
I don't get/seek distractions	-0.00107	0.00600	0.00437	-0.00636	0.0422
	(0.00872)	(0.00641)	(0.00731)	(0)	(0.0719)
Other = o,	-			-	
Distractions: Online lecture					
Smartphone	0.0118	-0.0444	-0.0807	0.0199	0.125
	(0.0161)	(0.0992)	(0.113)	(0)	(0.189)
Laptop/tablet	0.0108	-0.0467	-0.0804	-0.00399	0.113
	(0.0163)	(0.0990)	(0.113)	(0)	(0.191)
Other technological devices	-0.000123	-0.0181	-0.0663		-0.00392
	(0.0182)	(0.0997)	(0.114)		(0.211)
Environment	0.00851	-0.0540	-0.0908		0.132
	(0.0164)	(0.0988)	(0.113)		(0.186)
I don't get/seek distractions	0.00894	-0.0410	-0.0814	0.00482	0.133
	(0.0162)	(0.0988)	(0.113)	(0)	(0.188)
Other	0.0115	-0.0386	-0.0737		0.116
	(0.0177)	(0.100)	(0.114)		(0.190)
Distractions: Studying in a public space					
Smartphone	-0.0537	0.161	0.174		0.0678
	(0.0685)	(0.163)	(0.186)		(0.196)
Laptop/tablet	-0.0618	0.163	0.187	-0.0130	0.0653
	(0.0684)	(0.163)	(0.185)	(0)	(0.194)
Other technological devices	-0.0512	0.151	0.173		
	(0.0707)	(0.164)	(0.187)		
Environment	-0.0520	0.168	0.185	0.00831	0.0729
	(0.0686)	(0.163)	(0.186)	(0)	(0.196)
I don't get/seek distractions	-0.0528	0.165	0.182	0.00165	0.0681
	(0.0686)	(0.163)	(0.186)	(0)	(0.195)
Other	-0.0573	0.114	0.133	0.0789	0.0835
	(0.0687)	(0.166)	(0.189)	(0)	(0.221)
Observations	225	88	88	32	58
R-squared	0.228	0.606	0.539	1.000	0.658
Cond. on ever treated		y	y	y	y

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1.23: Predictors of Assignment to and Intensity of the Intervention – Continued.

	Ever treated?	Ever downloaded?	Ever used?	Ever complied?	Ever used beyond?
Distractions: Studying at home					
Smartphone	0.00740	-0.0253	-0.0200	-0.0415	0.0107
	(0.00614)	(0.0259)	(0.0295)	(0)	(0.0631)
Laptop/tablet	0.0172**	-0.0180	-0.0187	-0.00461	0.0337
	(0.00732)	(0.0267)	(0.0304)	(0)	(0.0698)
Other technological devices	0.0192*	-0.0494*	-0.0403		0.122
	(0.0107)	(0.0269)	(0.0307)		(0.174)
Environment	0.00629	-0.0134	-0.0108	-0.0424	0.0167
	(0.00650)	(0.0252)	(0.0287)	(0)	(0.0633)
I don't get/seek distractions	0.00803	-0.0247	-0.0168	-0.0221	0.0159
	(0.00621)	(0.0255)	(0.0291)	(0)	(0.0682)
Other	0.00394	-0.0391	-0.0403	-0.0418	0.0369
	(0.00891)	(0.0352)	(0.0401)	(0)	(0.0753)
Expected GPA					
Fully on campus	-0.0214	-0.000751	0.00414		0.0601
	(0.0138)	(0.0182)	(0.0208)		(0.0555)
Half on campus, half online	0.00494	0.0321	0.0238		-0.0447
	(0.0205)	(0.0308)	(0.0351)		(0.153)
Fully online	-0.0148	0.0426	0.0201	0.00942	-0.00903
	(0.0182)	(0.0293)	(0.0334)	(0)	(0.109)
Not attending	0.0329**	-0.0360	-0.0234	0.106	-0.0275
	(0.0154)	(0.0285)	(0.0325)	(0)	(0.0810)
Personality Measures					
Discounting *(slider: 0-100)*	-0.00194	-0.00189	-0.00182	-0.00635	-0.00435
	(0.00143)	(0.00226)	(0.00258)	(0)	(0.00577)
Risk taking *(slider: 0-100)*	-0.00132	-0.00336	-0.00487	0.00670	-0.00578
	(0.00164)	(0.00256)	(0.00292)	(0)	(0.00602)
Competitiveness *(slider: 0-100)*	0.000172	0.00475*	0.00180	-0.00998	0.00759
	(0.00160)	(0.00277)	(0.00316)	(0)	(0.00710)
Grit *(scale: 0-8)*	0.128*	0.0301	0.00434		0.141
	(0.0664)	(0.107)	(0.122)		(0.220)
Constant	3.788	-11.39	-9.134	-0.295	-25.60
	(6.548)	(8.549)	(9.750)	(0)	(25.11)
Observations	225	88	88	32	58
R-squared	0.228	0.606	0.539	1.000	0.658
Cond. on ever treated		y	y	y	y

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

devices when studying at home, expecting a higher GPA in a scenario of non-attendance of any lecture, and having a higher grit score predict willingness to participate in the intervention. Posting stories on social media, being less distracted by other technological devices when studying at home, and reporting a higher level of competitiveness predict the take up of the intervention, by at least downloading the app. None of the other behaviors (actively using the app at least once, complying with the minimum requirements to be eligible for the lottery, keep using the app after the end of the intervention) are significantly predicted by the reported measures.

1.6 Treatment Effect Estimation

After outlining the propensity score matching mechanism and after providing evidence of how matching on observable characteristics is able to balance my sample, in this section I present my results and I carry out some heterogeneity analysis.

1.6.1 Propensity Score Matching to Solve for Selection

To offset the differences based on observable characteristics, I build a fictional counterfactual by matching participants and non-participants who are observationally similar, i.e. who share similar pre-treatment characteristics, in order to then compare the average difference between these two matched groups.

To balance the two groups I rely on background administrative data. Discussing a vector of features X_i may increase the complexity of matching every single aspect, hence I solve this issue by adopting a propensity score, which reflects the probability of taking part in the program conditional on X. The groups of individuals are therefore comparable on all the observed covariates, even with a large number of variables. The basic assumption underlying propensity score matching is that the participation to the program is affected only by the observed characteristics used in the computation of the score.

More formally, Rosenbaum and Rubin (1983) define the propensity score as "the propensity towards exposure to treatment given the observed covariate", i.e. the conditional probability of receiving a treatment given pre-existing characteristics:

$$p(X) \equiv Pr\{D = 1 \mid X\} = \mathbb{E}\{D \mid X\} \tag{1.1}$$

where the indicator $D = \{0, 1\}$ is exposure to the treatment, and the multidimensional vector X represents the exogenous characteristics.

The propensity score can be estimated using any standard probability model, as Becker and Ichino (2002) suggest, for example defining the propensity score as $Pr(D_i = 1 \mid X_i) = F(h(X_i))$ with $F(\cdot)$ being a cumulative distribution like the logistic distribution

$$P(D_i = 1 \mid X_i) = \frac{exp(h(X_i))}{1 + exp(h(X_i))} \tag{1.2}$$

with $h(X_i)$ a function of the covariates.

Using the propensity score to solve the problem of non-randomness in this context, the average treatment effect on the treated can be estimated as follows:

$$ATT = \mathbb{E}\{\mathbb{E}[Y_i(1) \mid D_i = 1, p(X_i)] - \mathbb{E}[Y_i(0) \mid D_i = 0, p(X_i)] \mid D_i = 1\} \quad (1.3)$$

where the outer expectation is over the distribution of $(p(X_i) \mid D_i = 1)$ and $Y_i(1)$ and $Y_i(0)$ are the potential outcomes in the two counterfactual situations of (respectively) treatment and no treatment (Becker and Ichino (2002)).

Two fundamental conditions need to be met in order to obtain unbiased estimates of the treatment effect. First of all, assignment to the treatment and the outcome need to be independent conditional on the covariates, that is

$$D_i \perp\!\!\!\perp (Y_i(0), Y_i(1)) \mid X_i \quad (1.4)$$

ensuring that the means of potential outcomes are not affected by the treatment. This is called the "unconfoundedness" condition.

Second, for each individual it should be possible to get any treatment level, so that D is not perfectly predictable given X:

$$0 < Pr(D_i = 1 \mid X_i) < 1 \quad (1.5)$$

This is known as the "common support condition".

When both conditions hold, the "strong ignorability condition" is achieved. In order to check for the validity of this assumption, some tests may be run. The unconfoundedness assumption is not testable, but two approaches can be followed. The idea of this assumption is that the conditional distribution of the outcome under the control treatment, $Y_i(0)$, given active treatment and covariates, is identical to the distribution of the outcome under control treatment given control treatment and covariates, and the same holds for the outcome given receipt of the active treatment, $Y_i(1)$; hence one possible way to perform a placebo test is to estimate the effect of the treatment on a pseudo outcome, or to estimate the effect of a pseudo treatment on the outcome.

The second condition, also know as the "overlap" assumption, can be graphically tested; one way is to plot the distribution of the covariates by treatment group if they are not many, or alternatively in the multivariate case it is possible to plot the distribution of the propensity score in treatment and control groups.

1.6.2 Empirical Specification

I am going to estimate results in terms of intention to treat (ITT) using as treated group ($D_i = 1$) the students assigned to the intervention (i.e. those who volunteered to participate) and as control group ($D_i = 0$) the students who engaged with the project by filling in the surveys but who never wanted to join the intervention. The average treatment effect (ATT) can be written as follows:

$$ATT = E(Y_{ic}(1) \mid D_i = 1, p(X_i)) - E(Y_{ic}(0) \mid D_i = 1, p(X_i)) \tag{1.6}$$

where Y_{ic} is outcome Y (e.g. the midterm grade, or the course evaluation, and so on) of student i for course c; $D_i \in \{0, 1\}$ is the treatment condition; $p(X_i)$ is the propensity score constructed using the variables in $\mathbf{X}_i$, i.e. individual characteristics as presented in section (1.6.3).

1.6.3 Propensity Score Balance Checks

Table 1.24 presents the variables from administrative data included in the propensity score.

Table 1.24: Description of the administrative variables used for the estimation of the propensity score.

Variable	Description	Range	Average
Year of birth	Year of birth	{1996, 2003}	2001.2
Female	Gender, dummy = 1 if female	{0,1}	.45
Foreign born	Dummy = 1 if not born in Italy	{0,1}	.18
Bachelor program	Bachelor code	{1,9}	
High school GPA	Average of 11^{th} and 12^{th} grade GPA	{6.3, 10}	8.52

In constructing the propensity score I use the administrative variables reported in Table 1.24 and the variables that at baseline showed some imbalances, namely those from Table 1.16. My main results use as outcomes the grades of Fall and Spring midterms. I also explore survey measures related to expected grades, expected percent chance of passing the midterms, course evaluations, anxiety, study time.

In Tables A.30 to A.39 in the Appendix I report summary tables with only p-scores related to the balancing of these covariates between the two groups for all the analytic samples related to the above-mentioned outcomes. These tables show that the propensity score is able to obtain two comparable groups in terms of all the variables included in the analysis. I also present the related graphs representing the overlap of treated and control students (Figures from A.46 to A.63).

The analysis was carried out only considering the observations on the common support.

1.6.4 Results

The Hypotheses. In this section I am going to explore the most important results obtained in my framework, with the outcomes outlined in section (1.3.4). I start by detailing the most important hypotheses I am going to test.

- First, I want to test whether there is an intention-to-treat (ITT) effect on midterm grades, by comparing students assigned to the treatment *versus* not assigned. This is the most straightforward outcome, as these grades are obtained right at the end of the intervention period and should reflect eventual improvements in learning.

- Second, I use survey data to see whether there is an effect on own expected performance, in terms of both expected percent chances of passing and expected grade (conditional on passing the exam, i.e. obtaining a grade of at least 18/30). In a subjective production function not only "hard" inputs matter. The use of the app may affect individuals' expectations e.g. if students perceive that their study effort has been more effective thanks to the app, thus boosting their confidence.

- Third, given that the intervention operates both during study time and lectures, one potential effect of using the app while attending classes is that students may differently appreciate the topics or the teacher. I therefore use survey data on post-midterm course evaluations[22] to check for potential effects.

- Fourth, I expect a potential impact on anxiety levels. On the one hand, exam anxiety may be decreased if students perceive that they have studied profitably (similarly to the second hypothesis outlined above), but on the other hand a reduced exposure to smartphone features like social media and messaging may increase social anxiety, i.e. "FOMO" (fear of missing out).

- Last, I investigate potential changes in reported study time as the app may affect this input in the learning production function. On the one hand, if the app is purely eliminating the distractions while studying, then in principle total study time should

[22] Official course evaluations are administered by Bocconi at the end of the semester, with more informal and open-question assessments before the midterm break. I do not have these data.

not change as the student may not adapt their overall behavior to take into account the more efficient use of time. On the other hand, a student may either perceive to be more effective, and thus decrease total study time, or may miss digital distractions and may increase smartphone time outside of the intervention, thus crowding out the potential allocation of other time to sutyding.

Section (A.7) in the Appendix explores some heterogeneity in the results for midterm grades.

Midterm grades. Table 1.25 presents the effect of the intervention on the midterm exam grades. Across both semesters all treatment effects are positive, even if not statistically significant. The only statistically significant result is for the course of Macroeconomics in the Spring semester, where the increase of 1.09 points (on a scale out of 30) represents an improvement of 0.302σ.

To increase my sample size and look for statistical power, I exploit the maximum information I have available. I drop the use of the survey measures in the construction of the propensity score and I only use the administrative variables seen in Table 1.24. This allows me to use observations for which I do not have these survey measures available. I then expand my sample in two ways: first, I focus my attention on the full control group, i.e. all the students who ever engaged with the intervention by answering to at least a survey (Table 1.26); second, I include in my control group all the students for which I have administrative information available, i.e. all the students who engaged with the intervention/surveys and the peers that were nominated in the surveys (Table 1.27). In this way I am able to see that treatment effects remain positive and expand to other subjects: Management in Fall (+0.84 points, corresponding to 0.22σ), and Law (+1.43 points, corresponding to 0.41σ) and Other exams (+1.49 points, corresponding to 0.54σ) in Spring. The magnitude of the effect on the Macroeconomics exam drops from +1.09 to 0.82, corresponding to 0.24σ.

Results from these two semesters confirm the idea that more knowledge-based subjects like Law or Management can profit more from a more focused study time compared to more intuitive subjects like Math.

In order to confirm this intuition, I repeat the same analysis aggregating the grades according to some categories. I report the ITT results looking at students who were ever assigned to the treatment, either in one semester or both. I aggregate the exams looking

Table 1.25: Fall & Spring Midterms Grades – Treatment Effects

The Fall exams in the 'Math' and 'Other' categories expressed midterm grades only as a Pass (grade=1) *versus* Fail (grade=0). Some microeconomics courses adopted the same grading system and have been excluded in this analysis.

	Management	**Math**	**Micro**	**Other**	**Macro**	**Math**	**Computer Sc.**	**Law**	**Other**
ATT	0.629	-0.008	2.829	0.000	1.089*	0.576	0.543	0.562	1.409
	(0.493)	(0.028)	(1.880)	(0.000)	(0.555)	(0.499)	(0.498)	(1.062)	(0.745)
Treated	25.891	0.974	26.444	1.000	26.273	26.700	28.314	25.588	28.857
Control	25.263	0.982	23.615	1.000	25.184	26.124	27.772	25.027	27.449
N	365	356	51	41	301	289	373	90	69

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes administrative variables and survey measures that were unbalanced at baseline.
Sample: all students who ever engaged with the intervention and/or surveys.

Table 1.26: Fall & Spring Midterms Grades – Treatment Effects with Propensity Score using Administrative Data Only, Conditional on Ever Engaging

The Fall exams in the 'Math' and 'Other' categories expressed midterm grades only as a Pass (grade=1) *versus* Fail (grade=0). Some microeconomics courses adopted the same grading system and have been excluded in this analysis.

	Management	**Math**	**Micro**	**Other**	**Macro**	**Math**	**Computer Sc.**	**Law**	**Other**
ATT	0.836*	-0.007	1.444	0.000	1.001*	0.498	0.482	1.091	1.412
	(0.462)	(0.026)	(1.118)	(0.000)	(0.430)	(0.354)	(0.368)	(0.755)	(0.804)
Treated	25.904	0.976	26.538	1.000	26.366	26.738	28.419	26.138	28.700
Control	25.068	0.983	25.094	1.000	25.365	26.239	27.937	25.047	27.288
N	496	476	91	59	421	418	525	113	83

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes only administrative variables.
Sample: all students who ever engaged with the intervention and/or surveys.

Table 1.27: Fall & Spring Midterms Grades – Treatment Effects with Propensity Score using Administrative Data Only

The Fall exams in the 'Math' and 'Other' categories expressed midterm grades only as a Pass (grade=1) *versus* Fail (grade=0). Some microeconomics courses adopted the same grading system and have been excluded in this analysis.

	Management	Math	Micro	Other	Macro	Math	Computer Sc.	Law	Other
ATT	0.836*	-0.007	1.444	0.000	0.822*	0.427	0.227	1.432*	1.489*
	(0.462)	(0.026)	(1.118)	(0.000)	(0.398)	(0.328)	(0.337)	(0.711)	(0.710)
Treated	25.904	0.976	26.538	1.000	26.366	26.738	28.419	26.138	28.700
Control	25.068	0.983	25.094	1.000	25.544	26.310	28.192	24.706	27.211
N	496	476	91	59	913	916	1116	244	144

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes only administrative variables.
Sample: all students for which administrative data was available.

at the kind of preparation and type of study required[23], and I create four categories:

- *Quantitative exams*: Mathematics and Computer Science exams in both semesters;
- *Qualitative exams*: Management and Law exams in both semesters;
- *Economic Principles exams*: Microeconomics and Macroeconomics exams in both semesters;
- *Other exams*: residual category of exams.

Table 1.28 presents the results. In the Appendix I report the two other version with the propensity score including only administrative variables and using only the students who ever engaged with the surveys (Table A.40) and all those for which I have the administrative information (Table A.41). The hypothesis that concept-based (qualitative) subjects are more affected by the treatment is confirmed, as in the two expanded samples the positive effect is statistically significant for this category. The magnitude of this effect ranges from 0.23σ for the standard control group matched without the survey measures, to 0.29σ for the wider control group for which administrative information is available.

I then construct the average midterm-GPA of the students in my sample, and I estimate the effects using the three combinations of different samples and propensity scores as seen

[23] I investigated other literatures to use a consolidated categorisation of the subjects, but I did not find references. Hence I will use this working hypothesis for the interpretation of my results.

Table 1.28: Aggregated Midterms Grades, Fall & Spring – Treatment Effects

	Quantitative	Qualitative	Economic Principles	Other
ATT	0.480	0.669	0.521	0.607
	(0.585)	(0.488)	(0.715)	(0.859)
Treated	26.596	25.337	24.389	28.200
Control	26.116	24.669	23.868	27.593
N	417	381	394	71

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Propensity score includes administrative variables and survey measures that were unbalanced at baseline. Sample: all students who ever engaged with the intervention and/or surveys.

until now (Table 1.29). In this case I still detect a positive effect on the midterm-GPA, even though they are not statistically significant.

Table 1.29: Midterm GPA, Fall & Spring – Treatment Effects with three different Propensity Scores

	(1)	(2)	(3)
ATT	0.382	0.733	0.302
	(0.585)	(0.449)	(0.412)
Treated	25.655	25.841	25.841
Control	25.272	25.108	25.538
N	298	433	938
Mean N Midterms	4	4	3

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Propensity scores include: administrative variables and survey measures that were unbalanced at baseline (1); only administrative variables (2, 3). Controlling for the number of taken midterms. Samples: all students who ever engaged with the intervention and/or surveys (1, 2); all students for which administrative data was available (3).

Midterm expected performance. Table 1.30 shows that in both semesters there is no clear direction in the changes of grade expectations. No result is statistically significant.

Similarly Table 1.31 presents the analysis on the subjective percent chance of passing: after the midterms students expect lower chances in Microeconomics and Math (Spring only). The other results are not significant, but they are positive for Management and Macroeconomics. This might suggest that students do not perceive a benefit from using the app as there is no positive effect on their perceived learning efficacy or confidence in facing the examinations. Ersoy (2020) finds that when students are given information about the average effort-performance relationship, this makes their beliefs converge towards the information given, and similarly when given anecdotal evidence. Therefore participating students may have not perceived that the app actually helped them boost their performance, even if for some subjects it did, and providing them with information about their improved learning efficacy may also boost their confidence.

Tables A.42 and A.43 in the Appendix present the same results by excluding the survey measures from the propensity score. In particular, the significance for the results concerning the percent chance of passing is lost.

Table 1.30: Fall & Spring Midterms, Expected Grades – Treatment Effects

	Management	**Math**	**Micro**	**Other**	**Macro**	**Math**	**Computer Sc.**	**Law**	**Other**
ATT	1.231	-0.409	1.415	-0.945	-0.649	-0.783	-0.041	.	.
	(1.302)	(1.746)	(1.276)	(1.788)	(0.923)	(1.126)	(1.036)	.	.
Treated	24.533	23.915	24.008	24.423	24.019	25.587	27.560	27.075	25.570
Control	23.302	24.324	22.593	25.368	24.668	26.371	27.601	.	.
N	79	72	74	67	41	41	50	7	14

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes administrative variables and survey measures that were unbalanced at baseline.
Sample: all students who ever engaged with the intervention and/or surveys.

Table 1.31: Fall & Spring Midterms, Percent Chance of Passing – Treatment Effects

	Management	Math	Micro	Other	Macro	Math	Computer Sc.	Law	Other
ATT	13.573	.	-19.961*	.	3.931	-11.701*	-0.576	.	-11.657
	(7.717)	.	(8.394)	.	(5.266)	(4.210)	(3.983)	.	(14.361)
Treated	86.438	79.250	66.667	.	80.125	84.298	87.700	91.667	79.269
Control	72.864	.	86.627	.	76.194	95.999	88.276	.	90.926
N	29	18	49	.	85	88	106	20	27

Standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Propensity score includes administrative variables and survey measures that were unbalanced at baseline.
Sample: all students who ever engaged with the intervention and/or surveys.

Course evaluations. Looking at the effects on the course evaluations, I refer to four categories that are also used in the official Bocconi evaluations: first, *The lecturer is good at stimulating interest towards the subject and the classes*; second, *The topics taught in this course are hard*; third, *I am interested in the topics of this course*; fourth, *The online activities were helpful*. While the official questions are measured on a Likert scale, in my surveys I use sliders from 0 to 100 to express intensity. Results are presented in Tables from 1.32 to 1.35. There are no significant effects overall. However, when repeating the analysis using only administrative variables in the propensity score (Tables from A.44 to A.47 in the Appendix) there is one significant effect, namely students in the Spring Math course appreciated more their lecturer in stimulating their interest for the subject (+11 points out of 100).

Table 1.32: Fall & Spring Course Evaluations (Lecturer stimulates interest) – Treatment Effects

	Management	**Math**	**Micro**	**Other**	**Macro**	**Math**	**Computer Sc.**	**Law**	**Other**
ATT	-1.705	3.588	-0.451	-3.815	7.521	4.423	0.610	.	-6.573
	(5.178)	(4.504)	(4.536)	(6.224)	(6.216)	(6.510)	(5.774)	.	(14.807)
Treated	80.483	72.750	79.414	53.397	75.961	75.708	74.717	75.786	71.077
Control	82.188	69.162	79.865	57.212	68.439	71.285	74.107	.	77.650
N	108	122	100	111	91	90	107	22	27

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes administrative variables and survey measures that were unbalanced at baseline.
Sample: all students who ever engaged with the intervention and/or surveys.

Table 1.33: Fall & Spring Course Evaluations (Topics are hard) – Treatment Effects

	Management	**Math**	**Micro**	**Other**	**Macro**	**Math**	**Computer Sc.**	**Law**	**Other**
ATT	1.577	-0.078	-6.019	-3.332	-7.193	1.538	-8.891	.	10.473
	(4.232)	(4.621)	(4.670)	(6.607)	(5.177)	(5.449)	(5.546)	.	(20.469)
Treated	51.517	69.313	61.414	41.552	65.176	64.623	44.883	39.071	58.192
Control	49.941	69.390	67.433	44.883	72.370	63.084	53.774	.	47.720
N	108	123	101	111	91	90	107	22	27

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes administrative variables and survey measures that were unbalanced at baseline.
Sample: all students who ever engaged with the intervention and/or surveys.

Table 1.34: Fall & Spring Course Evaluations (Personal interest) – Treatment Effects

	Management	Math	Micro	Other	Macro	Math	Computer Sc.	Law	Other
ATT	-0.044	-4.929	1.421	0.341	0.173	-4.334	6.317	.	-16.792
	(4.375)	(6.695)	(3.901)	(6.243)	(5.786)	(6.321)	(6.054)	.	(15.873)
Treated	84.138	59.313	79.172	55.793	78.902	64.623	74.417	70.429	75.462
Control	84.182	64.241	77.752	58.134	78.729	68.957	68.100	.	92.253
N	108	123	101	112	91	90	107	22	27

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes administrative variables and survey measures that were unbalanced at baseline.
Sample: all students who ever engaged with the intervention and/or surveys.

Table 1.35: Fall & Spring Course Evaluations (Online activities helpful) – Treatment Effects

	Management	Math	Micro	Other	Macro	Math	Computer Sc.	Law	Other
ATT	6.307	8.918	8.904	-0.628	-4.901	-8.702	-4.679	.	-1.391
	(6.268)	(5.475)	(5.800)	(7.281)	(6.990)	(6.389)	(5.699)	.	(21.650)
Treated	71.138	72.625	75.690	53.862	58.157	64.000	70.433	62.643	59.769
Control	64.831	63.707	66.786	54.490	63.058	72.702	75.113	.	61.160
N	98	116	94	97	90	89	106	22	26

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes administrative variables and survey measures that were unbalanced at baseline.
Sample: all students who ever engaged with the intervention and/or surveys.

Anxiety. Table 1.36 shows that treated and control students do not present statistically significant different levels of anxiety before the exams (in Fall) or right after (in Spring), nor at the end of each semester. There seems to be a decrease in anxiety levels by the end of the Spring semester, even though not significant.

In Table A.48 in the Appendix there are still no significant results, but differences in scores are negative around the midterms and positive at the end of both semesters.

Table 1.36: Fall & Spring Anxiety Levels – Treatment Effects

	Fall		Spring	
	Pre Midterms	**End Semester**	**Post Midterms**	**End Semester**
ATT	3.802	2.446	1.347	-1.309
	(2.991)	(2.911)	(2.655)	(3.509)
Treated	54.556	56.548	54.942	51.023
Control	50.753	54.103	53.595	52.332
N	87	97	95	80

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Propensity score includes administrative variables and survey measures that were unbalanced at baseline. Sample: all students who ever engaged with the intervention and/or surveys.

Study time. One of the potential confounders in this setting is that study time can be both an input for the performance and an outcome of the intervention. The former is true as more study time contributes to improved performance. The latter situation arises if for example a student has a target in terms of tasks (e.g. number of pages to read, or exercises to solve) instead of an allocated slot of time: if the app allows the student to finish their tasks faster, then study time changes as a consequence of the treatment.

In Table 1.37 I use self-reported weekly study time in both semesters to investigate this issue. Results are all non-significant, even though there seems to be an upward shift in study hours. Table A.49 in the Appendix presents the results with the administrative-variable only propensity score.

Instead of relying on the categories, I construct a more continuous measure of self-reported study time. To each student I assign the mean value of the selected bracket, thus assuming that the distribution of study hours within each bracket is uniform. Table 1.38 presents the results obtained with both propensity scores (controlling in both cases for

Table 1.37: Fall & Spring Semester Study Time, Controlling for Planned Time – Treatment Effects

	Fall				Spring			
	15-28h	**29-42h**	**43-56h**	**> 56h**	**15-28h**	**29-42h**	**43-56h**	**> 56h**
ATT	-0.063	-0.199	0.184	0.034	0.090	-0.069	-0.107	0.031
	(0.160)	(0.164)	(0.099)	(0.056)	(0.163)	(0.166)	(0.093)	(0.031)
Treated	0.276	0.379	0.207	0.034	0.437	0.406	0.062	0.031
Control	0.338	0.578	0.023	0.000	0.348	0.475	0.169	0
N	71	71	71	71	61	61	61	61

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes administrative variables and survey measures unbalanced at baseline.
Sample: all students who ever engaged with the intervention and/or surveys.

self-reported planned study hours at Baseline). While the estimates are not statistically significant, it seems that students in the Spring semester decreased their study time.

Table 1.38: Fall & Spring Semester Study Time (Continuous), Controlling for Planned Time – Treatment Effects

	(1)		(2)	
	Fall	**Spring**	**Fall**	**Spring**
ATT	5.040	-0.764	2.802	-3.658
	(2.979)	(3.044)	(4.256)	(3.557)
Treated	32.595	30.023	32.242	29.625
Control	27.554	30.787	29.440	33.283
N	85	69	71	61

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Propensity scores include: administrative variables and survey measures unbalanced at baseline (1); only administrative variables (2). Sample: all students who ever engaged with the intervention and/or surveys.

1.7 Robustness Checks

1.7.1 Lee Bounds on the Estimates

In settings where self-selection may be a threat to the causality of the results, estimating bounds on the effects is a common procedure. I follow Lee (2009) by identifying the excess number of individuals induced to be selected because of the treatment and trimming the upper and lower tails of the outcome distribution yielding a worst-case scenario. The assumptions for identifying the bounds are: the regressor of interest is independent of the errors in the outcome and selection equation; the selection equation can be written as a standard latent variable binary response model.

To estimate bounds I use the command `leebounds` in Stata. The lower and upper bound correspond to extreme assumptions about the missing information that are consistent with the observed data. The trimmed proportion, as indicated in the tables, refers to the quantile of the outcome variable that corresponds to the share of excess observations in this group. Calculating group differentials in mean outcome yields the lower and the upper bound for the treatment effect, depending on whether trimming is from below or above. I do not include covariates in this analysis.

Tables 1.39 and 1.40 present the analysis for the Fall semester. While Table 1.39 shows that there are no significant estimates, Table 1.40 shows that lower bounds on the estimates are not statistically different from zero but upper bounds are positive for all the subjects except Microeconomics.

Table 1.39: Fall Midterms Grades – Lee Bounds

	Management		**Math**		**Microeconomics**		**Other**	
N		605		605		217		605
Trimming port.		0.169		0.208		0.457		0.709
Effect 95%	[-1.509	2.741]	[-0.051	0.039]	[-5.189	4.507]	[-0.214	0.331]

Table 1.41 supports the significant effect in the Macroeconomics midterm; Table 1.42 shows that lower bounds on the estimates are not statistically different from zero except for Macroeconomics, while upper bounds are positive for all the subjects except Math.

Tables 1.43 and 1.44 repeat the analysis on the aggregated subjects, showing how only

Table 1.40: Fall Midterms Grades – Lee Bounds

	Coefficients	Std Err	P	95% Confidence	Interval
Management					
Lower	-0.499	0.614	0.417	-1.703	0.705
Upper	1.838	0.549	0.001	0.763	2.913
Math					
Lower	-0.021	0.018	0.253	-0.057	0.015
Upper	0.002	0.022	0.913	-.040	0.045
Microeconomics					
Lower	-2.407	1.691	0.155	-5.722	0.908
Upper	3.296	0.736	0.000	1.852	4.439
Other					
Lower	0.080	0.173	0.645	-0.259	0.419
Upper	0.229	0.060	0.000	.111	.347

Bootstrap standard errors.
*** p<0.01, ** p<0.05, * p<0.1

Table 1.41: Spring Midterms Grades – Lee Bounds

	Macroeconomics		Math		Law		Other	
N		559		602		626		531
Trimming port.		0.010		0.034		0.299		0.355
Effect 95%	[0.059	1.960]	[-0.321	1.464]	[-2.464	4.698]	[-2.110	4.496]

Table 1.42: Spring Midterms Grades – Lee Bounds

	Coefficients	Std Err	P	95% Confidence	Interval
Macroeconomics					
Lower	0.956	0.487	0.050	0.002	1.910
Upper	1.088	0.474	0.022	0.159	2.016
Math					
Lower	0.338	0.392	0.388	-0.430	1.107
Upper	0.758	0.420	0.071	-0.065	1.581
Law					
Lower	-0.752	1.040	0.470	-2.792	1.287
Upper	2.871	1.111	0.010	0.693	5.048
Other					
Lower	-0.294	1.104	0.790	-2.458	1.871
Upper	2.864	0.992	0.004	0.918	4.809

Bootstrap standard errors.
*** p<0.01, ** p<0.05, * p<0.1

the upper bound on the Qualitative exams estimate remains statistically significant.

Table 1.43: Aggregated Midterms Grades, Fall & Spring – Lee Bounds

	Quantitative		Qualitative		Economic Principles		Other	
N		244		244		244		244
Trimming port.		0.021		0.316		0.094		0.309
Effect 95%	[-0.940	1.358]	[-2.417	4.478]	[-2.174	2.442]	[-2.443	4.728]

Table 1.44: Aggregated Midterms Grades, Fall & Spring – Lee Bounds

	Coefficients	Std Err	P	95% Confidence	Interval
Quantitative					
Lower	-0.022	0.533	0.967	-1.068	1.024
Upper	0.384	0.566	0.497	-0.725	1.493
Qualitative					
Lower	-1.324	0.665	0.046	-2.627	-0.021
Upper	3.208	0.772	0.000	1.696	4.721
Economic Principles					
Lower	-0.785	0.844	0.352	-2.439	0.869
Upper	1.033	0.856	0.228	-0.645	2.711
Other					
Lower	-0.747	1.031	0.469	-2.769	1.275
Upper	2.523	1.340	0.060	-0.104	5.151

Bootstrap standard errors.
*** p<0.01, ** p<0.05, * p<0.1

1.7.2 Using an Instrumental Variable

Out of the 9 bachelor programs considered at Bocconi, 5 of them have at least two classes[24]. Conditional on the chosen bachelor, students are allocated across these classes randomly.

I exploit the random allocation of students to classes to consider the different course schedules. In particular, given that the app is activated by intervention design during the afternoon, I check whether all the lectures of a particular subject in a class are scheduled in the morning ($dummy = 0$) or whether at least one is scheduled in the afternoon ($dummy = 1$). Having at least one lecture of a subject held during the intervention time window is random as, conditional on enrolling in a certain bachelor, students do not decide their class allocation or their schedule[25].

In Table 1.45 I detail the variation of treatment exposure for each subject across the classes of each multi-class bachelor. Treatment exposure is measured looking at the percentage of classes within a bachelor that have at least one lecture of that subject scheduled in the afternoon. For example, the Economics & Management bachelor (row 1)

[24]In the Economics&Management programs the Italian one (CLEAM) has 8 and the English one (BIEM) has 4; in the Economics&Finance programs the Italian one (CLEF) has 2 and the English one (BIEF) has 2; the Italian program in Economics&Arts has 2.

[25]During a.y. 2020/21 in the first half of both semesters classes where held in a hybrid mode, with students coming to campus on alternate weeks and following the rest online. Online attendance was encouraged and monitored.

has 8 classes; we can see that 7 of them (i.e. 87.5%) had at least one managent lecture scheduled in the afternoon, meaning that only one class never had their management course in the afternoon (i.e. when participating students were asked to activate the app). Unfortunately for courses like Computer Science there is no variation, meaning that all the classes considered here had at least one Computer Science class scheduled in the afternoon in their standard week.

Table 1.45: Variation of random treatment exposure based on the random allocation of students to classes and schedules.

		Fall semester				Spring Semester				
Bachelor	**Classes**	**Management**	**Math**	**Micro**	**Other**	**Macro**	**Math**	**Computer Sc.**	**Law**	**Other**
Management (It)	8	87.5%	100%	62.5%	75%	75%	87.5%	100%	37.5%	0%
Management (En)	4	100%	75%	75%	25%	100%	50%	100%	75%	0%
Finance (It)	2	100%	100%	100%	0%	100%	0%	100%	50%	0%
Finance (En)	2	100%	100%	100%	0%	100%	100%	100%	50%	0%
Econ&Arts (It)	2	100%	100%	0%	100%	50%	0%	100%	0%	100%

I run a simple IV regression (using `ivreg2`) using random exposure to the treatment, by class and by subject, as instrument for treatment assignment. I control for the same administrative variables used as covariates in the administrative propensity score (thus excluding the survey measures). Tables 1.46 and 1.47 present the estimates for the two semesters.

Table 1.46: IV estimates – Fall semester.

	Management	**Math**
Treatment Assignment	16.43	-0.862
	(17.24)	(1.094)
Year of birth	-0.487	0.0457
	(0.967)	(0.0629)
Female *(dummy)*	-1.452***	-0.0270
	(0.558)	(0.0265)
Non-Italian citizen	-0.801	-0.0426
	(1.115)	(0.0609)
Bachelor programme	0.199	-0.00543
	(0.223)	(0.00884)
High School GPA	1.863***	0.00980
	(0.433)	(0.0172)
Observations	442	460
R-squared	-1.077	-4.895
Outcome mean	25.09	0.987
F-statistic instruments	0.785	0.699

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Macroeconomics is the only case in which the class schedule is not a weak instrument (F statistic $>$ 10). Indeed I find a significant effect in this case.

Table 1.47: IV estimates – Spring semester.

	Macroeconomics	**Math**	**Computer Science**	**Law**
Treatment Assignment	11.07**	-4.207	-12.75	66.76
	(4.512)	(3.862)	(61.58)	(325.1)
Year of birth	-0.253	0.177	0.0357	-1.004
	(0.282)	(0.238)	(0.386)	(3.189)
Female *(dummy)*	-1.270***	-0.00317	0.363	-0.894
	(0.376)	(0.342)	(3.492)	(7.462)
Non-Italian citizen	-2.056***	-2.144***	-2.020***	-3.314
	(0.549)	(0.434)	(0.630)	(3.985)
Bachelor programme	-0.0556	0.207**	0.200	1.000
	(0.132)	(0.0959)	(1.169)	(3.245)
High School GPA	1.344***	0.667***	0.529	4.704
	(0.213)	(0.150)	(0.693)	(15.41)
Observations	851	711	840	202
R-squared	-0.572	-0.144	-2.034	-38.546
Outcome mean	25.59	26.84	14.36	25.27
F-statistic instruments	17.19	5.684	0.0660	0.0399

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

1.8 Conclusion

In this paper I design and implement an intervention to limit constant exposure to smartphone apps and notification by asking students to use a software that blocks access to these features. The block, or “Distraction Blackout”, needs to be manually activated every afternoon from Monday to Friday for four hours. The intervention runs for the four weeks that precede the midterm examinations of first-year bachelor students at Bocconi, studying economics-related courses, during both semesters of a.y. 2020/21. A set of online surveys is also administered to students belonging to this cohort throughout the whole academic year.

By implementing propensity score matching I find positive effects on some kinds of courses. Specifically there is a positive effect on the Management and Law exams, while there is no detectable effect on more quantitative courses like Math or Computer Science. I also find a positive effect on the Macroeconomics performance but not on the Microeconomics one. Statistically significant results are of a magnitude between 0.22 and 0.54 standard deviations, i.e. above the “policy interest” threshold. Using my survey measures I do not find significant differences in terms of expected percent chances of passing the exams, expected grades, course evaluations, anxiety levels, and self-reported study time.

My results suggest that the app may help students focus when dealing with particular subjects that may require different levels of concentration. In particular, quantitative courses that have more applied exams may be less impacted by external distractions, while more qualitative subjects (with more essay-type examination questions) may amplify the negative effect of a shallow level of focus.

To provide a clear metric to assess of how large the impact of smartphones on learning is, from my results it is straightforward to estimate by how much a student’s GPA could change over the years of university, keeping into account the bachelor-specific share of qualitative *versus* quantitative subjects. Using this information about the potential GPA increase I could calculate the increase in the chances of obtaining a job within the first year of graduation, or in the chances of obtaining a more stable contract, or the change in the starting salary. Unfortunately there is no availability of Bocconi data about students’ labor market outcomes matched with their past performances. It would however be possible to estimate these long-lasting effects using data from similar environments.

Moving forward it will be worthwhile exploring the mechanism behind my results. Once we establish that qualitative subjects are more affected than quantitative ones, the question is whether studying intuition-based lessons is less affected by interruptions, or whether this kind of studying is more absorbing and therefore distractions become less frequent and less relevant. A straightforward extension is then related to the setting of the intervention; insightful results may be obtained by studying the effect of digital distractions on workplace tasks, for example on routine activities *versus* creative processes *versus* interpersonal engagements.

It is important that both students and policy makers are aware of the impact of smartphones on learning. On the one hand, students may gain insights into how to improve their performance; on the other hand, policy makers need to recognize that some technologies can be introduced in the classroom under some circumstances but there could be drawbacks related to the tool's inner nature. Smartphones and social media are designed to attract attention[26], and it is therefore necessary that we acknowledge these features and how they modify our brains. Smartphones are pervasive tools in our everyday life: which is the extent of their influence on our concentration and on focus-intensive tasks? This question still needs to be investigated.

[26]See, for example, this article on vox.com about smartphones, or this article about social media in general, or this one about social media apps.

Chapter 2

The role of expectations on peers in educational choices

Francesca Garbin

Abstract

The influence of friends is an important driver in our life. Students make choices not only by directly looking at peers' behaviors, but also on the basis of what they think their peers will do. In this paper I use multiple waves of a survey that elicits beliefs about high school characteristics and gathers information concerning the network of friends. I look at the relevant factors for the choice of high school; by estimating a multinomial logit model I document that peer effects coming from beliefs about friends' future choices matter more than important academic-related aspects, such as the probability of liking the subjects taught at a certain school and the expected effort.

[*Field codes (JEL)*: C31, D91, J24]

[*Keywords*: peer effects, network, expectations, beliefs, high school choice, survey data, multinomial logit]

1 Introduction

Peer interactions play an essential role in personal and social development through established relationships and constant communication. When adopting behaviors and making individual decisions we look at others in order to find direction and support, but sometimes this influence is not directly considered. As economist, this means that the social component enters our utility function but we do not consider the fact that, for example, also others may be looking at us, thus making more complex the analysis of peer influence. This happens in every domain, and it has been widely studied also in the context of education (among others, Sacerdote (2011) and Epple and Romano (2011) review this literature).

An important step in a student's life is the choice of high school, which has to be made in a peculiar moment in life, i.e. early teens, when students are trying to define their identity and to build up their self-image. At this stage individuals are both testing their own innate abilities and at the same time making decisions that will impact their future human capital accumulation. Recognizing what is the best way to proceed is not easy if it is not clear which are the characteristics on which such a choice should be made. Adolescents often look up to their friends to get a sense of direction, and they do so because by making the same daily choices as their peers they feel understood and they fulfill the need to belong to the same group (Akerlof and Kranton (2002), Provantini and Arcari (2009)).

Understanding how students make up their minds and which are the drivers of this choice is fundamental. The decision concerning high school is made by all the students at the end of their eighth grade, and therefore most teenagers are gathering information in the same period and are making up their minds while they cannot observe what their peers have decided, because no definitive choice has been made indeed. Therefore, in this context students cannot rely on the observation of friends' realized outcomes, because they have not happened yet, but rather on the expectations that each student holds concerning their peers' future unrealized choices. This decision does not happen overnight: it is the product of a process that involves both collection of relevant information and bargaining within the family. Hence, when looking at peers who are experiencing the same process, what matters is not the final (unrealized) choice, but the likely options that are considered during this course of action. During the months that precede the pre-enrollment decision, friends talk and share concerns and hopes; thus one student who considers pros and cons of enrolling in a particular high school will act not on the basis of what their friend will actually do, but on the basis of how they *expect* their friend will behave. Realized outcomes have not materialized yet; only expectations about peers can drive the social influence at this stage.

Beliefs about peers' future choices are used in this paper in order to assess their influence on the pre-enrollment choice. I exploit multiple waves of a survey conducted in the city of Vicenza (Italy) over the six months preceding the pre-enrollment application. In this period, eighth-grade students and their parents need to gather the relevant information in order to make a choice regarding high school, and this decision is later formalized by submitting a pre-enrollment application to the schools. The surveys cover many areas from basic demographics to expectations regarding the prospective kind of high school. A section is also dedicated to the elicitation of the network of friends; over different waves, students can name up to ten peers with the only requirement that they are attending the eighth grade, i.e. friends facing the same choice at that time. For each peer, the student is asked to indicate which are their expectations regarding the possible curricula that the peer may choose and the probability that this scenario realizes, ranking up to three likely choices. I exploit the information on the network structure and on the beliefs about peers to test whether expectations about friends' future choices indeed matter for the selection of an educational path.

In Italy high school has two relevant features. First, it is an open enrollment system, hence admission is not competitive[1]. Second, a division into tracks is in place: the general track is more focused on preparing for university; the technical track is aimed at developing both theoretical and practical skills; and the vocational track is labor-market oriented. Each track offers different curricula. After high school, applying for university is possible for any student holding a high school diploma, regardless of the track or the curriculum attended.

In this paper I study whether – and if so, how – these expectations about friends' future behaviors affect the selection of a particular track. In order to do so, I need to overcome a reflection problem. In fact, whenever we observe a group of people we cannot identify the direction of the possible influence because it is likely that everyone exerts some leverage on the others while they are prone to it themselves. Endogenous effects arise when the average behavior of a group influences the behaviors of the individuals belonging to it,

[1]While some schools are currently introducing admission tests, the framework analysed in this paper does not allow for ranked admissions. Hence I consider a non-competitive framework.

and it is thus difficult to state where the movement originates and who responds to it. To overcome the issue of simultaneity when identifying peer effects, I exploit an approach used by Bramoullé, Djebbari, and Fortin (2009) and De Giorgi, Pellizzari, and Redaelli (2010). The keys to these models are the individual-specific peer groups and using as instruments the excluded peers, i.e. the friends of one's friends that are not directly one's own friends (the second-degree neighbors). I am able to reconstruct each of the respondent students' network through the direct elicitation of peers in the surveys. I estimate a multinomial logit model to assess the influence of expected peers' choices on own choice of high school, using also data about subjective probabilities related to future school-specific outcomes.

My findings reveal how important beliefs about peers' choices are. By using perceived school characteristics like expected effort and probability of liking the subjects, I show that peer effects have a much bigger impact on the choice of a track compared to these more academic-related features. Moreover, I check the robustness of this result by looking at another measure of peer influence: the realized choice. I show that effects are much smaller than in the case of declared expectations, suggesting the possible role of a self-confirming bias when students think about their friends' choices. I also vary the degree of influence of each friend in the network by changing the weights attributed to each peer.

My contribution is related to three strands of literature. First, I document an important channel through which peers affect educational outcomes, namely the choice of a high school track. Second, I contribute to non-linear choice models by extending the strategy of "excluded peers" as instrumental variables in a network framework. Third, I explore the role of subjective expectations thanks to the availability of unique data on beliefs; in a situation with simultaneous choice, peer effects do not go through the observation of a realization but rather rely on the individual perception of the anticipated behaviors.

This paper is organized as follows. Section (2) summarizes the literature in the field of education and networks by presenting some of the contributions closest to my work. Section (3) depicts the institutional setting and then describes the dataset, detailing the information gathered through the surveys, the network reconstruction, and the most important measures used in the analysis. Section (4) introduces the theoretical model. Section (5) presents the empirical estimation method, and section (6) the results obtained under different specifications. Section (7) concludes.

2 Relevant Literature

The literature on peer effects is broad and continuously expanding in new directions. From the discussion around conditions for the identification of effects to the correct specification of the network, works are countless. In this section I outline some of the most important papers and developments.

This paper contributes to three strands of literature: first of all, peer effects in education; second, peer effects in non-linear choice models; third, the role of subjective expectations in choices. I discuss some works related to each of them and I highlight my contribution.

Linear-in-means models in education. Despite later criticism, Manski (1993) remains the most important milestone in the literature on peer effects. He was the first one to point out that whenever we face a closed group taken as reference, then the average behavior includes the behavior of the observed individual, and peer effects cannot be disentangled if there is no external source of variation. The so-called "reflection problem" arises whenever we cannot distinguish the clear direction of the influence. In particular, when individuals in a group tend to behave similarly, Manski (1993) spells out three hypotheses related to possible effects at work: first, we may observe endogenous effects, i.e. an individual behavior is affected by peer behavior; second, exogenous effects materialise when an individual's behavior is affected by (exogenous) peers' characteristics; third, correlated effects arise when individuals in a group behave similarly because of exposure to similar environments.

The baseline linear-in-means specification of Manski (1993) has become the benchmark for later contributions. For example, in order to obtain credible exogenous variation in peer groups, in the context of education Hoxby (2000) uses the changes in adjacent school cohorts' gender and racial composition within a grade within a school; she finds evidence of substantial peer effects: an exogenous change in peers' reading scores increases student's own score.

Among the works that have tried to overcome the issue of simultaneity when identifying peer effects, Bramoullé, Djebbari, and Fortin (2009) extend the linear-in-means model by Manski to characterize a network where exogenous and endogenous effects can be separately identified. In fact, when correlated effects are present, these can be excluded through a within transformation at network level. Their models assumes that the individual outcomes depend on the mean behavior of the individual's friends (endogenous effect), the individual's own characteristics, and the mean characteristics of the friends (exogenous effect). The network is represented in the structural model through an interaction matrix. Their main intuition is that characteristics of the friends' friends (in a network they are known as "second neighbors", i.e. second-degree connections) of a student may be used as instruments for their own friends ("first neighbors") if these friends' friends are not among the student's friends: second-neighbors' exogenous characteristics can be used as instrument for first-neighbors' behaviors under the standard IV assumptions of relevance and exclusion restriction. Their identification is based on having enough variation in the individual-specific reference groups. De Giorgi, Pellizzari, and Redaelli (2010) simultaneously develop a strategy similar to the model by Bramoullé, Djebbari, and Fortin (2009); they call "excluded peers" the friends of friends generated by partially overlapping groups, i.e. those that act as exclusion restrictions in the simultaneous equation model of social interactions, solving the reflection problem. Angrist (2014) later comments Bramoullé, Djebbari, and Fortin (2009) by illustrating a situation of identification failure, indeed emphasising how measurement errors on observed characteristics can lead to inflated peer effect estimates. The review by Bramoullé, Djebbari, and Fortin (2020) summarises well the evolution in the literature since Bramoullé, Djebbari, and Fortin (2009), focusing on linear-in-means models, issues related to correlated effects, and incomplete knowledge of network interactions.

Some of the first contributions in this field did not use individual-specific network data, but rather they had to exploit some other mechanisms that could guarantee the exogeneity of the reference group in order to overcome the reflection problem. The definition of this benchmark group is a central issue in most of the works, depending also on the outcome of interest. For example, De Giorgi, Pellizzari, and Redaelli (2010) and Bramoullé, Djebbari, and Fortin (2009) rely on different definitions of peers groups; the first ones look at educational outcomes in an academic context assuming that students who attend some courses together are peers, while the second ones use survey data where students name peers selecting them from a school list, thus obtaining individual-specific networks.

Many papers exploit available data on university students to build credible reference groups. Sacerdote (2005) constructs peer groups thanks to the random assignment mechanism of freshmen at Dartmouth to dorms and rooms, and checks how the student's abilities on top of their roommate's abilities and GPA impact the student's own GPA. Using dorm fixed effects, roommate behavior has no effect on some non-academic outcomes such as fraternity membership, while average dorm behavior has. The most important takeaway is that a smart redistribution of students may improve academic and social outcomes; similarly to what found by Golsteyn, Non, and Zölitz (2017), peer effects are heterogeneous across groups, and when it comes to GPA the best performing roommates are those having the stronger positive influence on the lowest performing students. More importantly, the effects of the roommate or of the dorm on average have different intensities in different contexts; Sacerdote thus highlights that the reference group can change a lot according to the considered activity. Moreover, most of the times it is assumed that peer effects are homogeneous across categories, but empirical applications often show that some observable characteristics may amplify spillovers; for example, Beugnot et al. (2019) generalize the standard linear-in-means approach where men and women are exposed to different peer effects in a lab experiment, and find indeed strong gender differences according to the network structure. Boucher et al. (2014) investigate the presence of peer effects in students' achievements, by assuming that the interaction groups are known and that the individual outcome is determined by a linear-in-means model with group fixed effects to differentiate out the correlated effects; they apply Lee (2007)'s methodology, hence variation in the average peer attributes is created by the exclusion of each individual's own characteristics from the group average.

At the university level, De Giorgi, Pellizzari, and Redaelli (2010) study how peers might be important for long-term lifetime outcomes (i.e. wage, employment, job satisfaction) through the choice of major during the bachelor. The authors identify the peer groups thanks to the random attribution of students to classes, and the simultaneous attendance of multiple courses; thus, the relevant peers are those that take more than half of the first-year courses in the same class. The authors argue that peers' influence can lead to choosing a major against students' own abilities, leading to lower graduation marks, lower-paid jobs, and a higher skill-mismatch in the labor force. Inefficient schooling decisions at this stage hinder the earning potential of the individual, who is not able to use their own abilities to the fullest and may experience lower degrees of personal gratification, and create a skill mismatch on the labor market that is harmful for the employer as well. My contribution to the literature goes in the same direction as De Giorgi, Pellizzari, and Redaelli (2010): I argue that peers affect high school track choice and this can have long-lasting effects. While I cannot claim that influences in my setting go against students' own abilities or that they impact future earning potentials, still I find it credible given that De Giorgi, Pellizzari, and Redaelli (2010) find harmful consequences stemming from the switch from an economics to a business curriculum within the same university; choosing completely different fields in high school, and then as a result choosing completely different fields in university or not even attending it, may have even stronger impacts.

Peer effects in education: other channels and outcomes. During university, the channels through which friends affect educational outcomes and behaviors are multiple and have been widely explored. Stinebrickner and Stinebrickner (2008) look at how peers influence study effort, and do so by exploiting the random allocation to roommates who own distracting video games. They argue that educational outcomes are more influenced by good examples of time use rather than high ability students helping out their struggling low achieving peers. Related to this result, Conley et al. (2017) bring strong evidence that friends' study time has a substantial effect on one's own study time, which is an important ingredient of academic achievement. Lerner and Malmendier (2013) find that in a business MBA program having a higher share of entrepreneurial peers decreases entrepreneurship; this is actually a positive result, as it is driven by a reduction in unsuccessful entrepreneurial ventures. Algan et al. (2019) instead assess the influence of friendship ties on political opinions among French freshmen, where network connections decrease polarization acting through discouragement of divergence rather than encouragement of convergence.

In a context similar to the random allocation of university students to different classes of De Giorgi, Pellizzari, and Redaelli (2010), Golsteyn, Non, and Zölitz (2017) focus on non-cognitive skills and study how the personality of individuals in one class can affect the performance of their colleagues. Using features such as risk attitude, self-confidence, anxiety, and motivation, their analysis reveals that there is a positive effect on exam grades of having more persistent peers, and a negative effect of high risk tolerance in the colleagues; anxiety and self-confidence are not significant. The effects seem to be heterogeneous across groups, with for example the least persistent students benefiting more from being exposed to highly persistent peers; this has important policy implications when it comes to enhance academic performance through the optimal allocation of students to classes. Furthermore, they suggest two possible channels through which this may happen; the first one is peer pressure that pushes students to work harder, while the second one is linked to the spillovers that come from studying more efficiently with highly productive students.

Lavy and Sand (2018) look at the length of friends' acquaintance and at its importance in shaping peer effects. The focus of this work is on studying how separating students from preexisting friends during the transition from elementary to middle school might hurt short and long-run academic achievements. The identification strategy relies on the conditional random assignment of students to classes within a school, given that assignment based on ability, family background and other student's characteristics is forbidden by the law. Short-term effects are evaluated on test scores at school, and it turns out that reciprocal friends (i.e. when both children name each other as "friend") have a positive effect on the academic performance. Long-term effects are identified thanks to administrative data that track students until the end of high school. Reciprocal friendships are the ones having a bigger impact on outcomes like the probability of receiving a matriculation diploma. Similarly, Ly and Riegert (2014) find that when moving to high school students gain from being in the same class as a former middle-school classmate. The effect is highly heterogeneous and mostly driven by low-performing and low-socio-economic status students, who profit from having a "persistent peer" regardless of the latter's academic performance. In a similar spirit, Patacchini, Rainone, and Zenou (2017) check for long-run effects of peers' behavior on own educational outcomes, by exploiting different waves of the AddHealth survey to define different types of friendships, either long or short-lived. Their results document how only long-lasting ties matter for long-run achievements, but in the short run both types of ties are important for the academic performance. To explain how this happens, they postulate a theoretical model in line with De Groot (1974) where individuals update their beliefs by taking the weighted average of their peers' beliefs, repeatedly; under some conditions, all the individuals in the same network will converge to the same beliefs. While the influence of the single person depends on their position in the network, the authors suggest that short-lived ties have a weak influence because in the updating process of i's beliefs their opinion is considered only once, while long-lived connections repeatedly interact.

Conti et al. (2013) simultaneously estimate the friendship formation process during high school and its effect on adult outcomes, finding a positive association between a warm early family environment and the number of friendship nominations given (defined as "outdegree") and received ("indegree"); this increases the social skills stock, leading later on to a wage advantage in adult life. In order to understand why students make more friends, Hsieh, Lee, and Boucher (2020) establish a theoretical model of both network formation and network interactions using a unified framework, hence considering that individuals anticipate the effect of network structure on the utility of network interactions when choosing links. Applying this model to AddHealth data, they study students' GPA and smoking habits and find a significant impact of a student's GPA on the formation of the network, but no effect from their smoking habits; peer effects for both activities are detected, in line with previous works.

Once the network architecture enters the picture, it is clear that not every agent in the social structure is equally affected by everybody. For example, the network structure is important for the spread of spillovers, and as Jain and Langer (2019) point out there is a trade off between how many people you know, and hence how many sources of information you can aggregate, and how time-consuming all these relationships are. In knowledge-intensive networks, like those of students in college, the possibility of easy access to information has the drawback of making these highly connected students too distracted to have productive engagements. The authors demonstrate that in an empirical academic application increasing the degree centrality is actually associated with poorer performance. This result could be read also thinking about how information circulates, and how uncertainty about peers' behaviors is important when coordination is needed. Charness et al. (2019) set up a lab experiment where groups of people play an extended stag hunt game and in which different kinds of communication among the members are possible, also depending on the structure of the network (which determines who talks to whom). They find that the diffusion of the messages is indeed contingent on the degree of network clustering. Centola (2010) studies the effect of the network structure on information diffusion in an online health experiment. Calvò-Armengol, Patacchini, and Zenou (2008) study the impact of the network structure on educational outcomes, testing how the heterogeneity in idiosyncratic characteristics and in the location in the network can differently affect the educational outcomes of students. The position in the network is crucial for determining the level of activity of the student as measured by school performance, as proved by their empirical estimation using AddHealth data. To achieve identification in this context, they exploit network fixed effects to distinguish correlated effects from endogenous effects, and peer groups with individual-level variation to allow for the separation of endogenous and exogenous effects. For reviews of network models and their relevance in economics, some of the relevant works are Jackson (2011) and Jackson, Rogers, and Zenou (2016).

Yet, if the goal of research is to make normative prescriptions about how to optimally allocate e.g. students to classes, we should beware that altering the mechanisms at play in endogenously-formed networks may be harmful. The experience of Carrell, Sacerdote, and West (2013) should warn us against optimal policy design and its implementation.

In their experiment, the exogenous formation of peer groups based on an optimal design leads to the segregation of low and high ability students into separate social networks, so that the predicted positive spillovers do not materialized. Nonetheless, Bramoullé, Djebbari, and Fortin (2020) suggest that the reason behind the failure of the social engineering experiment of Carrell, Sacerdote, and West (2013) lies in the fact that counterfactual predictions require a precise understanding of what drives peer effects; different mechanisms may not be identified even with standard linear-in-means parameter identifications because they are observationally equivalent. De Giorgi and Pellizzari (2014) also tackle the issue of optimal allocation of students to classes, and find that pairs of students who are more often allocated to the same classes are characterized by less dispersed outcomes and lower average performance; hence, in order to maximise average performance, preventing students from meeting too frequently or limiting the possibility of mutual insurance are desirable features.

Other fields of application. Peer effects are at place in many aspects of our lives, and researchers are trying to uncover these mechanisms wherever possible. Among many, Atefi and Pourmasoudi (2019) focus on peer effects in the workplace and in particular on salespeople, reviewing the relevant literature and proposing solutions for a more precise measurement of peer effects; Hartmann et al. (2008) survey the literature on social interactions and networks, discussing how models of social interaction can be used to provide guidelines for marketing policy and encouraging future cross-disciplinary research; Villeval (2020) reviews studies on the impact of receiving performance feedback and of peers' performance on own performance, both in the field and in the laboratory. McGloin and Thomas (2019) review the literature in criminology, assessing how criminal behavior may be either learned through communication, or encouraged from approving peers, or be result of a lack of supervision (both as social control and self-control); Bhuller et al. (2018) instead discusses the role of family ties and role models in incarceration probability. Bhattacharya, Dupas, and Kanaya (2019) aim to understand how spillover effects work for maximising the adoption of a new technology (i.e. bed nets to contain the diffusion of malaria) in order to properly carry out an economic policy evaluation, as welfare analysis with spillovers requires knowing all the different channels through which social interactions may influence the process.

Discrete outcomes. Outcomes can also be discrete, and in particular binary when looking at behavior adoption. Soetevent and Kooreman (2007) focus on social interactions in small groups with discrete choice variables, and use a large sample of schools for which they have information on some behaviors of the students within each class to test their empirical model. Their results indicate that, out of five discrete behaviors, the social interaction effects at school are stronger the more the behavior is related to schooling (i.e. truancy *versus* smoking, moped and cellphone ownership *versus* asking parents' permission for purchases), and that intra-gender interactions are more intense. In this context it is worth noting that, as Sacerdote (2005) suggests, different outcomes depend on different social structures, and therefore it is reasonable that behaviors less related to schooling are also less related to the school peers.

Another case of an often used binary outcome is smoking. Nakajima (2007) builds a random utility model and then tests it on US data to see whether peers influence smoking decisions. To check whether the probability of smoking of an individual is indeed related to the fraction of smokers in their peer group, the challenges faced are the endogenous choice of peers and the identification issue raised by Manski (1993). The reference group considered is the school cohort, and the author finds evidence of positive effects of peers on smoking behaviors, stronger both within gender and within race. Interestingly, Yang and Lee (2017) design a game where structures on expected utilities of individuals are imposed, and they apply it to same dataset on smoking behavior used by Nakajima (2007); the difference lies in the fact that they do not assume that all characteristics are common knowledge, and prove that their model provides a valuable selection criterion.

Non-linear models. Within the literature on peer effects in education, my aim is to bring a contribution to non-linear choice models. Brock and Durlauf (2001) build on Manski (1993) and define a theoretical model of discrete choice with social interactions. In particular, they assume that individuals maximise their utility functions which depend on private components and on others' actions. The literature in the peer effects field is dominated by linear models, as should be clear from the literature review outlined so far. Multinomial and hybrid choice models have been discussed as well, for example by Rasouli and Timmermans (2016) and Kim, Rasouli, and Timmermans (2017). My contribution in this context is to apply a non-linear choice model, i.e. a multinomial logit, to a network structure where peer effects can be identified thanks to its architecture, i.e. exploiting the excluded peers as instruments.

Expectations. On top of the peer effects in education and choice models, a third branch of literature to which I refer is the less explored one on expectations. The role of individual beliefs on uncertain future outcomes is an important determinant in the decision-making process, in the education field as well. Arcidiacono, Hotz, and Kang (2010) and Delavande and Zafar (2019) establish how university choices are affected by earnings expectations; other works like Zafar (2011a) and Zafar (2011b) explore how these expectations are formed and whether the use of subjective data is appropriate in choice models. Other works also explore how individual beliefs shape the decision of university attendance and major (Stinebrickner and Stinebrickner (2014), Montmarquette, Cannings, and Mahseredjian (2002), Beffy, Fougère, and Maurel (2012), Arcidiacono (2004)).

In my application, subjective beliefs are about two different dimensions. The first one is expectations about peers' future choices, hence unrealized outcomes on which the agent has partial information; the second one is expectations about uncertain future outcomes stemming from each choice, more similar to what explored by Delavande and Zafar (2019) and Zafar (2011b).

In the context of choice with interactions and expectations, when agents maximise their utility, they are considering rational expectations about other people's actions; unfortunately rationality implies the complete knowledge of the involved agents' characteristics. The work by Li and Lee (2009) directly addresses this issue and studies peer influence on a binary choice with empirical data on subjective expectations. Their analysis considers a US pre-election survey where people nominate the peers with whom they talk more often about politics, together with the voting intentions that they expect from their peers. Hence the individuals actually define their reference group, but these discussants may or may not be in the observed sample; moreover, nonrandom selection of peers with whom they discuss politics may bias the estimates of social influence. Nonetheless the authors show that their model with subjective expectations is better at predicting voting outcomes rather than rational expectation models such as Brock and Durlauf (2001). The same authors take into account heterogeneous rational beliefs in a later contribution, namely Lee, Li, and Lin (2014), where they however still assume that friendship links are exogenously given. My paper builds on these contributions by adding a more structured network dimension and by trying to overcome the endogeneity both of behaviors and of link formation.

Contribution. This paper contributes to the literature on the empirical analysis of network effects in education, enriching its non-linear choice model by using expectations from survey data. The contribution of my work is to uncover another relevant factor in the choice of high school. In particular, by looking at expectations about peers' future behaviors I want to show that what is important is not the (future) realization *per se*, but rather the projection of beliefs during the decision-making process. Differently from other papers, I am able to directly incorporate subjective expectations of individuals with respect to their peers, without having to assume rationality. In the current analysis I also include many relevant factors for high school choice as perceived by the individual, such as the subjective probability of enjoying the subjects taught or the expected effort and performance; still, I show that beliefs about peers are important, even more than actual behaviors.

3 The institutional Setting and the Study

3.1 The Institutional Setting

Italian students attending eighth grade, i.e. their third and last year in the junior high (middle) school, face the choice of their high school track and curriculum. The possible alternatives can be divided into three main tracks: general, technical, vocational. The general track is more focused on preparing for university; the technical track is aimed at developing both theoretical and practical skills; the vocational track is labor-market oriented. Every track is usually offered in separate schools, and each of them offers different curricula; children can switch track during high school, even if this is infrequent[2] and costly time-wise.

High-school enrollment in Italy is non-selective[3]. In this open-enrollment system, there are no geographical or institutional constraints that force students to apply to a specific school (e.g. the nearest one, or one in the same area of residence), and enrollment decisions in almost all the cases lead to admission to the school[4]. Moreover, middle-school teachers make non-binding suggestions and have no power in enforcing any indication.

Minimum schooling age in Italy is 16, hence a regular student should be eligible for dropping out only after three years. After five years of high school[5], students earn a diploma ("diploma di maturità") that allows them to either enter a professional career or apply for university, without any restriction of field connected to the kind of high school attended. University enrollment is possible for any student who holds a "diploma di maturità", independently of the high school track attended, even if some tracks are less suited to prepare for a higher education; this means that choosing a certain track at the age of 14 may not be binding but has an impact on the human capital accumulation process and on the skill mismatch that may occur between high school preparation and the following career choice (either going on studying at university or starting working).

[2]Buzzi (2005) says that in 2004 Italian students switching during high school were ca. 6.9% of the total, with one third of these movings happening across curricula but within track. Table B.1 in the Appendix shows the average percentage of changes in Veneto in a.y. 2007/08.

[3]While some high schools have introduced admission tests in the last years, this is not true in the context analysed in this paper, that is the city of Vicenza in the a.y. 2011/12.

[4]First-choice high schools may need to decline admission if the number of requests is too high compared to their availability. In that case, the application form is automatically forwarded to the second choice listed on the form. In case the number of requests is too high, each high school has specific admission criteria listed on their website.

[5]Some schools in the vocational track offer professional diplomas after three years, but unlike the "diploma di maturità", earned after five years, the professional diploma does not allow access to university.

Students in my sample make their high school decision in the a.y. 2011/12, thus entering high school in September 2012. Table 1 presents the alternatives available in the city of Vicenza in the academic year considered in this analysis[6]. Each of the three tracks offers curricula. When students pre-enroll, they can rank up to three possible choices in terms of specific schools, hence possibly listing three alternatives within the same curriculum or the same track.

Table 1: Supplied curricula in the city of Vicenza, a.y. 2011-12.

Track	**Curriculum**
General	Humanities
General	Languages
General	Mathematics & Science
General	Art
General	Music & Choral
General	Social Sciences
Technical	Economic Sector
Technical	Technology Sector
Vocational	Services
Vocational	Industry & Crafts
Vocational	Professional Training

Table B.2 in the Appendix shows some statistics about Italian students that obtained a high school degree in 2011, thus a population that may have represented a source of information for students in my sample; four years later Istat data[7] show that less than 8% of those that had attended either Humanities or Languages or Math&Science within the general track had never enrolled in any kind of university education, compared to 56% of those graduating from a technical high school and almost 80% of those with a vocational education. For comparison purposes with my sample (graduating in the a.y. 2016/17), Table B.3 in the Appendix presents information about the 2017 high school graduate population in some of the high schools of Vicenza, giving a snapshot of the students' academic status after one year of university: 9% of those that had attended either Humanities or Math&Science within the general track had not enrolled in any kind of university education, compared to the 53% of those graduating from a technical high

[6]Figure B.1 in the Appendix presents the geographical distribution of these schools, divided by track. Most of these schools offer more than one (within-track) curriculum. The distance from school 7 to school 8 (i.e. approximately the sinister diagonal, from the upper right corner to the bottom left one) is around 4 km by car through the city center. Most schools are connected through the public transportation system.

[7]Source: Istat, "I percorsi di studio e lavoro dei diplomati e dei laureati: Indagine 2015 su diplomati e laureati 2011", September 29, 2016 (Table 2, page 4). Available at www.istat.it. See also Table B.2.

school. These numbers are therefore in line with the ones presented by Istat referring to an older cohort, with the caveat that Istat presents data four years after the high school diploma and not one year after like in Table B.3[8]. Table B.4 in the Appendix presents some statistics about the same population, i.e. high school graduates in a.y. 2016/17 in Vicenza one year after the diploma, but providing some information about employment status.

3.2 The Dataset: Survey Design

The data used for this work come from a survey designed to assess how the process for the choice of a high school track works.

Sampling and timeline. The survey has been administered to a sample of children in eighth grade and their parents in Vicenza (Italy) in four different waves within a six-month period (October 2011-April 2012); three waves happen before the pre-enrollment choice is made, while the last one happens afterwards. Out of the 11 public middle schools in Vicenza, 10 agreed to participate, so that around 900 families were involved. Here I present a more detailed timeline:

- **Survey Wave 1 (W1), October 2011**: the first wave of the survey is administered to both parents and children; the questionnaires are separate but most of the questions are overlapping;
- **Survey W2, December 2011**: second wave of the questionnaire, separately filled in by parents and children but mostly with common questions;
- **Survey W3, January 2012**: third wave of the questionnaire, separately filled in by parents and children but mostly with common questions;
- **February 2012**: the pre-enrollment application needs to be submitted within a given time window;
- **Survey W4, April 2012**: fourth wave of the questionnaire, for children only;
- **July 2012**: formalization of the enrollment application.

The survey waves were designed in order to observe pre-enrollment choices and the decision-making process. The observed final choices, for both the individual and their

[8]Source: Eduscopio. See discussion in the Appendix.

peers, are elicited in Wave 4[9]. Official enrollment is then confirmed after the end of the academic year, in July; deviations from the previous pre-enrollment application are infrequent.

Administration and participation. The paper questionnaire was self-administered at home; completion time was around 60 minutes, and respondents had 10-15 days to fill it privately and return it to the school in a sealed envelope. In total, Wave 1 saw the participation through a fully or partially completed questionnaire of approximately 72% of the students (i.e. 649) and 68% parents (619). Table B.5 in the Appendix presents data about the number of participating students, and Table B.6 in the Appendix summarises the rate of students' participation to each survey. To incentivise participation, the following scheme was implemented. Children who answered and returned all 4 questionnaires were entered a lottery awarding 1 scientific calculator in each participating school and class (the total number of participating classes is 47). Additionally, families whose parents took and returned all 3 questionnaires were entered a lottery awarding one €100 voucher in each participating school and class to be spent toward purchase of ninth-grade textbooks for the children.

Questions. The information content is very detailed for what concerns family structure, abilities, preferences and habits, time management and extracurricular activities, and measures of awareness of alternatives and belief ambiguity with respect to the possible schools that could be chosen. The analysis concerning the perceived awareness of alternative options and the belief ambiguity about the likelihood of certain consequences stemming from the high school choice is carried out in Giustinelli and Pavoni (2017). In the following paragraph I briefly summarise the main topics covered by the surveys administered to the children.

Each survey starts with questions about the information gathering process; questions concern: whether the student (she) has thought about the choice and particular alternatives in the previous period; whether she has talked about them and with whom; and whether she has actively gathered information from specific sources (e.g. leaflets, websites, fairs). After this set of questions, awareness about the existence of the available options is elicited; students are then asked to rank their favorite alternatives as if they had to make

[9] In some cases, also the questionnaire in Wave 3 might have been filled in after the student had submitted their pre-enrollment form. Nonetheless, this information about early pre-enrollment is available, and I can distinguish pre and post decision periods. The school rankings of their peers, as declared by an early pre-enrolled student in Wave 3, will still qualify as expectations.

the choice on that day. Another section of the questionnaire is about expectations related to each alternative; the questions are about: the expected appreciation of the subjects taught in each curriculum; the expected match between the subjects taught in each curriculum and the personal skills; the subjective probability of having the right preparation to successfully face each option; the expected GPA in each alternative, conditional on exerting a certain effort (i.e. for different amounts of daily study time). Expectations about after-high school outcomes are also elicited, in terms of expected flexibility in choosing between university and labor market after each alternative, or flexibility in choosing among different university fields. Finally, questions about friends conclude the second, third, and fourth surveys; this part is discussed in the next section of the paper.

3.3 The Network: Construction and Statistics

An important part of this work is the reconstruction of the peer network. In fact, in different waves both students and parents are asked to report a list of friends, with whom the child may or may not have coordinated for choosing the high school.

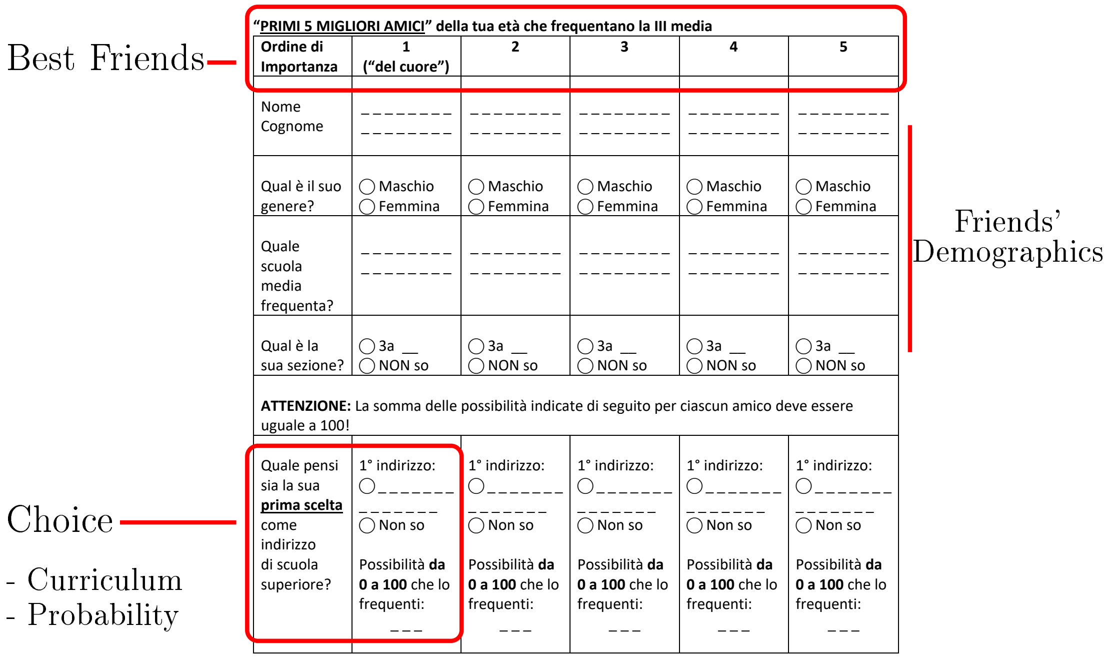
The section related to network information of the Vicenza Project survey was designed following the AddHealth questionnaires; in my case pupils could name up to 10 peers attending their same grade, but they were not restricted neither in the gender of peers nor in choosing from a school list, as happens in AddHealth. It is hence possible that students did not clearly identify their peers and wrote down ambiguous names. This has the drawback of making the reconstruction of the network a more challenging process, but it avoids some biases that can arise from imposing constraints on gender and school.

One of the main advantages of the Vicenza Project design is the repeated elicitation of the network in subsequent questionnaires. In Waves 2 and 3, i.e. before the pre-enrollment decision, students face a partially overlapping set of questions regarding their friends. In both surveys they are asked whether they have friends attending eighth grade (not necessarily classmate or schoolmates); it is also possible to list up to 5 older peers already attending high school.

Both Waves 2 and 3 require to list up to 10 eighth-grade “best friends”, asking for name, gender, school and class attended. Then students are asked to declare which ones they think would be the preferred curricula by each of their peers; they can list up to three (ranked) expected choices, indicating for each of them which is the probability of true selection, and the sum of the three probabilities must be 100. Hence, if student i

thinks their peer number 1 is uncertain between two schools, with one slightly more likely than the other, they will list both of them as ranked first and second and they will write respectively "60%" and "40%". An example of the structure of the table can be seen in Figure 1: the chart is an extract from Wave 3 and focuses on the peers 1 to 5 but is shortened below as only the first (most likely) expected choice is ranked out of the three asked (the question is about the *"prima scelta"*, the preferred option).

Figure 1: Sample of questions on the first 5 friends in Wave 3.



"PRIMI 5 MIGLIORI AMICI" della tua età che frequentano la III media

Ordine di Importanza	1 ("del cuore")	2	3	4	5
Nome Cognome	________ ________	________ ________	________ ________	________ ________	________ ________
Qual è il suo genere?	◯ Maschio ◯ Femmina	◯ Maschio ◯ Femmina	◯ Maschio ◯ Femmina	◯ Maschio ◯ Femmina	◯ Maschio ◯ Femmina
Quale scuola media frequenta?	________ ________	________ ________	________ ________	________ ________	________ ________
Qual è la sua sezione?	◯ 3a __ ◯ NON so	◯ 3a __ ◯ NON so	◯ 3a __ ◯ NON so	◯ 3a __ ◯ NON so	◯ 3a __ ◯ NON so
ATTENZIONE: La somma delle possibilità indicate di seguito per ciascun amico deve essere uguale a 100!					
Quale pensi sia la sua **prima scelta** come indirizzo di scuola superiore?	1° indirizzo: ◯_______ _______ ◯ Non so Possibilità **da 0 a 100** che lo frequenti: ___	1° indirizzo: ◯_______ _______ ◯ Non so Possibilità **da 0 a 100** che lo frequenti: ___	1° indirizzo: ◯_______ _______ ◯ Non so Possibilità **da 0 a 100** che lo frequenti: ___	1° indirizzo: ◯_______ _______ ◯ Non so Possibilità **da 0 a 100** che lo frequenti: ___	1° indirizzo: ◯_______ _______ ◯ Non so Possibilità **da 0 a 100** che lo frequenti: ___

The table asks to list the "first five best friends of your same age that attend the 8^{th} grade". The required information is the name and surname, the gender, the name of the middle school attended and the class section (e.g. A, or B). Then it moves on to ask "What do you think is his/her first choice in terms of high school curriculum?", with the possibility of writing down the percent chance that this scenario will realize. The table also gives a warning: for each friend, the sum across the reported possible choices (up to three) must be 100.
This table concerns peers ranked 1 to 5, and is cut below as only the question concerning the most likely school choice ("the first choice") is represented. The full table allows to name up to three curricula. The same structure is afterwards used for peers 6 to 10.

On top of eliciting friends and expectations about friends' future choices, the surveys gather additional information on the friendship links. Wave 2 asks questions on the strength of the relationship, i.e. how long the student and each peer have known each other and which activities they do together; Wave 3 is more concerned about coordination issues about choice, and therefore the student is asked whether they have tried to coordinate with their peers (and, if so, on what) and whether their parents know about this and consent to it. Parents' Wave 3 questionnaire also addresses the issue of the elicitation of peers and whether they are aware of a possible coordination among the teenagers concerning the high school choice, but I do not exploit this information in this paper.

For what concerns the after-enrollment period, Wave 4 presents the same questions of Wave 3, including those on coordination and parents' involvement, but the student must report only the selected option given that the final choice has already been made at this point in time. In this analysis I exploit Wave 4 only to collect data about realized choices, but I disregard the information about the network structure.

On top of the ambiguous nomination of peers in the network, two other issues may give rise to mismeasurement in the network. The first one is survey non-response, which happens not at random due to self-selection and attrition, and which may hinder not only the assessment of expectations but also the deduction of the complete network. Tables B.7 and B.8 in the Appendix help us have a deeper look into the differences of respondents across waves. The second problem is related to top-coding the number of edges, as individuals are asked to report up to 10 peers and many report exactly 10. By asking for ten names, on the one hand I risk having people leaving out relevant friends, but on the other hand students may be biased by this reference number and feel that they "have to" fill in the table completely (a cognitive bias known as "anchoring"). The layout of the page involved the elicitation of friends in groups of five, i.e. there was first a table reserved for the first five friends, and then a subsequent identical table devoted to friends from six to ten. Many students filled in completely either the first one or both of them, as if compelled to do so. Figure B.2 in the Appendix combines data from Waves 2 and 3 and counts how many friends each student nominated (the so-called outdegree); a student may have filled in only one wave, or maybe both writing down always the same set of friends (possibly with different rankings) or a different one. There are peaks around 5 and 10. A representation of the indegree (i.e. how many times the student herself was nominated by others) can be found in Figure B.3 in the Appendix. Goldsmith-Pinkham and Imbens (2013) discuss possible corrections of the network structure when repeated observations of it are available. They present evidence that it is not safe to assume that self-reported friendship connections capture all the relationships that are important for correlations in outcomes. However, in longitudinal studies if measurement error is random and if a link is reported as existing in the current period, then it is likely that it was there also in the previous period; hence, if there is no link today but its existence was reported in the previous observation, it is more likely that a link is indeed present now. This applies to my case, given that the reported network of friends is measured repeatedly and it is likely

Table 2: Network statistics.

Statistics	
N. Nodes	1285
N. Edges	2214
Avg. Degree	3.446
Avg. Clustering	0.155
N. Communities	22

Waves 2 and 3
Undirected graph

to be stable across waves, collected a few months apart during the same school year.

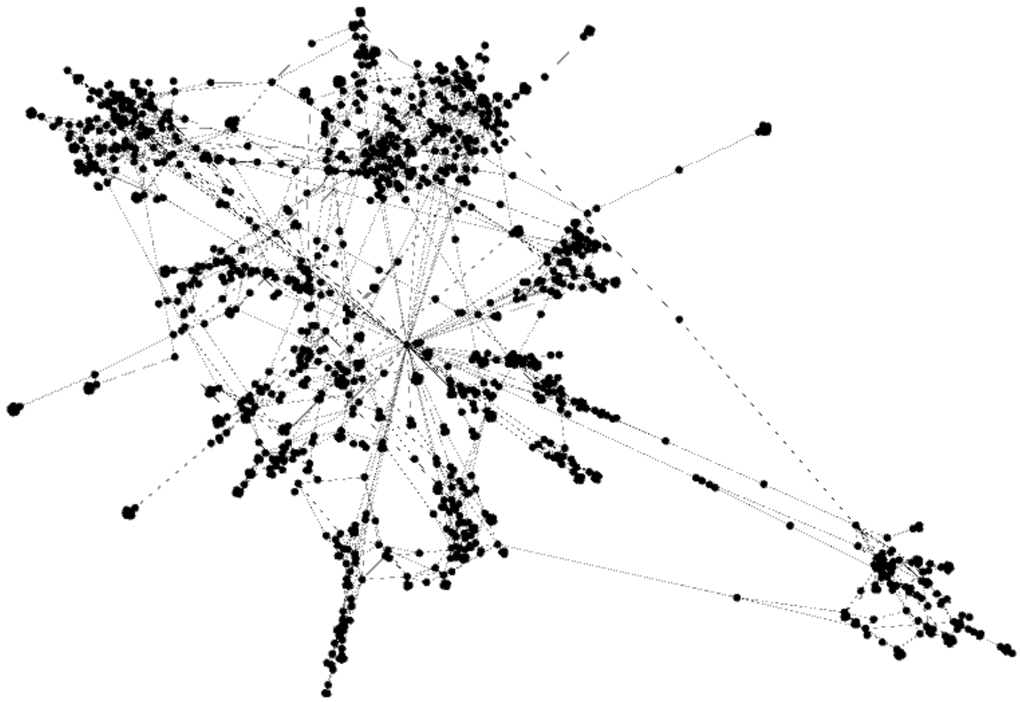
Given the focus on the pre-enrollment phase, I exploit the information coming from Waves 2 and 3 in order to reconstruct the network and to detail the elicitation of subjective beliefs. I prioritize information from Wave 3 as it is closer to the final decision, and I complement it with information from Wave 2. I assume that friendship is mutual, hence if a student nominates a peer but they are not reciprocated in this peer's own list (possibly because of the missing survey response of this individual), still there will be a link back from the peer to the student. Therefore if A reports B as friend, then B will be considered to have A among his/her friends as well, despite the fact that B may have not answered the survey or have answered it without mentioning A. This means that friendship links are "undirected": they do not go from A to B but rather they just exist among these two individuals.

Figure 2 represents the undirected network stemming from the combination of Waves 2 and 3. Table 2 reports some statistics describing the network. The dots ("nodes") represent students, and the lines among them ("edges") represent friendship links.

Having 10 middle schools involved, it is not surprising to find "communities" in this network, i.e. groups of nodes that are more densely connected internally than with the rest of the network. The clustering coefficient in general ranges from 0 to 1 and gives us an idea of how much the nodes tend to be connected among themselves; a clustering coefficient of 1 means that, on average, if I take a node i and I look at its first degree neighbors (i.e. its direct connections), then all of them are connected among themselves (100% of the possible edges among them is in place). In this case it is relatively low (0.15) possibly because of missing nodes (students) and in particular edges (connections) due to attrition.

In order to understand the kind of friendships that exist among these teenagers, it is

Figure 2: Network representation – Aggregation of Waves 2 and 3.



The dots ("nodes") represent students, and the lines among them ("edges") represent friendship links. Given that the network is incomplete, I consider these links as "undirected".

useful to look at the information provided in Wave 2 when students are asked to declare how long they have been knowing their peers and which kind of activities they do together. Most of the reported peers are classmates during middle school. Table B.9 in the Appendix reports some statistics concerning the percentage of peers met during either middle school, or elementary school, or kindergarten. For example, if I look at the best friend I can see that 45% of the first peers reported had met during the previous two years (i.e. while attending middle school), and more than 60% of them are classmates. These percentages are more or less stable across the reported peers, with 45% to 61% of peers that have been friends for less than two years and 49% to 67% being classmates in middle school.

Paired with the fact that relevant peers are the result of relationships born during the previous years, I also provide evidence that students did not start discussing about high school choices longer before the actual choice takes place. Table B.10 in the Appendix summarises some statistics that reveal how more than 20% of students had never talked about high school with their peers as of Wave 1. Moreover, of those that do approach the topic with friends by Wave 3, only 27% declare having talked about a specific school or curriculum, versus 24% of general conversations.

3.4 Measurements and Relevant Covariates

My outcome of interest is the pre-enrollment decision, declared by the student in Wave 4 (or in Wave 3 if an early pre-enrollment decision had already been submitted). In this case, the student declares which curriculum and which particular high school institution is chosen. I use as outcome variable the chosen track, aggregating the information according to the mapping presented in Table 1.

The demographic information was elicited in the first wave of the survey, when most of the students and parents participated. Hence, the exogenous characteristics for most of the nodes of the network can be inferred by matching parents and children and are available regardless of the possibly missing network information coming from following waves.

The individual perception of particular school characteristics, namely the subjective probability of liking the subjects, was assessed over multiple waves, including Waves 2 and 3.

Table 3 describes the most important covariates used in the analysis.

In my multinomial logit estimation, I need to separate the covariates in two sets. I

Table 3: Description of the relevant variables in the estimation.

Variable	Description
Individual-specific	
Female	gender, dummy = 1 if female
Foreign born	country of birth, dummy = 1 if foreign born
No. siblings	number of siblings
Mother with edu hs+	dummy =1 if mother has education >= high school
Father with edu hs+	dummy =1 if father has education >= high school
7^{th} grade GPA	GPA of the previous academic year, $\in [6, 10]$
School-specific	
Prob. Like	probability each HS matches tastes
Prob. Apt	prob. each HS fits abilities
Prob. Trained	prob. student is prepared for each HS
Flexibility1 Both	prob. each HS allows for flexible choice work/university
Flexibility1 Uni	prob. each HS allows for university choice (not flexibly)
Flexibility1 Work	prob. each HS allows for work choice (not flexibly)
Flexibility2 Humanities	prob. each HS prepares for Humanities at university
Flexibility2 Sciences	prob. each HS prepares for Sciences at university
Flexibility2 Law	prob. each HS prepares for Law at university
Exp. tot hours studying	expected amount of daily study hours required by each HS
Exp. GPA for studying <1h	exp. GPA if studying daily less than 1 hour in each HS
Exp. GPA for studying 1<h<2	exp. GPA if studying daily between 1 and 2 hours in each HS
Exp. GPA for studying 2<h<3	exp. GPA if studying daily between 2 and 3 hours in each HS
Exp. GPA for studying>3h	exp. GPA if studying daily more than 3 hours in each HS
Δ exp. tot hours	(Current amount of daily study hours)-(Expected amount by each HS)
Δ exp. GPA for studying X	(Current GPA)-(exp. GPA if studying daily X hours in each HS)

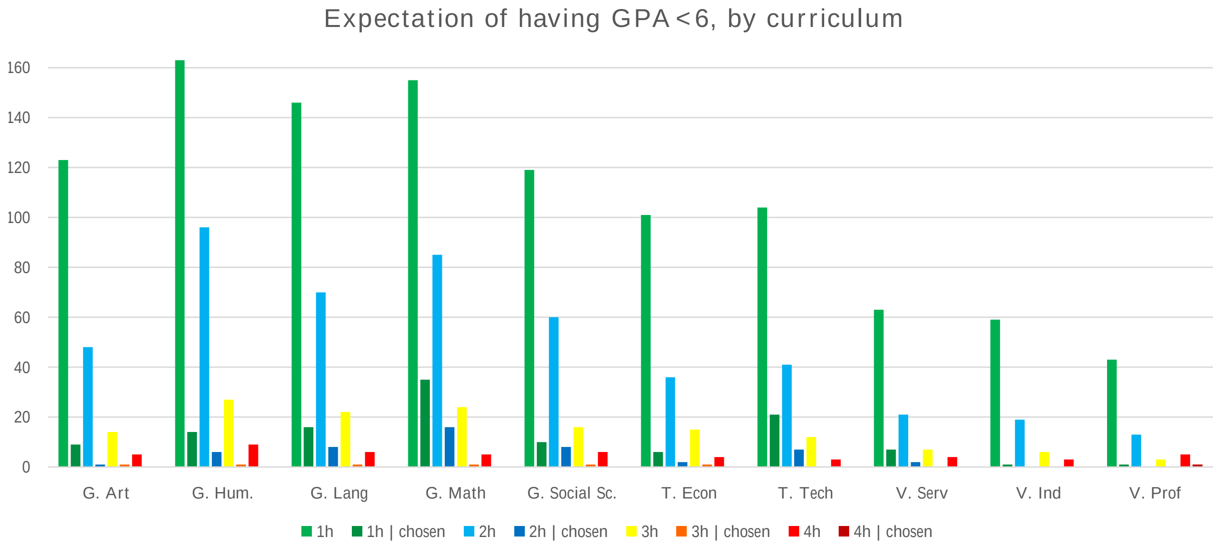
HS: high school. Exp.: Expected. Prob.: Probability.

have case-specific variables, i.e. the exogenous characteristics of the student that are fixed across alternatives but by definition change from individual to individual, and alternative-specific variables, i.e. whose values within individual can change for each possible chosen alternative.

The exogenous individual-specific characteristics detailed in the first panel of Table 3 will be denoted with $\mathbf{x}$, while I will refer to all the school-specific perceptions as $\mathbf{z}$.

Of particular interest is the bottom group in the lower panel of Table 3, where I introduce the measures of expected effort and performance. In the surveys, for each high school curriculum students are asked how much time they expect they would need to devote to study every day, and which GPA they would expect to get if they studied either less than 1 hour, between 1 and 2 hours, between 2 and 3 hours, or more than 3 hours per day. Let us now have a look at some histograms where data are still disaggregated into the original curricula. Figure 3 displays the fact that the expectations of failing in a certain curriculum (i.e. having a GPA below 6/10) are related to the amount of study hours that the student would need to put in practice, as it would be expected. There are

Figure 3: Frequency of having an expected GPA below 6 (fail) for varying levels of effort, by curriculum.



For each curriculum there are 8 columns of four colors. Each color represents a study bucket, i.e. having an expected GPA below 6 if studying respectively less than 1 hour, between 1 and 2 hours, between 2 and 3 hours, or more than 3 hours. The two bars of the same color but different intensity represent respectively the whole sample (lighter shade) *vs* conditional on choosing that curriculum (darker shade).

nonetheless two important things to point out. The first one is that with an increasing effort the probability of having an expected GPA below passing grade decreases, for all curricula. The second one is that there seems to be a pattern related to the track, in fact the highest probabilities of failing are associated with the curricula of the general track. Nonetheless, the fact that some observations expecting a failing grade persist in every curricula even for more than three hours of study per day means that students perceive that performing well is not only related to effort, but also to abilities.

Figure B.4 in the Appendix tells us a similar story about a possible "ranking" across curricula. Here I am not using expected GPA and study hours in absolute terms, but rather their differences with respect to actual (reported) GPA and study hours in middle school. The pattern in the red columns highlights the fact that students perceive as more likely to decrease their GPA even with higher effort in more demanding curricula like those of the general track. The same conclusion can be drawn from the blue columns, that show how students would expect their GPA to increase in less demanding curricula even while exerting lower effort. Figure B.5 in the Appendix focuses on the Math&Sciences curriculum in the general track, considered to be one of the hardest ones; in Wave 1 the expected probability of completing high school in the regular time is quite spread across the whole distribution, and the frequency of low expected probabilities remains relatively high.

The correlations between own characteristics and the average characteristics of friends can be seen in Table 4.

Table 4: CORRELATIONS BETWEEN OWN CHARACTERISTICS AND AVERAGE OF FRIENDS.

Female	0.735***
Foreign country of birth	0.064**
Number of siblings	-0.151***
Mother has education college+	-0.094**
Father has education college+	-0. 28
7th-grade GPA	0.193***
Observations	311

4 The Model

In my basic model I want to outline how a student chooses their high school track.

Student i chooses a school track s out of the possible S alternatives, and the outcome is denoted as y_i. I set $y_i = s$ if the alternative chosen is s, with $s = 1, ..., S$. Student i has $j = 1, ..., n_i$ peers that i believes are making choice y_j^i.

For individual i and alternative s I suppose that the payoff determining the choice is a latent variable denoted as y_{is}^*. I can divide the relevant characteristics into three categories: a private deterministic component, a social deterministic component, and the stochastic part. The payoff of student i from choice s, y_{is}^*, is a latent variable defined as the sum of these three components:

$$\begin{aligned} y_{is}^* = & \underbrace{\sum_{m=1}^{M} \beta_{ms} x_i^m + \sum_{h=1}^{H} \theta_h z_{is}^h}_{\text{Private deterministic component}} \\ & \underbrace{+ \lambda \left(\frac{1}{n_i} \sum_{j=1}^{n_i} \mathbb{1}(y_j^i = s) \right) + \left[\frac{1}{n_i} \sum_{m=1}^{M} \sum_{j=1}^{n_i} \gamma_{ms} g_{ij} x_j^m \right] \mathbb{1}(y_j^i = s)}_{\text{Social deterministic component}} \\ & + \underbrace{\epsilon_{is}}_{\text{Stochastic component}} \end{aligned} \tag{2.1}$$

Important factors for the private deterministic component are two. First of all, I consider the M observable characteristics of student i, denoted as $\mathbf{x_i} = \{x_i^m\}_{m=1}^M$. Second, I have H characteristics of high school s as perceived by i (expected costs and benefits), i.e. $\mathbf{z_{is}} = \{z_{is}^h\}_{h=1}^H$; these include the perceived mismatch in abilities, the probability of being interested in the subjects taught at school, the expected future outcomes after the diploma.

My observables then include a social component. I consider in the first place the benefit stemming from the share of peers that i expects are going to make their same choice. I denote the belief about j's choice as y_j^i, such that $y_j^i = s$ if student i believes that their jth peer will choose school s. I further use an indicator function $\mathbb{1}(y_j^i = s)$, such that it is equal to 1 in case student i is choosing alternative s and i expects their jth peer to make the same decision, so that $y_j^i = s (= y_i)$, and it is 0 otherwise. I include in the model also the M characteristics of peers, $\mathbf{x_j} = \{x_j^m\}_{m=1}^M$ weighted by $\frac{g_{ij}}{n_i}$ such that $g_{ij} = 1$ if there exists a relationship between i and j, and $g_{ij} = 0$ otherwise. Depending on the chosen alternative, I will show that own and peers' characteristics have a different effect.

The model in equation (2.1) can be written in a more compact way. To introduce the matrix formulation, I need to enrich the notation relative to the network component. In particular, I define $G = [g_{ij}]$ as the adjacency matrix such that $g_{ij} = 1$ if i and j are friends, $g_{ij} = 0$ otherwise. I will use here $\hat{G}$, i.e. the row-normalized version of G. It is such that $\hat{G} = [\hat{g}_{ij}]$, where $\hat{g}_{ij} = \frac{g_{ij}}{n_i}$, and by construction $0 \leq \hat{g}_{ij} \leq 1$ and $\sum_{j=1}^{n_i} \hat{g}_{ij} = 1\ \forall i$. Thus equation (2.1) becomes

$$y^*_{is} = \boldsymbol{\beta_s}\mathbf{x}_i + \boldsymbol{\theta}\mathbf{z}_{is} + \lambda\hat{G}\mathbf{y^i_j} + \boldsymbol{\gamma_s}\hat{G}\mathbf{x}_j + \epsilon_{is} \tag{2.2}$$

such that $\boldsymbol{\beta_s} = \{\beta_{ms}\}_{m=1}^M$, $\boldsymbol{\theta} = \{\theta_h\}_{h=1}^H$, and $\boldsymbol{\gamma_s} = \{\gamma_{ms}\}_{m=1}^M$. Moreover, I write $\mathbf{y^i_j} = \{y^i_j\}_{j=1}^{n_i}$ in order to denote i's expectations about her $j = 1, ..., n_i$ peers. I will call $\mathbf{x}_i$ case-specific regressors, and $\mathbf{z}_{is}$ and $\mathbf{y^i_j}$ alternative-specific regressors.

I here detail the relevant coefficients:

- Vector $\{\beta_{ms}\}_{m=1}^M$: effect of own characteristics;
- Vector $\{\gamma_{ms}\}_{m=1}^M$: *exogenous (contextual) effect* - social interaction effect, different across characteristics. In the estimation this will be excluded;
- Vector $\{\theta_h\}_{h=1}^H$: effect of the perceived high school characteristics;
- λ: *endogenous effect (peer effect).*

In some of the empirical specifications I will also introduce a middle-school fixed effect in the estimation: this captures the *correlated effect*, like in Cohen-Cole, Liu, and Zenou (2017) and Nakajima (2007). This is coherent with a two-step link formation model: in the first step, individuals self-select into different networks based on the school characteristics (e.g. geographical location, neighborhood, quality of teachers, etc) and then in the second step link formation takes place within networks (i.e. within schools) based on the observable individual characteristics.

The choice of student i arises from a maximization across all alternatives. I observe the outcome $y_i = s$ if alternative s gives the highest payoff, hence it follows that

$$p_{is} = Pr(y_i = s) = Pr(y^*_{is} \geq y^*_{iv}), \quad \forall v \in S, \text{ with } v \neq s \tag{2.3}$$

The basic model presented in equation (2.2) refers to the baseline case of an unweighted network, where every peer of i has the same weight in computing the group average of behaviors and characteristics. As a robustness check I will also introduce variations where each peer receives a weight w_{ij} that depends first of all on the ranking that i attributes to j, and second on the total number of peers reported by i. I then need to distinguish two cases. In case of an undirected link, i.e. both i and j report each other as peers, then possibly $w_{ij} \neq w_{ji}$ depending on each individual statement. The second case of a directed link, i.e. i has nominated j but the converse is not true, can happen for two reasons: either j has not reported i, or j has not answered to the network questions. In this case, I set $w_{ij} = w_{ji}$. This looks reasonable, as in case the first option is correct, it is unlikely that i has nominated j among the best friends, hence the relative weight attributed to this link will be low; the second situation does not allow us to make any assumption on the strength of the relationship, and hence I use i's information as proxy for j's.

Needless to say, given the row normalization and the weights accrued to the peers, this is a local-average model, i.e. a model of influence where what matters is the average behavior of the group of people that agent i considers closer to her. As Liu, Patacchini, and Zenou (2014) clarify, in this setting I can affect individual behavior only by changing the social norm of the group; for a policy to be effective, I cannot target one agent only but I need to affect most people in the network.

Expectations vs. outcomes. It might be argue that this is not a standard reflection problem because it lacks the usual endogenous effect, i.e. peers' outcomes. In this paper I use own expectations about future peers' outcomes instead of the outcome themselves, and I argue that this process is valid for the following reasons. First, during the decision-making process choices are not realized and therefore are not observed. Second, expectations about peers are formed through interactions with these peers; in the surveys students are asked to report their own potential future choices *as if* they had to decide on that day, thus translating expectations into un-realized future choices. This makes today's expectations as good as tomorrow's choices. Third, most of expectations on peers are correct, but not all of them (the correlation between expectations and actual choice is 0.71). The private error component may be due to informational gaps, errors in projecting today's expectations, or errors in attributing to the peer an expectation that self-confirms own preferences.

5 Empirical Strategy and Methodology

Identification of endogenous and exogenous peer effects is achieved as long as the peer groups are individual-specific and partially overlapping. In this way I am able to isolate the characteristics of friends' friends of i that explain the behavior of i's friends but do not directly influence i's outcome. I therefore instrument i's friends' behavior with the "excluded peers" (as in De Giorgi, Pellizzari, and Redaelli (2010)); in other words, if i and j are friends, and k is only a friend to j but not to i, I can instrument j's behavior with k's characteristics, so that I can distinguish in j's behavior the part that is predicted by her friends not in common with i.

Another issue is the endogeneity of link formation. As argued by Bramoullé, Djebbari, and Fortin (2009), by controlling for own characteristics $\mathbf{x}$ I also control for the network-formation mechanism as long as the observable features used are those that affect the creation of a friendship link.

In my two-stage approach, I estimate the first stage as follows. I predict the expected choice of j (i.e. the beliefs of i about j) with j's peers k exogenous characteristics:

$$\widehat{y_j^i} = \frac{1}{n_j} \sum_{m=1}^{M} \sum_{k=1}^{n_j} \zeta_m g_{jk} x_k^m \tag{2.4}$$

with n_j being the number of j's peers, M the observable characteristics $\mathbf{x_k} = \{x_k^m\}_{m=1}^M$, and $g_{jk} = \begin{cases} 1 \text{ if } k \in j\text{'s network,} \\ 0 \text{ else} \end{cases}$.

The coefficients in this first stage are:

- $\boldsymbol{\zeta} = \{\zeta_m\}_{m=1}^M$ represents the coefficients associated with the M baseline characteristics of j's peers (i.e. i's second peers).

In matrix form, I will refer to $g_{jk}x_k^m$ as being the $G^2\mathbf{x}$ to individual i, i.e. the matrix of characteristics of the second neighbors resulting from the matrix of interactions G multiplied.

In the second stage I estimate a multinomial logit with both individual-specific and alternative-specific regressors.

Let us define the deterministic component of y_{is}^* as ν_{is}, so that equation (2.1) can be rewritten as

$$y_{is}^* = \nu_{is} + \epsilon_{is} \tag{2.5}$$

My assumption on the error term is that it follows a logistic distribution, such that the probability of choosing alternative s can be estimated as

$$\begin{aligned} p_{is} &= Prob(y_i = s) \\ &= Pr(y^*_{is} \geq y^*_{iv}), \quad \forall v \in S, \text{ with } v \neq s \\ \Rightarrow p_{is} &= \frac{e^{\nu_{is}}}{\sum_v e^{\nu_{iv}}} \end{aligned} \tag{2.6}$$

In section (4) I called $\mathbf{x}_i$ "individual-specific characteristics", or "case-specific regressors". This means that these variables change across individuals but not within them, and in order to ensure model identification I need to restrict one of the $\boldsymbol{\beta_s}$ coefficients equal to zero. Coefficients are then interpreted with respect to that category, the "base" one. These $\boldsymbol{\beta_s}$ coefficients may be interpreted as reflecting the effects of the covariates on the odds of making a given choice with respect to the base alternative. In the following analysis, the base alternative is the general track.

School-specific variables instead change across alternative, like student i's perception of high school s characteristics, $\mathbf{z}_{is}$, and student i's expectations about their peers' choices, $\mathbf{y_{is}}$. Nonetheless, I consider their effect to be equal across alternatives, and therefore I estimate only one coefficient.

Controlling for the network formation mechanism. The set of variables $\mathbf{x}_i$ that I use in my analysis was chosen because it represents the set of observable characteristics that drive the network formation mechanism. I include gender, citizenship (Italian *versus* foreign-born), previous-year GPA, and indicators related to the socio-economic background, namely the number of siblings and parental education. These indicators are actual predictors of link formation, as will be discussed in section (6.7).

6 The Influence of (Expectations on) Peers in High School Choice: Evidence

This section presents the role of peer effects in high school choice. In the tables I refer to the share of peers expected to attend a certain high school track simply as the "share of peers". I build on different specifications in order to achieve a final estimation with all the relevant variables, including the expected share of peers that will attend a certain track and school-specific expectations. In the robustness checks I use the actual realized outcome of peers, and I also introduce different specifications of the network.

6.1 Evidence on Peer Effects

In the first two columns of Table 5 I estimate the baseline model, i.e. a model in which regressors are only own characteristics ($\mathbf{x}$), but I disregard school characteristics ($\mathbf{z}$) and peers' characteristics ($G\mathbf{x}$). I repeat the estimation twice, as in column (2) I also add school fixed effects. In the second part of the table I add as controls the friends' characteristics ($G\mathbf{x}$) to both the first and second stage; I present results both without (column (3)) and with (column (4)) school fixed effects in this case too.

Results are presented using both βs and e^{β}s from the multinomial logit estimation for explanatory purposes. The share of peers in a given track affects the prospective choice of enrolling in that track. Increasing the share of peers by one unit for a given track increases the odds of choosing that track; thus, I should consider the βs and e^{β}s as referring to a case where I switch from 0 to 100% of a student's peers expected to pre-enroll in a given track. Considering the baseline case with no fixed effects (column (1)), increasing the expected share of peers in a track by 10% increases the probability of choosing that same track by around 15 times. Lower are the effects that result from adding $G\mathbf{x}$ as a regressor (column (3)); for a 10% change, the increase in probability is around 1.2 times.

In this specification, when I include fixed effects in columns (2) and (4) results are not significant anymore. This might arise from the fact that school fixed effect may capture factors that correlate also with attrition and diligence in filling in properly all the survey question, as the response pattern may be influenced by teachers and peer pressure. However, in the next estimations I will show that by adding all the relevant variables the inclusion of fixed effects does not affect my results.

The two lower panels of Table 5 present the log-odds and odds of choosing the technical

Table 5: ESTIMATION RESULTS FOR THE BASELINE CASE AND WITH THE INTRODUCTION OF GX, WITH AND WITHOUT MIDDLE SCHOOL FIXED EFFECTS.

	Baseline				**Additional GX**			
	(1)		(2)		(3)		(4)	
	β	e^{β}	β	e^{β}	β	e^{β}	β	e^{β}
Share of peers	5.046***	155.4	3.024	20.573	4.797**	121.146	1.892	6.633
	(1.675)		(2.041)		(1.950)		(2.106)	
Technical vs General								
Female	.399	1.49	-.070	.932	.524	1.689	.039	1.04
	(.489)		(.524)		(.758)		(.778)	
Foreign born	-.885	.413	-.375	.687	-1.031	.357	-.685	.504
	(.873)		(.905)		(.901)		(.933)	
No. siblings	.490	1.632	.473	1.605	.459	1.582	.475	1.608
	(.318)		(.335)		(.336)		(.348)	
Mother with edu hs+	.087	1.091	.349	1.418	.061	1.063	.443	1.557
	(.445)		(.476)		(.473)		(.483)	
Father with edu hs+	.758*	2.134	.922**	2.514	.774*	2.168	.932**	2.54
	(.424)		(.447)		(.435)		(.456)	
7^{th} grade GPA	-.787***	.455	-.975***	.377	-.793***	.452	-1.136***	.321
	(.263)		(.332)		(.285)		(.351)	
Vocational vs General								
Female	.659	1.933	.252	1.287	-.513	.599	-1.036	.355
	(.530)		(.590)		(.818)		(.893)	
Foreign born	.312	1.366	.999	2.716	.262	1.3	.822	2.275
	(.693)		(.773)		(.765)		(.821)	
No. siblings	.388	1.474	.293	1.34	.336	1.399	.131	1.14
	(.344)		(.372)		(.377)		(.400)	
Mother with edu hs+	-.443	.642	-.382	.682	-.254	.776	-.225	.799
	(.529)		(.586)		(.578)		(.627)	
Father with edu hs+	.548	1.73	.740	2.096	.392	1.48	.767	2.153
	(.524)		(.585)		(.566)		(.614)	
7^{th} grade GPA	-.879***	.415	-1.335***	.263	-.821**	.44	-1.346***	.262
	(.330)		(.453)		(.368)		(.474)	
N	224		224		224		224	
Pseudo R^2	.191		.275		.230		.306	
School FE	no		yes		no		yes	
Covariates	X		X		X, GX		X, GX	

Standard errors in parentheses. * p< 10%, ** p< 5%, *** p< 1%.

Predictors: *female:* dummy=1 if student is female; *foreign born:* dummy=1 if student is foreign-born; *no. siblings:* number of siblings (between 0 and 3); *mother with edu hs+:* dummy=1 if student's mother has at least high school education; *father with edu hs+:* dummy=1 if student's father has at least high school education; *7^{th}-grade GPA:* student's GPA in the 7th grade end-of-year report (between 6 and 10).

versus the general track (the base alternative) or the vocational *versus* the general track. Two covariates are worth mentioning, i.e. father's education and seventh-grade GPA. If the student's father has at least an high school degree, then the student is more likely to choose the technical track instead of the general, but the same is not true for the vocational case. On the other hand, I see a consistent pattern in academic performance, namely a higher GPA decreases the odds of both choosing a technical or a vocational track *versus* the general one, with a stronger effect in the vocational case. This is coherent with the existing evidence that the best students usually choose a curriculum belonging to the general track (see, among others, Romito (2016)), where a higher academic propensity is required in order to perform, compared to the other two tracks that have the reputation of requiring less effort.

The Pseudo-R^2 reflects the change in terms of log-likelihood from the intercept-only model to the currently estimated model.

The fact that by adding covariates ($G\mathbf{x}$) I reduce the magnitude of the coefficients of interest is not striking. Notwithstanding the fact that the explanatory power of the model increases, as can be seen by comparing the pseudo R^2 of column (1) vs. (3) and (2) vs. (4), yet my favorite specification remains the baseline case without the inclusion of $G\mathbf{x}$. The motivation lies in the fact that these peers' exogenous characteristics are assumed to capture some effect that can be attribute to network composition, and hence redundant with the information already provided by the mere inclusion of own characteristics $\mathbf{x}$.

Mirroring the structure of Table 5, Table B.11 in the Appendix presents the marginal effects for the case with the friends' covariates included. As expected, given that one of the alternatives has been chosen, own-effects are positive and cross-effects on alternative choice are negative. This means that a unit increase in the share of peers expected to choose track t increases the probability of choosing this same track t and decreases the probability of choosing any other one, as the sum of the probabilities across alternatives must be 0. Marginal effects at means are estimated by holding the independent variables constant at their grand mean while plugging in a range of relevant values for my focal variable, and may hence be considered not so informative given that they refer to the individual that has average values for all the characteristics, dummies included. Average marginal effects are estimated by varying the focal variables while holding everything else at their value and are therefore more informative, but the very high standard errors hinder the availability of significant results. Coefficients are statistically significant only for the cases without school fixed effect.

6.2 Peer Effects and School Characteristics

In section (3.4) I presented some measures related to the probability that each high school would be a good fit on the basis of interests, abilities, and preparation, and that each curriculum could afterwards allow the student to choose more or less flexibly between work or university and among different university fields. Given that these measures were assessed at the curriculum level, in order to use them for my analysis I need to aggregated them by track. I used the average by track of each measure, computed considering the number of available answers (e.g. if out of the five general curriculum two answers were missing, the average has been computed by considering only the three valid ones). At the end of this subsection I discuss two other alternative ways of summarising this information, and I argue that the average is the most appropriate measure to use.

The first two columns of Table 6 present estimates obtained from regressions with a reduced list of these measures, while the third and fourth columns use the full set. I alternate columns without and with the school fixed effects, as previously done. The expected share of peers in a given track still presents a positive and statistically significant coefficient, even if lower than the one in the baseline case because of the additional variables introduced. Among the latter, however, only one seems to have a positive influence on choice, i.e. the probability of liking the subjects taught at a certain high school.

Table B.12 in the Appendix repeats the same analysis but excluding the network component, hence looking only at how the perception about prospective high schools and exogenous individual characteristics affect the outcome. Again I present the analysis with a reduced and the full set of covariates, and the probability of liking the taught subjects seems to be the most relevant factor. However, its coefficients are somewhat lower than in the previous case, and also the pseudo-R^2 is lower in Table B.12 than in Table 6. Beliefs about peers' future choices then have an important role on top of the right match with perceived school features.

Table B.13 in the Appendix displays the comparison among three different ways of aggregating the curriculum-specific measures in order to reconcile them with my analysis by track; Table B.14 in the Appendix presents the marginal effects. The first two columns of Table B.13 present the results obtained using the average value and a reduced set of covariates, as already seen in the first columns of Table 6. The specification labeled as "Minimum" exploits for each track only the minimum value indicated for any curriculum in that track, while "High rank" uses only the value associated with the curriculum that

Table 6: Estimation results with a reduced and a full list of school features, with and without middle school fixed effects.

	Short list		Full list	
	(1)	(2)	(3)	(4)
	β	β	β	β
Share of peers	3.838*	3.507	4.029*	3.379
	(2.135)	(2.715)	(2.259)	(2.841)
Prob. Like	.073***	.073***	.057***	.058***
	.010	(.010)	(.012)	(.014)
Prob. Apt			.012	.012
			(.012)	(.015)
Prob. Trained			.022*	.016
			(.011)	(.012)
Flexibility Uni/Work Both	-.001	-.001	.003	.004
	(.000)	(.001)	(.005)	(.006)
Flexibility Uni/Work Uni			-.003	-.005
			(.004)	(.005)
Flexibility Uni/Work Work			-.001	-.000
			(.006)	(.006)
Flexibility Field Humanities			.000	-.001
			(.001)	(.001)
Flexibility Field Sciences			-.000	.001
			(.001)	(.001)
Flexibility Field Law			-.001	-.001
			(.001)	(.001)
Technical vs General				
Female	.836	.614	.936	.604
	(.609)	(.731)	(.633)	(.768)
Foreign born	-.367	.730	-.301	.736
	(1.169)	(.471)	(1.262)	(.516)
No. siblings	.503	-.304	.437	-.085
	(.404)	(1.312)	(.442)	(1.383)
Mother with edu hs+	-.362	-.279	-.541	-.346
	(.584)	(.635)	(.607)	(.647)
Father with edu hs+	.977*	1.135*	.900	1.094*
	(.557)	(.589)	(.577)	(.613)
7^{th} grade GPA	-.502	-.542	-.458	-.555
	(.334)	(.443)	(.348)	(.475)
Vocational vs General				
Female	.881	.811	1.082	.878
	(.665)	(.811)	(.729)	(.854)
Foreign born	-.571	.407	-.587	.541
	(1.167)	(.497)	(1.242)	(.528)
No. siblings	.371	-.665	.395	-.559
	(.433)	(1.376)	(.457)	(1.433)
Mother with edu hs+	-.432	-.567	-.824	-.974
	(.672)	(.771)	(.729)	(.828)
Father with edu hs+	1.279*	1.391*	1.315*	1.452*
	(.675)	(.771)	(.732)	(.843)
7^{th} grade GPA	-.607	-.912*	-.359	-.719
	(.391)	(.545)	(.419)	(.592)
N		224	224	224
Pseudo R^2	.491	.545	.522	.
School FE	no	yes	no	yes

Standard errors in parentheses. * p< 10%, ** p< 5%, *** p< 1%.

School-specific predictors: *prob. like:* reported subjective probability of liking the subjects taught; *prob. apt:* reported subjective probability of having the appropriate set of skills; *prob. trained:* reported subjective probability of having an adequate preparation; *flexibility uni/work both:* reported subjective probability of flexible choice between both work or university afterwards; *flexibility uni/work uni:* reported subjective probability of being able to choose only university afterwards; *flexibility uni/work work:* reported subjective probability of being able to choose only work afterwards; *flexibility field K:* reported subjective probability of being able to choose a K major at university. **Predictors:** *female:* dummy=1 if student is female; *foreign born:* dummy=1 if student is foreign-born; *no. siblings:* number of siblings (between 0 and 3); *mother with edu hs+:* dummy=1 if student's mother has at least high school education; *father with edu hs+:* dummy=1 if student's father has at least high school education; *7^{th}-grade GPA:* student's GPA in the 7th grade end-of-year report (between 6 and 10).

in that track was ranked highest (e.g. for the chosen track, I am considering the chosen curriculum; for other tracks, I rely on survey rankings). As usual, all the three specifications are presented both without and with middle-school fixed effects, respectively. It is interesting to see how the probability of liking that track remains significant across all columns, while the peer effect is actually non-statistically significant when considering the values of the highest-ranked option in all the tracks. This might happen for two reasons. The first one is that by aggregating peers based on track and by analysing variables based on curriculum I am actually confusing the two levels. The second is that students do not rank homogeneously all the curricula in a track and do not attribute the probability of liking a curriculum uniformly. This sounds reasonable; in fact, a student interested in the scientific and technical field may rank highest the Math&Science general curriculum and as second choice the Technical curriculum in the technical track, and they may have very different perceptions about the probability of liking the Humanities or the Social Sciences curricula in the general track. Once again, by using curriculum-specific measures I am confusing the levels of analysis. Hence using an average measure may be more appropriate in order to capture private inclinations.

6.3 Peer Effects and Expected Effort

I now introduce the relevant measures of perceived effort and performance. In the surveys, for each high school curriculum students are asked how much time they expect they would need to devote to study every day, and which GPA they would expect to get if they studied either less than 1 hour, between 1 and 2 hours, between 2 and 3 hours, or more than 3 hours per day. On top of these "absolute" perceptions, I also compare these expected future measures with the actual declared GPA and the actual declared time spent studying in eighth grade. For more details, refer to the bottom panel of Table 3.

These measures have been observed multiple times. Here I prefer reports from Wave 3, but when absent I replace them with those observed in Wave 2. Given that the questions refer to specific curricula, in order to aggregate them by track I use averages.

Table 7 presents the analysis of the multinomial logit including the covariates related to expected effort and performance. There are three important considerations to make in this case. First of all, it is interesting to note that here results of estimations that include school fixed effects are higher than those that do not consider them for the first specification with a reduced set of covariates, namely the share of peers and the expected amount of study

Table 7: Estimation of results introducing expected GPA and effort, with and without middle school fixed effects.

	Effort		Effort & Performance		Differential		Relevant	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	β	β	β	β	β	β	β	β
Share of peers	3.990***	5.337***	3.208***	3.105*	3.894***	3.184**	3.197***	2.549*
	(1.260)	(2.084)	(1.173)	(1.671)	(1.162)	(1.595)	(1.159)	(1.558)
Exp. tot hours studying	.201***	.226**	.229***	.264***			.186**	.223**
	(.084)	(.091)	(.085)	(.094)			(.085)	(.095)
Exp. GPA for studying <1h			.030	.008			.064	.046
			(.152)	(.174)			(.106)	(.105)
Exp. GPA for studying 1<h<2			-.049	-.042				
			(.110)	(.123)				
Exp. GPA for studying 2<h<3			.143	.158				
			(.098)	(.111)				
Exp. GPA for studying>3h			-.062	-.074				
			(.056)	(.061)				
Δ exp. tot hours					-.041	-.026		
					(.080)	(.086)		
Δ exp. GPA for studying <1h					.657**	.714**	.520**	.524**
					(.276)	(.287)	(.244)	(.258)
Δ exp. GPA for studying 1<h<2					-.122	-.149		
					(.289)	(.263)		
Δ exp. GPA for studying 2<h<3					-.820**	-.808**	-.607**	-.612*
					(.385)	(.390)	(.300)	(.316)
Δ exp. GPA for studying>3h					.266*	.222		
					(.156)	(.144)		
Technical vs General								
Female	.114	.238	-.053	-.187	.024	-.215	-.071	-.240
	(.442)	(.525)	(.434)	(.482)	(.437)	(.478)	(.437)	(.480)
Foreign born	-.021	.050	-.009	.011	-.029	. 024	-.014	.025
	(.176)	(.203)	(.086)	(.194)	(.178)	(.189)	(.174)	(.192)
No. siblings	-.010	-.062	-.009	-.026	-.009	-.056	-.015	-.049
	(.086)	(.097)	(.086)	(.095)	(.085)	(.094)	(.087)	(.096)
Mother with edu hs+	-.177	-.252	-.107	-.091	-.220	-.088	-.162	-.063
	(.271)	(.283)	(.273)	(.280)	(.287)	(.288)	(.281)	(.283)
Father with edu hs+	.420	.478*	.378	.342	.511*	.381	.426	.318
	(.259)	(.262)	(.258)	(.256)	(.279)	(.268)	(.273)	(.259)
7^{th} grade GPA	-.096	-.076	-.116*	-.111	-.115*	-.132*	-.106*	-.111
	(.061)	(.070)	(.065)	(.071)	(.065)	(.073)	(.064)	(.073)
Vocational vs General								
Female	.330	.600	.243	.286	.266	.121	.248	.153
	(.521)	(.609)	(.517)	(.580)	(.511)	(.558)	(.518)	(.565)
Foreign born	.172	.134	.207	.162	.143	.122	.199	.163
	(.196)	(.212)	(.195)	(.206)	(.189)	(.196)	(.194)	(.204)
No. siblings	-.155*	-.197**	-.167*	-.169*	-.111	-.117	-.156*	-.166*
	(.091)	(.098)	(.091)	(.097)	(.087)	(.096)	(.090)	(.099)
Mother with edu hs+	.471**	.529**	.491***	.583***	.393**	.488**	-.472**	.581***
	(.188)	(.219)	(.191)	(.216)	(.185)	(.222)	(.189)	(.219)
Father with edu hs+	-.198*	-.263**	-.202*	-.293**	-.138	-.197	-.184	-.266**
	(.118)	(.129)	(.118)	(.127)	(.124)	(.146)	(.117)	(.129)
7^{th} grade GPA	-.129*	-.100	-.156**	-.164*	-.125*	-.171*	-.149**	-.182**
	(.068)	(.094)	(.069)	(.088)	(.068)	(.088)	(.069)	(.090)
N	224	224	224	224	224	224	224	224
Pseudo R^2	.156	.231	.155	.230	.154	.220	.167	.230
School FE	no	yes	no	yes	no	yes	no	yes

Standard errors in parentheses. * p< 10%, ** p< 5%, *** p< 1%.

School-specific predictors: *exp. tot hours studying:* expected amount of study hours; *exp. GPA for studying X:* expected GPA for each amount X of daily study hours; Δ *exp. tot hours:* expected change in study hours with respect to 8th grade; Δ *exp. GPA for studying X:* expected change in GPA with respect to 8th grade for each amount X of daily study hours. **Predictors:** *female:* dummy=1 if student is female; *foreign born:* dummy=1 if student is foreign-born; *no. siblings:* number of siblings (between 0 and 3); *mother with edu hs+:* dummy=1 if student's mother has at least high school education; *father with edu hs+:* dummy=1 if student's father has at least high school education; *7^{th}-grade GPA:* student's GPA in the 7th grade end-of-year report (between 6 and 10).

hours (column (2) *versus* (1)). Thus, it is not always true that fixed effects take away significance, as was happening in the previous specifications. Second, surprisingly I can see that the expected amount of total hours has a positive and significant effect on track choice, both when considered as unique alternative-specific covariate together with the expected share of peers (columns (1) and (2)) and when including the absolute value of expected GPA for different amounts of study time (columns (3) and (4)). This means that students value a higher required effort, probably signaling something about the selection of the sample fo respondents to the survey. Third, when instead using differentials of expected effort and performance with respect to their current values (columns (5) and (6)), I see a different trend. In fact, what is relevant is the expected change in GPA for two particular study levels: for a positive GPA differential when studying less than one hour, students are more likely to choose this track, while they are less likely to choose it if the differential is positive for more than 2 hours of daily effort. This means that students are not willing to increase much their daily study hours even if it would mean increasing their GPA, and they would therefore favor an “easier” track that allows them to study less or to maintain a constant performance.

On top of these considerations, looking at the case-specific covariates I can still detect a consistent pattern for previous-year GPA (a higher GPA decreases the odds of choosing both the technical and the vocational tracks *versus* the general one); parental education and family composition are also relevant when it comes to the comparison between the vocational and the technical track, as having a father with lower education, a mother with a higher education and more siblings makes you more likely to choose the vocational *versus* the general track. Marginal effects are presented in Table B.15 in the Appendix.

Columns (7) and (8) re-run the estimation using only the variables that have a significant impact on choice. When combined they maintain a positive and significant effect, even when adding middle-school fixed effects.

Table B.16 in the Appendix presents the same analysis but leaving out the peer effects. Considerations about significance and signs are the same as reported above for the case that include expectations on peers, and magnitudes are similar.

6.4 The Estimation with the Complete Set of Variables

I separately showed the influence of the most relevant variables in order to assess potential differences in the results. Table 8 compares the magnitude and significance of the effects,

Table 8: ESTIMATION OF RESULTS WITH ALL THE RELEVANT COVARIATES, WITH AND WITHOUT MIDDLE SCHOOL FIXED EFFECTS.

	(1)	(2)
	β	β
Share of peers	4.881***	5.229**
	(1.774)	(2.245)
Exp. tot hours studying	-.025	-.006
	(.101)	(.107)
Δ exp. GPA for studying <1h	.240	.221
	(.209)	(.210)
Δ exp. GPA for studying 2<h<3	-.276	-.225
	(.251)	(.248)
Prob. Like	.065***	.065***
	(.010)	(.010)
Flexibility Uni/Work Both	-.001	-.001
	(.001)	(.001)
Technical vs General		
Female	.724	.596
	(.568)	(.635)
Foreign born	.075	.171
	(.225)	(.271)
No. siblings	-.026	-.088
	(.099)	(.121)
Mother with edu hs+	-.482	-.553
	(.377)	(.390)
Father with edu hs+	.568	.576
	(.379)	(.386)
7^{th} grade GPA	-.058	-.022
	(.071)	(.082)
Vocational vs General		
Female	.706	.809
	(.636)	(.733)
Foreign born	.260	.303
	(.244)	(.280)
No. siblings	-.201*	-.223
	(.177)	(.139)
Mother with edu hs+	.211	.159
	(.240)	(.267)
Father with edu hs+	-.117	-.130
	(.185)	(.196)
7^{th} grade GPA	-.041	-.025
	(.078)	(.097)
N	224	224
Pseudo R^2	.484	.522
School FE	no	yes

Standard errors in parentheses. * p< 10%, ** p< 5%, *** p< 1%.

School-specific predictors: *exp. tot hours studying:* expected amount of study hours; Δ *exp. GPA for studying X:* expected change in GPA with respect to 8th grade for each amount X of daily study hours; *prob. like:* reported subjective probability of liking the subjects taught; *flexibility uni/work both:* reported subjective probability of flexible choice between both work or university afterwards. **Predictors:** *female:* dummy=1 if student is female; *foreign born:* dummy=1 if student is foreign-born; *no. siblings:* number of siblings (between 0 and 3); *mother with edu hs+:* dummy=1 if student's mother has at least high school education; *father with edu hs+:* dummy=1 if student's father has at least high school education; *7^{th}-grade GPA:* student's GPA in the 7th grade end-of-year report (between 6 and 10).

using as regressors the usual individual information about demographics, family, and GPA, and the alternative-specific share of peers in that track, the expected amount of study hours, the difference between the expected GPA and the current one when studying either less than one hour or more than two, the probability of liking that track, the probability that the track will afterwards allow for a flexible choice between working and attending university.

I can see that the peer effect is consistently positive and significant also when adding school fixed effects. The same applies to the probability of liking the school. None of the other variables have significant effects, but some interesting results can be seen in the robustness check that accounts for different specifications of the network.

In the Appendix Table B.19 I present the same estimation by dividing the sample by gender.

6.5 Robustness Check: Accounting for the Actual Choice

In Table 9 instead of using beliefs from Waves 2 and 3 to instrument the share of peers that each student expects will make a certain choice, I use as predictor the actual share of peers choosing that track. This means that for each peer I am using their true final choice as stated in Wave 4. I instrument this variable with the usual $G^2\mathbf{x}$ as this is the most straightforward case of behavior reflection. This specification is interesting because it allows us to compare results with respect to the previous case, and moreover it lets us see whether there are still significant effects coming from expectations on top of the actual choice.

In columns (1) and (2) of Table 9 I am estimating the same relationship without and with school fixed effects, respectively. It is worth noting that here also the latter case presents significant results. Overall, I get a larger number of statistically significant coefficients compared to the baseline case, possibly because of the increased sample size. While my previous considerations concerning fathers' education and GPA are still valid here, other variables need attention. In particular, being born in Italy *versus* abroad, having a higher number of siblings and having a mother with education equal to or above high school increases the chances of choosing a curriculum in the technical track rather than in the general one. While mother's education is in line with father's, what is striking is the coefficient associated with foreign-born, considering the fact that this feature remains relevant also after conditioning for other covariates (including family characteristics and

Table 9: COMPARISON BETWEEN ESTIMATION RESULTS USING CHOICE ONLY, AND USING CHOICE AND BELIEFS.

	Actual Choice		**Choice & Expectation**	
	(1)	(2)	(3)	(4)
	β	β	β	β
(Predicted) Actual share of peers	2.562***	2.804***	1.823***	1.543
	(.561)	(.999)	(.439)	(1.031)
Expectations on share of peers			1.208***	1.167
			(.236)	(.257)
Technical vs General				
Female	.023	.138	.159	.204
	(.219)	(.264)	(.236)	(.270)
Foreign born	-1.166**	-.877	-1.102**	-.750
	(.531)	(.577)	(.551)	(.572)
No. siblings	.251*	.314**	.302**	.344**
	(.146)	(.158)	(.152)	(.157)
Mother with edu hs+	.534**	.670***	.600**	.685***
	(.227)	(.260)	(.239)	(.262)
Father with edu hs+	.927***	1.020***	1.012***	.981***
	(.221)	(.269)	(.238)	(.269)
7^{th} grade GPA	-.719***	-.854***	-.849***	-.959***
	(.127)	(.168)	(.136)	(.175)
Vocational vs General				
Female	.008	-.315	-.073	-.236
	(.312)	(.363)	(.323)	(.376)
Foreign born	.155	.605	.255	.751
	(.501)	(.568)	(.521)	(.561)
No. siblings	.302	.366	.355**	.307
	(.207)	(.230)	(.212)	(.228)
Mother with edu hs+	-.791**	-1.044***	-.678**	-.869**
	(.333)	(.385)	(.346)	(.392)
Father with edu hs+	.850***	.557	.748**	.433
	(.321)	(.364)	(.328)	(.366)
7^{th} grade GPA	-.940***	-1.321	-.918***	-1.386***
	(.183)	(.235)	(.188)	(.240)
N	781	757	757	757
Pseudo R^2	.136	.278	.230	.297
School FE	no	yes	no	yes

Standard errors in parentheses. * p< 10%, ** p< 5%, *** p< 1%.

Predictors: *female:* dummy=1 if student is female; *foreign born:* dummy=1 if student is foreign-born; *no. siblings:* number of siblings (between 0 and 3); *mother with edu hs+:* dummy=1 if student's mother has at least high school education; *father with edu hs+:* dummy=1 if student's father has at least high school education; *7^{th}-grade GPA:* student's GPA in the 7th grade end-of-year report (between 6 and 10).

GPA); however, in the sample only 6.4% of the students are indeed born abroad. On the other hand, a higher maternal education decreases the chances of attending a vocational *versus* a general school.

Columns (3) and (4) repeat this analysis but on top of the predicted share of peers choosing a certain track, $G\hat{\mathbf{y}}_j$, I also add as additional alternative-specific regressor the expected (on the basis of students' beliefs) share of peers, not instrumented, $G\mathbf{y}_j^i$:

$$y_{is}^* = \boldsymbol{\beta_s}\mathbf{x}_i + \lambda G\mathbf{y}_j^i + \rho G\hat{\mathbf{y}}_j + \epsilon_{is} \tag{2.7}$$

This specification can be deemed valid by arguing that the endogenous variable is represented by the actual share of peers in a given track, i.e. the realizations; expectations instead can be treated as exogenous, as in Li and Lee (2009). While in the previous analysis I was considering beliefs as being the guidance during the decision-making process, it is also true that most of the expectations concerning peers are right. Therefore, I could directly use the realized outcomes in the estimation and instrument them under the standard IV validity and relevance assumptions, and add previous beliefs as additional regressors that could capture both the "true" part relative to the future choice and a possible private "error" component (exogenous). In this case I see that peer effects coming from the actual realization of choices are still positive and significant, but much lower than in other specifications; moreover, also the coefficient associated with expectations is positive and significant. This finding may signal that peer effects stemming from beliefs are more important (in terms of magnitude of the coefficients) because the errors that students make are self-confirming: the effect of what i expects from their friends is stronger if i thinks that e.g. j will make their same choice, while j will not. Therefore, it is reasonable assuming that the mistakes that students make in their predictions are those that drive the stronger peer effects from expectations, as these errors are reinforcing student i's beliefs about their own choice.

Table B.20 in the Appendix presents marginal effects mirroring the structure of Table 9, depicting positive own-effects and negative cross-effects of changes in the share of peers in a given track on the probability of choosing it.

6.6 Robustness Check: Different Specification of the Network

In Table 10 I estimate three different specifications of the network. Column (1), the baseline case ("unweighted"), considers the peers as all having the same weight in the mind of the student, and therefore network measures are just simple averages (i.e. it is an unweighted network); this column present the same results displayed in the first column of Table 5, where the specification was defined as the "baseline", including only own characteristics as covariates and excluded school fixed effects. The unweighted network has been used so far in all the estimations.

Columns (2) and (3) instead exploit the information about friends' rankings. In column (2), denominated "equal weights", all the nth peers are given the same weight, i.e. all the peers ranked as first are given a weight of 18.2%, second 16.4%, and so on, until 1.8% given to the tenth peer. Column (3), labeled as "proportional weights", considers both the ranking and the total number of peers reported by each observation. For example, if two students both report three peers but ranked in a different way, their weights differ; if student i has nominated their first, second, and third best friends then they would receive a weight of respectively 50%, 33.3%, and 18.7%, while if the other student j has valid observations[10] for peers 2, 4, and 5, then the weights would be respectively 45.45%, 36.36%, and 18.18%.

The share of peers in a given track affects the prospective choice of enrolling in that track, as can be seen across the three specifications. Increasing the expected share of peers in a track by 10% increases the probability of choosing that same track by around 15 times in the baseline case, as already seen. Much lower are the effects that result from the other two network specifications weighted by peer ranking; for a 10% change, the increase in probability is around $1.5 - 1.6$ times.

The two lower panels of Table 10 present the log-odds and odds of choosing the technical or the vocational track *versus* the general track, our baseline case. In line with Table 5, father's education and seventh-grade GPA are important across all three settings. This table is estimated not considering school fixed effects.

For the three different network specifications without school fixed effects I present marginal effects in Table B.21 in the Appendix. Given that one of the alternatives has been chosen, own-effects are positive and cross-effects are negative.

Table 11 expands Table 8. It compares the magnitude and significance of the effects across the three ways of aggregating the network effect, using as regressors the usual individual information about demographics, family, and GPA, and the alternative-specific expected share of peers in that track, the expected amount of study hours, the difference between the expected GPA and the current one when studying either less than one hour

[10] A "valid" observation may account for the fact that for one peer no expectations were reported.

Table 10: COMPARISON OF RESULTS BETWEEN BASELINE CASE AND DIFFERENT WEIGHTED NETWORKS.

	Unweighted		**Equal weights**		**Proport. weights**	
	(1)		(2)		(3)	
	β	e^{β}	β	e^{β}	β	e^{β}
Share of peers	5.046***	155.4	2.703***	14.924	2.775***	16.039
	(1.675)		(.709)		(.740)	
Technical vs General						
Female	.399	1.49	-.017	.983	.012	1.012
	(.489)		(.417)		(.420)	
Foreign born	-.885	.413	-.585	.557	-.571	.565
	(.873)		(904.)		(.894)	
No. siblings	.490	1.632	.270	1.31	.283	1.327
	(.318)		(.303)		(.302)	
Mother with edu hs+	.087	1.091	.369	1.446	.358	1.43
	(.445)		(.429)		(.428)	
Father with edu hs+	.758*	2.134	.975**	2.651	.963**	2.62
	(.424)		(.435)		(.433)	
7^{th} grade GPA	-.787***	.455	-.899***	.407	-.883***	.414
	(.263)		(.251)		(.250)	
Vocational vs General						
Female	.659	1.933	.580	1.786	.581	1.788
	(.530)		(.549)		(.548)	
Foreign born	.312	1.366	.342	1.408	.340	1.405
	(.693)		(.791)		(.777)	
No. siblings	.388	1.474	.260	1.297	.262	1.3
	(.344)		(.361)		(.359)	
Mother with edu hs+	-.443	.642	-.368	.692	-.377	.686
	(.529)		(.563)		(.561)	
Father with edu hs+	.548	1.73	.874	2.396	.873	2.394
	(.524)		(.568)		(.566)	
7^{th} grade GPA	-.879***	.415	-1.230	.292	-1.216***	.296
	(.330)		(.338)		(.336)	
N	224		211		211	
Pseudo R^2	.191		.204		.202	
School FE	no		no		no	

Standard errors in parentheses. * p< 10%, ** p< 5%, *** p< 1%.

Predictors: *female:* dummy=1 if student is female; *foreign born:* dummy=1 if student is foreign-born; *no. siblings:* number of siblings (between 0 and 3); *mother with edu hs+:* dummy=1 if student's mother has at least high school education; *father with edu hs+:* dummy=1 if student's father has at least high school education; *7^{th}-grade GPA:* student's GPA in the 7th grade end-of-year report (between 6 and 10).

Table 11: COMPARISON OF RESULTS ACROSS DIFFERENT WEIGHTED NETWORKS, INCLUDING ONLY THE RELEVANT COVARIATES.

	Unweighted		**Equal weights**		**Proport. weights**	
	(1)	(2)	(3)	(4)	(5)	(6)
	β	β	β	β	β	β
Share of peers	4.881***	5.229**	4.499**	3.693**	3.550**	3.505*
	(1.774)	(2.245)	(1.920)	(1.706)	(1.814)	(1.806)
Exp. tot hours studying	-.025	-.006	-.041	.027	-.031	.021
	(.101)	(.107)	(.111)	(.115)	(.112)	(.114)
Δ exp. GPA for studying <1h	.240	.221	.195	.146	.191	.159
	(.209)	(.210)	(.190)	(.219)	(.191)	(.219)
Δ exp. GPA for studying 2<h<3	-.276	-.225	-.219	-.167	-.225	-.179
	(.251)	(.248)	(.225)	(.259)	(.228)	(.261)
Prob. Like	.065***	.065***	.071***	.073***	.072***	.073***
	(.010)	(.010)	(.011)	(.012)	(.011)	(.012)
Flexibility Uni/Work Both	-.001	-.001	-.002**	-.002*	-.002**	-.002*
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Technical vs General						
Female	.724	.596	.902	.501	.792	.505
	(.568)	(.635)	(.614)	(.614)	(.612)	(.626)
Foreign born	.075	.171	.148	.187	.155	.178
	(.225)	(.271)	(.106)	(.297)	(.233)	(.292)
No. siblings	-.026	-.088	-.036	-.096	-.046	-.093
	(.099)	(.121)	(.106)	(.119)	(.104)	(.119)
Mother with edu hs+	-.482	-.553	-.652	-.769	-.587	-.745
	(.377)	(.390)	(.421)	(.476)	(.410)	(.469)
Father with edu hs+	.568	.576	.663	.736	.602	.717
	(.379)	(.386)	(.418)	(.482)	(.409)	(.475)
7^{th} grade GPA	-.058	-.022	-.060	-.022	-.068	-.026
	(.071)	(.082)	(.072)	(.086)	(.072)	(.086)
Vocational vs General						
Female	.706	.809	.727	.734	.691	.729
	(.636)	(.733)	(.683)	(.798)	(.684)	(.792)
Foreign born	.260	.303	.254	.382	.277	.363
	(.244)	(.280)	(.288)	(.365)	(.287)	(.364)
No. siblings	-.201*	-.223	-.247**	-.272*	-.244**	-.265*
	(.177)	(.139)	(.125)	(.154)	(.124)	(.152)
Mother with edu hs+	.211	.159	.251	.174	.230	.159
	(.240)	(.267)	(.287)	(.312)	(.285)	(.309)
Father with edu hs+	-.117	-.130	-.080	-.145	-.076	-.126
	(.185)	(.196)	(.199)	(.203)	(.197)	(.204)
7^{th} grade GPA	-.041	-.025	-.068	-.076	-.077	-.071
	(.078)	(.097)	(.082)	(.096)	(.082)	(.099)
N	224	224	211	211	211	211
Pseudo R^2	.484	.522	.487	.528	.481	.525
School FE	no	yes	no	yes	no	yes

Standard errors in parentheses. * p< 10%, ** p< 5%, *** p< 1%.

School-specific predictors: *exp. tot hours studying:* expected amount of study hours; Δ *exp. GPA for studying X:* expected change in GPA with respect to 8th grade for each amount X of daily study hours; *prob. like:* reported subjective probability of liking the subjects taught; *flexibility uni/work both:* reported subjective probability of flexible choice between both work or university afterwards. **Predictors:** *female:* dummy=1 if student is female; *foreign born:* dummy=1 if student is foreign-born; *no. siblings:* number of siblings (between 0 and 3); *mother with edu hs+:* dummy=1 if student's mother has at least high school education; *father with edu hs+:* dummy=1 if student's father has at least high school education; *7^{th}-grade GPA:* student's GPA in the 7th grade end-of-year report (between 6 and 10).

or more than two, the probability of liking that track, the probability that the track will afterwards allow for a flexible choice between working and attending university.

The peer effect is consistently positive and significant across all the three specifications also when adding school fixed effects. The same applies to the probability of liking the school, while the feature of flexibility appears as relevant (negative and statistically significant) only in the two weighted specifications of the network. Similarly, the only individual-specific variable that presents negative and statistically significant coefficients is the number of siblings in the two weighted networks, meaning that a higher number of siblings decreases the odds of attending a vocational school *versus* a general one.

Table B.17 in the Appendix presents the marginal effects at means of the estimations without the school fixed effects. Table B.18 in the Appendix presents the same estimation of Table 11 but has Bootstrap errors in the second stage. In this case, the expected share of peers is statistically significant for all the network specifications without fixed effects; results with a network that gives equal weights to all the nominated peers remain significant both with and without school fixed effects.

6.7 Robustness Check: Simulating the Network

This section is a work in progress and needs to be completed.

In order to mitigate the bias stemming from an incomplete network, I simulate the missing connections among students. I start by using as nodes all the students for which I have the relevant exogenous characteristics, i.e. those that answered to the first waves of the survey. Then, by using the declared friendships, I predict the probability that they are indeed connected using their observable characteristics.

In the Appendix I provide some information about this potential network that could arise from connecting all the nodes for which I have information. Following Lee, Liu, et al. (2021) I use exogenous characteristics to predict a new adjacency matrix and in Table B.22 in the Appendix I provide summary information about the exogenous characteristics of the available nodes. I then expand my dataset in order to create all the possible friendship links[11] and I assess whether any two connected students share the same characteristics or not, using the exogenous characteristics elicited in the first surveys. Table B.23 in the Appendix summarises the fraction of potential edges that indeed have the same features. I then run a logistic regression to obtain the predicted adjacency matrix and the link

[11] From 766 nodes I obtain 585,990 potential edges.

formation probabilities, and I find evidence of homophily in the positive and significant coefficients for the following dummies: being of the same gender, being both foreign born, having parents that live together, having a stay-at-home mother, having a blue-collar father, or having a similar GPA in the previous academic year, as presented in Table B.24 in the Appendix. The McFadden's pseudo R^2 of the logistic regression is 0.05, suggesting that the dyadic characteristics considered may not be very informative in predicting the friendship formation.

Once I simulate the network I can use the full structure in order to exploit second neighbors' characteristics as predictors of first neighbors' behaviors. However, students' beliefs about expected friends' choices would be missing for those links that are only predicted but that are not in the data. More assumptions need to be made on the beliefs.

7 Conclusion

In this paper I show how having a higher share of peers expected to make one's same choice is relevant, even more than high school characteristics. I explore different specifications of the included variables and of the network importance, and I conclude that the expected share of peers attending the same high school track is more important than the subjective probability of liking the subjects taught, or the forecasted effort.

This can happen for three reasons. The first one is the mechanism of *status*, i.e. teenagers want to make choices that have a shared value and that enables them to feel part of a group of like-minded people (Akerlof and Kranton (2002)). The second one is related to the information-gathering process. In fact, students think about this decision for months, and in the meanwhile they talk about it with family, teachers, and friends. It may be that beliefs about peers matter not only for psychological benefits of attending the same high school track, but rather for the amount of information gathered on a certain alternative. Students who talk about a certain curriculum with their closest peers may be influenced in the sense that they are convinced by what these peers present as pros and cons of each alternative. Third, it is possible that beliefs about peers are only a mirror of own desires, and what each student thinks about their peers is biased by their own prospective decision in a self-confirming way.

Whether this influence is good or bad is still an open question. In the literature, most support educational choices that follow one's inclinations, but some argue for a positive impact of long-lasting friendships, disregarding a possible mismatch of skills. Moreover, whether these peer effects drive students to make decisions against their own talents is an unresolved question in this setting: administrative data concerning the future academic achievements of the analysed sample are not available and therefore I cannot track over time the performance of these students during high school and later on. However, my paper shows how some school-specific outcomes remain in the background, possibly because they are not known by the students. Decision-makers should be provided with all the relevant information about potential future outcomes in terms of academic success and occupational chances. From a policy-making point of view, it would be relevant to provide students (and in particular, the students most likely to switch tracks because of peer influence) with the right information about school-specific outcomes, in terms of university/work prospects and flexibility in the field of study/occupation.

While I show that peer effects exist in this context, the underlying mechanism needs to be further investigated in order to uncover the forces at play. Further research is needed to understand what drives expectations about peers, and how this impacts the match (or mismatch) of skills and the resulting future human capital accumulation.

Chapter 3

Whose Choice? Child-parent interactions and choice set heterogeneity in schooling decisions

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Work in progress

Abstract

We characterize and empirically study the main sets of choice alternatives processed by families with an adolescent child prior to a consequential human capital decision: the choice of a high school track in presence of curricular specialization. Using rich survey data collected from a sample of Italian 8th graders and their parents during the months preceding high school track choice, we document substantial heterogeneity in size and composition of awareness, agency, and consideration sets at the time of pre-enrollment and trace the evolution of the sets' size and composition over the decision process. We find substantial evidence of limited agency and limited consideration at the time of choice, but no limited awareness. During the decision-making process agents tend to expand their choice sets over time, with students' sets smaller than their parents' ones. We also detail how student and family characteristics affect the size of these sets and their composition in terms of number of tracks covered.

[*Field codes (JEL)*: C83, D19, D84, D91, I21.]

[*Key words*: High-school track choice, Decision process, Choice-set heterogeneity, Awareness, Agency, Consideration, Uncertainty, Subjective expectations, Parenting styles.]

1 Introduction

Every decision we make is based on selecting the most appealing option among a menu of alternatives. The objective of the econometrician is to uncover the selection process and how the weights attributed to different features affect the final decision, but it can be challenging when the menu of available options is not observed.

A standard assumption across most choice models is that the set of options is common, or better it is a “complete" choice set: agents know and consider all alternatives in order to make a decision. While this could be true under some scenarios, for example if the cardinality of the choice set is small, in some other circumstances it might not be feasible. Agents might be forced not consider all options because of external constraints on their availability (Gaynor, Propper, and Seiler (2016)), such as supply-side rules or in multi-agent decision making processes.

In this paper we consider a situation where heterogeneity arises from the child-parent interactions within the context of high school choice. When facing this decision both children and parents have private information and preferences which may or may not coincide. During the process the family is not a unified decision maker, but rather a setting where a principal-agent problem realizes. Heterogeneous choice sets are the product of each individual's preferences and information, their interaction with other agents' preferences and information, and the family-specific decision protocol. We consider multiple types of choice sets, i.e. different subsets of alternatives not necessarily nested. Each of them is defined according to a mechanism or class of mechanisms that may limit the set relative to the universal set of alternatives available to the agent. Starting from the universe of options, we distinguish: the awareness set (i.e. the set of choices on which there are no informational constraints); the feasible set (i.e. the set of choices on which the agent has ability to take action); the consideration set (i.e. the set of choices actively evaluated and attentively thought about by the agent); the application set (i.e. the set of ranked preferred alternatives that end up on the final application form)[1].

High school choice is an important milestone in every child's adolescence mostly for two reasons. First, it has an intertemporal and sequential value as high school sets the basis for later human capital accumulation through university or for success in the labor market. Second, this choice is made at a transitional age in which students - early teens, around 13-14 years old - are trying to state their independence and acquire some agency in their

[1] Shocker et al. (1991) gives the definitions of some of these subsets, namely awareness and consideration.

choices (Lundberg, Romich, and Tsang (2009), Provantini and Arcari (2009)). Children want to make independent decisions according to their own preferences, and parents may want to grant them some degree of freedom, while also paying attention to their own preferences; this conditional liberty of children and the way in which parents are able to impose constraints or to use persuasion determine the formation of heterogeneous choice sets across families, as a result of the interplay between these forces. In this application we will refer to the way in which parents try to impose their control as "parenting styles" using the categorization of Doepke and Zilibotti (2019).

This paper focuses on the transition between junior high school (grades 6^{th}-8^{th}) and high school (grades 9^{th}-13^{th}) in Italy, a turning point in students' human capital investment as in 9^{th} grade curricular specialization begins. In Italy students choose among three high school tracks (General, Technical, or Vocational) and their curricula, without institutional regulation about geographical distance nor any competition in entering each school[2]. Such variety implies that families rarely take into account all of the options available on the market, namely because some of them are discarded since the beginning due to starting preferences concentrated on some options and partial knowledge of the others, as documented in Giustinelli and Pavoni (2017). We exploit a rich dataset collected in the city of Vicenza in the a.y 2011/12. Students attending the 8^{th} grade and their parents filled in multiple waves of a survey eliciting their beliefs and knowledge about the possible high school choices they are about to make in the near future. While we observe only one definitive choice at the end (i.e. the pre-enrollment application), we also have access to multiple rankings of those options thanks to the questions asked across waves before the choice is made.

Using our survey data we characterize the size and composition of the choice sets defined above for the different agents involved, considering child- and parent-specific processes before the choice is made and evaluating a unique family outcome at choice. We then document the heterogeneity in size and composition of the sets across family characteristics, taking into account the forces that shape the choice sets and their evolution over time across the waves before the final choice and at the realization of the outcome. The peculiarity of the dataset allows for a richer understanding of how the choice process influences the choice sets over time through the child-parent interaction.

We find substantial evidence of limited agency and limited consideration at the time of

[2]While some high schools have introduced admission tests in the last years, this is not true in the context analysed in this paper, that is the city of Vicenza in the a.y. 2011/12.

choice, with families having more concentrated preference over fewer alternatives ranked as favorite and considered for the choice, but no limited awareness. During the decision-making process agents tend to expand their preferred alternatives, and the consideration, agency and awareness sets over time before the choice. We also find that students' perceptions of their parents' vetoing behavior imply on average smaller agency sets than their parents' ones. We detail how child's gender and GPA, parental occupation, being foreign-born and having older siblings affect the size of these sets and their composition in terms of number of tracks covered. Next, we are working on providing a solid foundation for mapping our survey measures into parenting styles, and see how these decision protocols affect our choice set sizes and compositions.

The paper is organized as follows. Section (2) reviews the relevant literature. Section (3) outlines the conceptual framework. Section (4) presents the institutional setting, the survey design, the choice set concepts and how they are measured. Section (5) documents the choice set size, composition and heterogeneity at the moment of choice, while section (6) provides the same analysis of the evolution over time during the decision-making process. Section (7) presents the agenda for the analysis on the parenting styles and section (8) concludes.

2 Literature Review

This paper relates to three strands of literature: first, heterogeneous choice models and choice sets; second, school choices and related expectations; third, parenting styles.

Heterogeneous choice models and different kinds of sets. The discussion on choice models has evolved since the introduction of the traditional approach to multinomial responses with the multinomial (or conditional) logit model by McFadden (1973), later extended by Ben-Akiva and Boccara (1995) through the incorporation of a probabilistic representation of the availability of different alternatives. The literature has been surveyed by many, among which Matzkin (2007) who mostly presents models where the unobserved heterogeneity enters in the equations in non-additive ways; Crawford, Griffith, and Iaria (2019) summarize the two main empirical approaches used in this context, i.e. “integrating over” and “differencing out” unobserved choice sets, and try to solve the problem of unobserved choice sets by introducing the concept of “sufficient sets", i.e. the set of consumers’ past observed choices paired with assumptions about the evolution of their unobserved choice sets over time when panel data are available.

The need to overcome the problem of unobserved choice sets has been advocated by many, despite some criticism (Keele and Park (2006)), including experimental works like the one by Bech, Kjaer, and Lauridsen (2011). More recently, other papers have focused on the problem of unobserved heterogeneity in choice sets across agents; among others, Barseghyan et al. (2019) focus on a discrete choice model with unobserved choice sets, allowing for partial identification of both the distribution of preferences and the distribution of choice set size; Yamamoto (2014) suggests a new model, called varying choice set logit (VCL) model, that relaxes IIA by allowing regression coefficients to vary across the groups of individuals defined by the alternatives available in their actual choice sets, by looking at the actual variation in choice sets that are present in data.

Heterogeneous choice sets may be present because of inattention, bounded rationality (Treisman and Gelade (1980)), search costs (Caplin, Dean, and Leahy (2018)), or because consumers face unobserved constraints on what options can be chosen (Gaynor, Propper, and Seiler (2016)). Notably, heterogeneous choice sets may arise in very different contexts. A common example is insurance, as the market offers many options from multiple providers and comparing them all implies both the feasibility of gathering the relevant information, and the ability of processing and understanding it (see e.g. Keane

(2004) and Ketcham, Kuminoff, and Powers (2019)). Other notable fields of application are transportation mode choice (starting from McFadden, Train, and Tye (1977)) and marketing (Shocker et al. (1991), Draganska and Klapper (2011), Wernerfelt and Hauser (1990), Honka, Hortacsu, and Vitorino (2017)), for example combining price expectations with the product learning process in a consumer choice model (Erdem et al. (2005)).

In this paper we characterize different types of choice sets. While we introduce the feasible (or agency) and the application sets, other definitions (awareness and consideration sets) are already common in some literatures, and the distinctions among these sets have been studied in the past decades, trying to estimate them in terms of both relative size and composition.

On a more theoretical level, Aguiar et al. (2018) test random consideration models at the population level and find that heterogeneous preferences provide a good explanation for choice behaviors in a lab setting, also documenting how higher consideration costs decrease the size of the consideration set. Caplin, Dean, and Leahy (2018) prove that consideration sets are the result of rational inattention; Abaluck and Adams-Prassl (2020) identify consideration probabilities exploiting the fact that imperfect consideration breaks the symmetry between cross-characteristic responses, while Dardanoni et al. (2020) show that these probabilities can be identified with homogeneous preferences from a single cross section of aggregate choice shares.

Our paper contributes to the literature by providing evidence of choice set heterogeneity within families, also considering how constraints and preferences affect the decision-making process.

Educational choices. Educational choices are important for human capital accumulation and have been studied under different points of view and at different levels keeping into account some peculiar features, as presented next.

First of all, educational choices are made under uncertainty about future consequences and relevant states and therefore carry option value. Recently there has been substantial progress in econometric modeling and empirical evidence in particular from survey expectations. Most of the work is on college choice and outcomes (Arcidiacono, Hotz, and Kang (2012), Stinebrickner and Stinebrickner (2014), Zafar (2012), Zafar (2013), Wiswall and Zafar (2015), Boneva and Rauh (2018), Boneva, Golin, and Rauh (2021)) and there is still limited evidence on high school plans, choices, and outcomes from expectations data (Attanasio and Kaufmann (2014), Giustinelli (2016), Giustinelli and Pavoni (2017), Kapor, Neilson, and Zimmerman (2020)).

An important standard assumption in empirical economic research is that parents make schooling decisions for their underage children, and students become solo decision makers when of age (with some exceptions, such as Giustinelli (2011)). At the age of thirteen, as in our application, children are transitioning into adolescence and need to exercise their decision-making skills. The choice of high school is perceived as an important moment when the child takes responsibility and exercises her autonomy (Provantini and Arcari (2009)), and for parents it represents an investment in the child's development (Lundberg, Romich, and Tsang (2009)). Most works that evaluate the *locus of decision* within families do so both in developed and developing countries in high school choices (Bursztyn and Coffman (2012), Attanasio and Kaufmann (2014), Giustinelli (2016), Giustinelli and Manski (2018)) and college (Kalenkoski (2008), Zafar (2012)).

In cases like the choice of high school it could be that not only child-parent relationships shape the choice sets, but also external forces like family-school dynamics and their interaction with family characteristics. For example teachers could make recommendations, and Giustinelli (2016) finds evidence that these suggestions predict high school choice beyond decision makers' beliefs. Based on qualitative evidence, Romito (2016) documents how such suggestions in Italy are disregarded by high and average socio-economic background families when in contrast with the child's or the parents' preferences; in fact Falk, Kosse, and Pinger (2020) document how child's socio-economic background is an important determinant of track selection, and Chise, Fort, and Monfardini (2019) estimate that the inter-generational persistence in STEM field of study at university is only partially attributable to the high school field of choice of Italian students: having STEM graduate parents matters. Moreover, academically educated parents tend to have higher expectations for their children (Raety (2006)), even if sometimes biased (Bergman (2020), Dizon-Ross (2018)).

The last relevant feature of educational choices is that usually they involve a limited number of options, differently from contexts like marketing and insurance. The standard assumption is that families are aware of and consider all alternatives, and know the "rules of the game," when making school choices. However, informational frictions and parental characteristics may determine otherwise. This is true for example in the case of New York City, as described by Sattin-Bajaj (2014), where students can pick from a 700-page directory and educational institutions give for granted the fact that parents are engaged and well-informed throughout the whole choice process[3]. Indeed Son (2020) documents how students are significantly less likely to apply to the schools listed in the last pages of that directory, suggesting that they might not be fully aware of all the alternatives. More in general, high school choice may be subject to a variety of constraints, for example informational (e.g. it is too costly time-wise or cognitively to search all alternatives, or learn about admission rules), financial (e.g. school tuition), geographical (e.g. the school is too far and there is no public transportation available), institutional (e.g. students need to attend schools in their neighborhood of residence, or need to pass a test to be admitted), or stemming from parental vetoing imposed to children depending on each agent's preferences. There is scant quantitative work on limited awareness in educational choices; among others, Dawes and Brown (2002) and Dawes and Brown (2005) focus on awareness, consideration, and choice sets in college choice exploit students' survey data; Giustinelli and Pavoni (2017) and Giustinelli and Pavoni (2019) provide evidence on students' and parents' awareness of choice alternatives in high school track choice; and Kapor, Neilson, and Zimmerman (2020) document parental beliefs about admission rules and chances under a specific assignment mechanism.

Our contribution to this branch of literature is to highlight how there are multiple actors involved in the high school choice, both having clashing preferences and expectations; we show that numerous constraints arise in this simple choice context with a limited set of alternatives, thus suggesting how these frictions may become even more important in complex settings.

Parenting styles. In this paper we take into account the way parents interact with their children in order to shape their choice sets, and we refer to some categories already existing in the literature in order to characterize them.

Baumrind (1967) and Baumrind (1971) define the concept of parenting styles starting from the notion of control. On this basis, three categories of parents can be identified: (1) permissive, characterized by low demandingness and high responsiveness to the child's needs; (2) authoritarian, characterized by high demandingness and low responsiveness; and (3) authoritative, characterized by high demandingness and high responsiveness. Maccoby and Martin (1983) expand her work by introducing a fourth category: the neglectful parent (low demandingness, low responsiveness). Doepke and Zilibotti (2017) and Doepke and Zilibotti (2019) build on Baumrind (1971) and Maccoby and Martin (1983) and defined

[3]Some quotes from interview in the book can be found in section (C.1) of the Appendix.

altruism and paternalism as the two driving forces of adult behavior (see also Saez-Marti and Zilibotti (2008)). In their analysis, parents exert their educational effort according to five main categories. The first one is the authoritarian style, that imposes constraints and rules to the child's behaviors and choices without justifying them, in a paternalistic way. The second is the authoritative parent, who interferes with the choice in a more subtle way through discussion and persuasion, making the child understand on his own but still directing the process. The intensive parenting style is a mixture of the first two, hence adults are very involved in the life of their child and tend to stir their beliefs through strong interference. The permissive parent is the one that allows the child to think on their own, thus without interfering directly in the choice process but still providing explanations and support. Finally, neglectful parenting is not interfering and mostly uninvolved in the child's life. Parenting style is very important in determining how much freedom a young child has, and in transmitting values and decision protocols; the impact of parenting styles has been empirically evaluated on many outcomes, from human capital (Cosconati (2011)) to non-cognitive skills and psychological traits (Lamborn et al. (1991)). Doepke and Zilibotti (2019) also argue that the most common source of tension in the family is due to the trade-off between short-term desirability and long-term consequences of actions, a situation that well describes why parents may want to meddle with their children's high school choice. The uncertainty that surrounds high school outcomes is an important factor because parental beliefs and expectations over them may also change over time, thus introducing a complex probabilistic dimension into the picture. Even paternalistic parents cannot be fully sure that one alternative is the best one, because individual future outcomes are not known and in many cases parents do not know even realized average lifetime outcomes associated with each school.

Our contribution to this literature on parenting styles is to provide evidence of how they shape interactions within the families and how they affect choice sets and the decision making process.

3 Conceptual Framework

A simple conceptual framework that can apply to this context is a classical choice-theory framework which explains the decision-making behavior as an outcome of a two-step recursive process (Manski (1977)).

First we define a *choice* as an operation mapping a set into one of its non-null elements and a *decision maker* as an agent performing choice operations according to a fixed rule.

Let us define $P_{\Gamma M}$, a choice-problem generating process, where the choice problem is a pair (C, m) where $C \in \Gamma$ is a choice set and $m \in M$ is a decision maker.

The choice-problem generating process $P_{\Gamma M}$ can be defined in terms of the choice-set generating process and the decision-maker generating process:

$$\begin{aligned} P_{\Gamma M}(C,m) =& P_{\Gamma}(C|m) \cdot P_M(m) \quad (3.1) \\ \text{where} \quad P_{\Gamma}(C|m) =& P_{\Gamma M}(C,m)/P_M(m) \\ P_M(m) =& \sum_{C \in \Gamma} P_{\Gamma M}(C,m) \end{aligned}$$

Given the generated choice set C, the decision maker m selects an alternative $a \in C$ according to a decision rule.

While most of the literature has focused on the problem of a decision maker choosing alternative given a choice set, in this paper we want to focus on the decision-maker generating process and the choice-set generating process. In particular, the generation of choice sets may be the outcome of decisions made by other decision makers $mm \in MM$, specifying whether each alternative will or will not be made available to each decision maker ($m \in M$). For instance, in this application, cases in which decision makers $mm \in MM$ are able to constrain the set of alternatives are when policy makers or institutions fix rules for admission decisions so that institutional administrators or allocation algorithms control the choice set generation for families; or again, parents may act as primary decision maker $mm \in MM$ and control the choice set generation for their children, making sure to include their preferred alternatives and to exclude the least appreciated ones.

It is important to notice that choice sets in this application will be smaller than the universal set, and may be heterogeneous across agents and families for many reasons. First of all, heterogeneous agency may shape the child's choice set differently on the basis of parental constraints, thus resulting in a child-specific choice set. Moreover, heterogeneity may arise from other sources, such as limited awareness or limited consideration.

In this context, we can define the optimal choice $a^* \in C$ according to different choice protocols. First, let us consider an individual choice, where the decision maker (either the child c or the parent p, $m \in \{c, p\}$) has some outcome-specific subjective utility u_n which depends on own characteristics x_m and to which she attaches a subjective probability p_m over each alternative $a \in C$ and across outcomes $n \in N$[4]:

$$a_m^* = \arg\max_{a \in C} \sum_{n=1}^{N} p_{man} \Delta u_n(x_m) \tag{3.2}$$

Second, the decision maker m may take an individual choice but considering others' (p's) inputs with weight $(1 - \omega_n^c)$:

$$a_m^* = \arg\max_{a \in C} \sum_{n=1}^{N} [\omega_n^c p_{can} + (1 - \omega_n^c) p_{pan}] \Delta u_n(x_m) \tag{3.3}$$

Last, a multilateral or group choice is the weighted outcome of the individual choices:

$$a_m^* = \arg\max_{a \in C} \Phi^c \left[\sum_{n=1}^{N} p_{can} \Delta u_n(x_c) \right] + (1 - \Phi^c) \left[\sum_{n=1}^{N} p_{pan} \Delta u_n(x_p) \right] \tag{3.4}$$

In this paper we consider a multilateral or group choice in which both parents and children have each outcome-specific utilities and attached subjective probabilities, and parents have different views across families about how much weight should be given to their own preferences. However, we do not *a priori* impose that children and parents need to decide together; weights in equation (3.4) may imply either a single-agent decision or a joint effort. In our setting these weights may be heterogeneous across families.

[4]Examples of outcomes over which agents may have expectations and preferences are: during-high school outcomes (e.g. expected interest in the subjects, expected level of effort to exert, expected performance); after-high school option values (e.g. expected flexibility in choosing between a job and attending university; expected job prospects or expected chances of enrolling in university; expected flexibility in choosing a college/job field); social outcomes (e.g. expected share of peers that will make the same choice, expected family appreciation for the choice).

4 Data Description

4.1 The institutional setting

Italian upper secondary education, i.e. high school, covers grades from 9^{th} to 13^{th} for students typically in the age group 14-19.

Students can choose to enroll in one of three tracks: the General, the Technical, or the Vocational track. The General track aims at preparing students for university, the Technical track provides both practical and theoretical skills, while the Vocational track is focused on job training related to a specific industry or trade. All these tracks are further specialized into curricula, defined by core subjects such as Humanities, or Math&Science, or Technology, and so on (see Table C.1 in the Appendix). Attending any of these tracks does not hinder the possibility to continue with college afterwards, as enrolling in universities only requires obtaining the final diploma after the "esame di stato" (i.e. a final exam after 5 years of high school)[5], regardless of the type of school where it was obtained. Usually schools are specialized in one track and can provide one or more curricula. Most of the high school education in Italy is in the hands of the public sector[6].

Students enter high school (and therefore tracking) at the age of 13 or 14. The choice of high school is in the hands of the families, even if schools and teachers may support this decision by providing indications labeled as "orientation suggestions" ("consiglio orientativo", Romito (2016)). Secondary school in Italy follows an open enrollment system, therefore when students apply they do not act strategically considering their chances of being admitted, as admissions are not based on GPA or test scores[7], at least in this setting. When submitting their applications students list up to three choices in their form, either different schools within the same track/curriculum or not. During the five years of high school students can switch curriculum or track, but this does not happen frequently (see Table C.2 in the Appendix).

[5]In Italy compulsory education is set until the student is 16 years old. Schools in the Vocational track may offer final exams after two or three years, but these do not award the final diploma needed for university enrollment.

[6]As of 2019, private high schools are 23% on a total of 6920 schools and they teach to 4% of the 2.7 million students enrolled in total. Source: ISTAT, dati.istat.it.

[7]First-choice high schools may need to decline admission if the number of requests is too high compared to their availability. In that case, the application form is automatically forwarded to the second choice listed on the form. In case the number of requests is too high, each high school has specific admission criteria listed on their website.

4.2 The survey design

Sampling. The study (labeled as "VI-S") took place in Vicenza, a mid-size city in the Italian North-Eastern region of Veneto, between October of 2011 and April of 2012.[8] Out of the 11 public junior high schools present in the Municipality, 10 endorsed the study. These schools were used as a sampling frame of 8^{th} graders (a little under 900 at the end of 2010) and their parents for the study.

The study's primary goal – i.e. to enable measurement and analysis of families' decision process of the high-school track for their children – motivated focus on 8^{th} graders and their parents, as the major decision effort by families is typically exerted during Fall and Winter of the final year of junior high school. Moreover, to enable measurement of children's friendship network and to maximize the probability that same-age friends would be included in the sample, all 8^{th} graders in endorsing schools and their parents were invited to participate.

Finally, to measure evolution of key components of families' decision process and of child-parent interaction during the process, while also observing pre-enrollment choices, a short-panel and across-the-decision design with repeated interviews of both children and parents during the relevant time frame were adopted.

Timeline. The VI-S encompassed four waves of data collection. The first three waves took place between mid October 2011 and mid February 2012, i.e., before the pre-enrollment deadline on February 20^{th} 2012. Each of these waves entailed fielding of two questionnaires, one for the child and one for parent(s). The final wave was administered at the beginning of April 2012, i.e. after pre-enrollment in high school, with only one questionnaire directed to the child. Consecutive waves were thus fielded 1.5-to-2 months apart from each other: the first during mid-end of October 2011, after the first month of school; the second around mid December of 2011, right before the Christmas break; the third in early-mid February of 2012, right before the pre-enrollment deadline; and the forth and final one at the beginning of April 2012, right before the Easter school break.

Survey mode and administration. All questionnaires were paper-and-pencil and self-administered by respondents. Each one took approximately 60 to 75 minutes to complete. Because of the longitudinal design requiring respondents to take 3-to-4 questionnaires

[8] At the end of 2010, the Municipality of Vicenza had approximately 116,000 inhabitants, and the Province approximately 870,000; of these, 999 and 8761 respectively were 12 years-old. About 16% of residents of the Vicenza Municipality were foreign born.

within 4-to-5 months, respondents were given 10-to-15 days to individually and privately complete each questionnaire at home and return it to school in a sealed envelope.

Trained interviewers introduced the study and described the first questionnaire to children in class, with a special focus on the mechanics of subjective expectations questions. Moreover, interviewers were personally in charge of distributing and collecting child and parent questionnaires in each wave, and of answering any clarification questions respondents may have and contact them about.

Participation. Approximately 650 students and their parents returned a fully or partially completed questionnaire in Wave 1 (i.e., a participation rate of 70%). This is a good participation rate given the self and at-home administration mode. Unfortunately, in-class administration was not an option for the VI-S, as its longitudinal design and the long length of the individual questionnaires were judged by school principals as potentially taking too much time from children's work and activities in school.

To incentivise participation, the following scheme was implemented. Children who answered and returned all four questionnaires were entered a lottery awarding one scientific calculator in each participating school and class (total participating classes=47). Additionally, families whose parents took and returned all three questionnaires were entered a lottery awarding one €100 voucher in each participating school and class to be spent toward purchase of ninth-grade textbooks for the children.

A snapshot of the samples. Basic demographic and physical characteristics of children were measured by questions eliciting their gender, month and year of birth, country of birth, year in which they moved to Italy (if born abroad), location where they live in Vicenza (to calculate their distance to different schools and curricula), approximate height and weight, and so on.

Additionally, the surveys collected extensive information on family composition and on demographic and socio-economic characteristics of parents and siblings (Wave 1), and of grandparents (Wave 2) (e.g., gender, age, country of birth, year in which each family member moved to Italy if applicable, main language(s) spoken at home, educational attainments, fields of secondary and tertiary degrees (if applicable), employment status, occupation, etc.). Finally, the survey included few questions on home environment and possessions (Wave 4), borrowed from the PISA questionnaire[9].

[9]OECD Programme for International Student Assessment, oecd.org/pisa.

Table 1: Respondents' Identity – Before & At Choice, Child & Parent.

	Child Sample Size[a]	%	*Parents* Both Parents	Mother Only	Father Only	Other Person	Sample Size[a]
Wave 1	649	100%	288 (48%)[c]	262 (44%)[c]	47 (8%)[c]	5 (1%)[c]	602 (100%)
Wave 2	388	60%[b]	114 (35%)[c]	176 (54%)[c]	33 (10%)[c]	6 (2%)[c]	329 (55%)[b]
Wave 3	308	48%[b]	80 (28%)[c]	176 (61%)[c]	31 (11%)[c]	2 (1%)[c]	289 (48%)[b]
Wave 4	272	42%[b]	-	-	-	-	-

[a]: After dropping observations with item non-response.
[b]: Comparison with the first-wave N.
[c]: Percentage out of the total sample size, by wave (each row sums to 100%).

Table 1 provides a snapshot of participating children and parents across waves. As already mentioned, parents were free to choose whether mother and father (when both present) would take the parent questionnaire together, or whether only one of them and whom would take it. However, they were asked to indicate their choice. Table 1 shows the sample distribution of respondents' (self-reported) identity. Interestingly, in the first wave almost half of participating parents opted for taking the first survey jointly, but this percentage declines in the following waves as the mother becomes the most prominent respondent. The share of families in which only the father took care of the surveys is stable around 10% for each wave.

Tables 2 and 3 show descriptive statistics of respondents' basic background characteristics, as elicited in Wave 1. Shown statistics are largely calculated based on survey answers provided by the corresponding respondent[10]. Descriptives are divided into two analytic samples: "evolution" and "at choice". This structure mirrors the two-part analysis carried out in the paper and highlights how the samples might change because of attrition.

Table 2 presents other characteristics related to the child, namely the gender composition of the sample (58-59% female), the family size (44-45% have older siblings), the average GPA (7.76-7.88 out of 10, where 6 is the passing grade). Table 3 presents some family characteristics. Mean age of the parents is between 43 and 48, with mothers slightly younger than fathers, and students are mainly regularly enrolled. Around 90% of the children in the sample was born in Italy, and otherwise foreign-born students have lived in the country on average 7 years; foreign-born parents are 13-14% and have lived in Italy

[10]Whenever the same information is asked to multiple family members, accuracy of answers may be improved, or item non-response mitigated, by combining answers to equivalent questions across family members.

Table 2: Background Characteristics – Before & At Choice, Child.

	Evolution[a]	**At Choice**
Child's Gender		
Male	142 (41.04%)	145 (42.03%)
Female	204 (58.96%)	200 (57.97%)
Sample Size (%)	346 (100%)	345 (100%)
Family Size		
Child has older siblings	143 (44.27%)	137 (44.77%)
Sample Size (%)	323 (100%)	306 (100%)
Child's GPA		
Mean	7.76	7.88
Std. Dev.	.97	.96
Min	6	6
Median	7.8	7.9
Max	9.8	9.8
Sample Size (%)	315 (100%)	263 (100%)
Child's GPA Relative to Sample Size GPA		
Below 25th percentile	78 (24.76%)	72 (27.38%)
Above 25th percentile	78 (24.76%)	76 (28.9%)
Sample Size (%)	315 (100%)	263 (100%)

Observations with item non-response have been dropped.

[a]: Participating to at least one of the relevant sets in the two consecutive waves of the before-the-choice period, i.e. Wave 1 and Wave 2, where Wave 2 has been replaced by Wave 3 if the respondent had not answered to Wave 2 but had answered to Wave 3 without submitting an early pre-enrollment.

15-20 years on average. Most of the parents have al least a high school diploma (64-65% of fathers, 66-68% of mothers); around one fourth of mothers are homemakers, while 22-23% of fathers have blue collar occupations.

4.3 Agents in the choice process

In this analysis the family can be a unitary decision maker, but also a group made up by two parties: the parent(s), and the child.

The decision protocol of a group is different from the decision protocol of a single unit, because it requires the aggregation of utility valuations and subjective probabilities over future uncertain outcomes. In this context the child is only thirteen years old and is not a "full" decision maker (Dauphin et al. (2011)), in the sense that she participates in the household's decision making but does not have the same status as her parents.

A principal-agent problem arises: parents can make decisions and take actions on behalf of their child, who will be the one bearing the consequences in terms of human capital accumulation and development. A model of collective bargaining assumes that a member's bargaining power is related to her outside option (McElroy and Horney (1981)); in this case the child has no outside option, as she is forced to remain in the family in any case. The bargaining power is therefore shaped by parental preferences over how much autonomy to grant and in which form, i.e. the parenting style. Parents may be either (1) imposing constraints and vetoes on the set of available alternatives without justifying them, thus leaving the child without the chance to express her preferences (authoritarian style); (2) discussing options with the child and try to persuade her to choose their preferred outcome, but still giving her the space to understand (authoritative style); (3) not interfering and leaving the floor to child, offering support and explanations when needed (permissive style); or (4) uninvolved and leaving complete freedom to the child (neglectful style). Style (1) and (2) can possibly co-exist, so that parents may be more aggressive in shaping their child's beliefs and stir her choice in their direction (intensive style/over-parenting/helicopter parenting). In the authoritarian case parents are the unique decision makers, and in the neglectful case children are the only ones involved; in all other cases, parents meddle with the child's decision in explicit or implicit ways.

In this analysis parents are treated as a unique entity, given that our data source (i.e. the surveys) does not allow us to fully distinguish the (eventual) two individuals in all our observations. While we assume that parental preferences are not conditioned by external

Table 3: Background Characteristics – Before & At Choice, Child & Parents.

	Evolution[a]			At Choice		
	Child	**Mother**	**Father**	**Child**	**Mother**	**Father**
Respondent's Age						
Mean	13.06	43.23	45.83	13.08	44.90	48.61
Std. Dev.	.36	10.26	13.10	.43	4.69	6.09
Min	12	35	36	12	32	37
Median	13	45	47	13	45	48
Max	15	55	68	15	55	68
Sample Size (%)	346 (100%)	302 (100%)	302 (100%)	342 (100%)	274 (100%)	271 (100%)
Child's Age Relative to 8th Grade Regular Age[b]						
Ahead (< 13)	12 (3.47%)			15 (4.39%)		
Regular (= 13)	303 (87.57%)			291 (85.09%)		
Behind (> 13)	31 (8.96%)			36 (10.52%)		
Sample Size (%)	346 (100%)			342 (100%)		
Respondent's Place of Birth						
Italy	314 (91.01%)	253 (86.05%)	255 (87.04%)	259 (89.62%)	238 (85.92%)	236 (85.51%)
Foreign Country	31 (8.99%)	41 (13.95%)	38 (12.96%)	30 (10.38%)	39 (14.08%)	40 (14.49%)
Sample Size (%)	345 (100%)	294 (100%)	293 (100%)	289 (100%)	277 (100%)	276 (100%)
Respondent's Years in Italy (Conditional on Being Foreign Born)						
Mean	7.19	16.05	20.19	5.6	14.64	17.18
Std. Dev.	3.61	9.86	12.82	3.91	10.36	11.99
Min	0	2	2	0	1	0
Median	8	15	19	6	11	13
Max	13	47	57	13	41	45
Sample Size (%)	31 (100%)	36 (100%)	31 (100%)	30 (100%)	33 (100%)	33 (100%)
Highest Educational Qualification						
No Qualification		1 (.35%)	-		2 (.74%)	1 (.37%)
Elementary Degree	346 (100%)	2 (.69%)	2 (.70%)	345 (100%)	-	1 (.37%)
Junior HS Degree		52 (18.06%)	65 (22.81%)		48 (17.65%)	56 (20.97%)
Professional Diploma		42 (14.58%)	36 (12.63%)		36 (13.24%)	34 (12.73%)
HS Diploma		107 (37.15%)	106 (37.19%)		103 (37.87%)	96 (35.96%)
College Diploma		10 (3.47%)	9 (3.16%)		13 (4.78%)	13 (4.87%)
College Degree		57 (19.79%)	46 (16.14%)		57 (20.96%)	49 (18.35%)
Higher-Educ. Degree		17 (5.90%)	21 (7.37%)		13 (4.78%)	17 (6.37%)
Sample Size (%)	346 (100%)	288 (100%)	285 (100%)	345 (100%)	272 (100%)	267 (100%)
Parent's Occupation						
Stay-at-home Mother		74 (24.83%)			74 (26.33%)	
Blue-collar Father			66 (22.92%)			59 (21.69%)
Sample Size (%)		298 (100%)	288 (100%)		281 (100%)	272 (100%)

Observations with item non-response have been dropped.

[a]: Participating to at least one of the relevant sets in the two consecutive waves of the before-the-choice period, i.e. Wave 1 and Wave 2, where Wave 2 has been replaced by Wave 3 if the respondent had not answered to Wave 2 but had answered to Wave 3 without submitting an early pre-enrollment.

forces, for children this may not be the case. In fact, authoritative or intensive parents may not directly interfere in their child's decisions but rather prefer shaping them, for example not making their child aware of some alternatives or discouraging some options in a way that does not look like a veto. Explicit prohibitions are easier to detect, but both direct and indirect bans affect the formation of child's choice sets, in terms of size and composition. According to the parenting style and the *locus* of decision, the primary decision maker can then be either the child, or the parents, or the family as a whole, in varying degrees.

In the next sections we present the definition of the relevant choice sets in this analysis and the survey measures used to document them. In section (7) we outline possible survey measures of parenting styles and how to include them in this setting.

4.4 Choice set concepts

In this paper we study different types of choice sets, i.e. different subsets of alternatives. Here we report their definitions[11], applying them to our setting. We start from the smallest one and we proceed each time adding an additional layer of choice set inclusion, but this does not necessarily imply nestedness of sets.

Chosen alternative(s), or Stated preferred alternative(s), or Application Set. Set of alternative(s) that results from the choice process, possibly ranked, or list of preferred options while the process is still ongoing.
In this application: ranked list of alternatives as reported in the pre-enrollment form (up to three), or, alternatively, ranked list of preferred options at a certain moment in time during the decision-making process. We consider two subsets: the actual choice, and the set of best alternatives (top three).

Actual choice, or Ranked-first alternative. Observed outcome of the choice process.
In this application: First-ranked curriculum indicated on the pre-enrollment form.

Top-three alternatives, or Application Set. Set of alternatives considered in the final decision phase. In educational choices where there are supply-side rules for admissions to institutions, the Application set represents the ranked

[11]Definitions of choice sets, consideration sets, awareness sets, and universal sets follow Shocker et al. (1991).

alternatives listed when submitting the official form.

In this application: Preferred alternatives, top three. This includes: before the choice, the ranked preferred choices; and at the moment of choice, the three different ranked alternatives listed in the pre-enrollment form.

Consideration set. Set of choice alternatives purposefully constructed as it consists of salient preference-satisfying options; options about which the agent has carefully thought about.

In this application: Curricula and schools actively considered by responding children and/or their families when making the pre-enrollment decision.

Feasible choice set(s). Set of choice alternatives that are feasible, i.e. alternatives on which there are no observed constraints e.g. of institutional or legal nature, financial, informational, related to time/space or to cognitive and health issues.

In this application: Set of high school alternatives that are geographically reachable, known, and from which the actor can freely choose. We consider two feasibility constraints: agency, and information.

Agency set(s). Subset of items from the universal set on which the actor has agency, i.e. she can freely chose what action to take without any constraint from the primary decision maker (i.e. the parent). The existence of agency sets stems from having two or more decision makers in non-symmetric power positions.

In this application: Set of alternatives that the child-decision maker is free to choose because there are no parental vetoes.

Awareness set. Subset of items from the universal set of which the agent is aware, i.e. she has some kind of knowledge, even superficial, of at least its existence.

In this application: Curricula and schools respondents “Know of,” or “Have heard of,” *versus* “Have never heard of”.

Universal choice set. The totality of all alternatives that could be chosen by any agent under any circumstance. Alternatives may be irrelevant or unobtainable by a given individual.

In this application: Universe of high school curricula offered in the area of Vicenza in the a.y. 2011/12 (i.e. ten curricula across three tracks).

We define these sets both at the moment of choice and before the choice, in the latter case paying attention at their evolution over time.

The survey measures for these indicators may not always be available for all the agents and in all the periods. For example, an explicit measure of at-the-moment-of-choice vetoing (considered as an actual constraint) is reported by children in Wave 4, after the pre-enrollment choice has been submitted; the same explicit question was not asked in the waves before the choice. Nonetheless, it is possible to reconstruct it in the decision-making phase by looking at perceived parental constraints on the choice set (elicited probabilistically), as described later.

These sets can be estimated separately for the child and the parents, or for the family as a whole. These three formulations need assumptions on the family style of choice. In fact, the problem for parents and children is not symmetric: from agent to agent we may have different structures and levels of nestedness of the choice sets. For example, in our framework there are no "hard" constraints of institutional or financial nature, nor there are admission procedures based on entry tests and past school performance. Hence feasibility has only two channels: information (awareness), and agency. Once children are aware of all the alternatives, the only constraints are the vetoes imposed by parents. This means that while children have agency sets influenced by their parents' opinions (if any), parents do not have constrained agency sets: a veto to their child is in their own perspective just a matter of preferences, not of feasibility. We assume that children cannot impose vetoes to their parents. In a more general setting, parents may be constrained by law to choose e.g. a high school in the neighborhood, but this is not true in our empirical application; the only constraint we consider for parents is in terms of knowledge/awareness, thus leading to a potential wedge between the universal set and the awareness set.

4.5 Survey measures

Tables 4 and 5 summarise the measures used to construct the sets both at the moment of choice and before (we will refer to the decision-making process as the "evolution" phase of the choice sets). There are three important considerations to make. First, at choice we do not define child- and parent-specific sets but we rather focus on the realized family outcome: we assume that children and parents interact while making up their minds, but eventually share the final pre-enrollment choice sets, as the latter represent a convergence of preferences and constraints. Before the choice instead we analyse children and parents

Table 4: Definition of the survey measures used to estimate the different sets at the time of choice – Family Outcome.

	Family outcome
Chosen alternative(s)	
Ranked-first alternative	Chosen alternative: ranked first in the pre-enrollment form
Top-three alternative(s)	Three options as ranked on the pre-enrollment form
Consideration set	Listed as considered (open question)
Feasibility sets	
Agency sets	
Implicit parental veto, lb[a]	Set of alternatives such that the probability of parental approval is strictly greater than 50
Implicit parental veto, ub[a]	Set of alternatives such that the probability of parental approval is strictly greater than 0
Explicit parental veto	Set of alternatives from which the child was allowed to choose
Awareness set	Alternatives of which they know of or have heard of
Universal choice set	All the 10 alternatives

Measures elicited in Waves 3 (if pre-enrolled) and 4.
[a]: *lb*: lower bound; *ub*: upper bound.

as separate agents. Second, measures may change between the two time periods: Waves 1 to 3 have a fairly similar structure and often repeat questions, being administered both to children and parents; Wave 4 instead was targeted at students only and had slightly different questions. In the next paragraphs we will see the differences in detail. Third, Wave 3 was administered in January when some families could already have submitted their applications; this is reported in the survey, and we therefore distinguish the information from these questionnaires according to their early application status: the Wave 3 information from agents that had not submitted their application at the time of filling in the surveys will be used to complement the information from Wave 2 if missing; the Wave 3 information from agents that had submitted an early pre-enrollment application at the time of filling in the surveys will be used to enrich the information from Wave 4 using the measures not available in the last wave.

The relevant survey questions discussed in the next paragraphs are presented in section (C.3) in the Appendix.

Universal choice set. The universe of alternatives is represented by the ten possible curricula available to all students, mapped into three tracks. In most of the cases more than one school in the Vicenza area offered the curriculum.

Awareness set. Respondents' awareness about existing curricula and about local schools was elicited asking for each of the alternatives whether the respondent knew of the option, had heard of it, or had never heard of it; if for a curriculum one of the first two answers was given then we consider it included in the awareness set. This question is available

Table 5: Definition of the survey measures used to estimate the different sets before the choice – Child & Parent.

	Respondent (Child, Parent)
Stated preferred alternative(s)	
Ranked-first alternative[a,b]	Highest ranked alternative, if choice had to be made today
Top-three alternative(s)[a,b]	Top three ranked alternatives, if choice had to be made today
Consideration set(s)	
Active consideration set	Set of alternatives that the respondent reported thinking about, talking about with someone else, or having researched in the period preceding the survey[c]
Cumulative consideration set, ub[c]	Set of alternatives that the respondent reported thinking about, talking about with someone else, or having researched since the start of the process
Feasibility sets	
Agency sets[a]	
Implicit parental veto, lb[d]	Set of alternatives such that the probability of parental approval is strictly greater than 50
Implicit parental veto, ub[d]	Set of alternatives such that the probability of parental approval is strictly greater than 0
Awareness set	Set of alternatives of which they know of or have heard of
Universal choice set	All the 10 alternatives

All these measures have been elicited in Waves 1, 2, 3 (if not pre-enrolled) in agent-specific questionnaires.
[a]: probabilistic measure.
[b]: Wave 1 had a cap of 3 alternatives to rank, while Waves 2 and 3 allowed for a longer school chart (and possibly ties).
[c]: the "preceding period" varies across surveys. In Wave 1 it refers to the past in general, i.e. any period since the start of the decision process. In Waves 2 and 3 it refers to the period between filling in the preceding survey and the current one.
[d]: *lb*: lower bound; *ub*: upper bound.

in Waves 1 to 3, but not in Wave 4. It is therefore measurable at choice only for those families where at least one between the child and the parent(s) responded to Wave 3 and reported already having filled in the pre-enrollment application.

Agency set. Wave 4 asks children a direct question about parental vetoing. Students were presented a list of the ten available curricula and had to check all those they had not been allowed to choose. We use this as a measure of at-choice parental veto, as perceived and reported by the child.

Before the choice we rely on a probabilistic measure of parental vetoing, and we label it "implicit" as opposed to the "explicit" measure elicited in Wave 4. The VI-S surveys in Wave 1 to 3 elicited children's and parents' probabilistic beliefs about parental vetoes on different high-school tracks the child may like to choose, under two different scenarios: "What curricula would your parents [you] accept for you [your child], if it were your [your child's] own choice and you [s/he] asked without providing any motivation for it?"[12] *versus* "What curricula would your parents [you] accept for you [your child], if it were your [your child's] own choice and you [s/he] asked providing some motivation for it?". We use this measure to obtain bounds on the implicit vetoes. Namely, we define an upper bound in which only the strictest implicit vetoes apply: only the alternatives for which at least one

[12]The question refers to the child's version of the questionnaire. The parentheses modify it so that it reflects the parents' questionnaire.

between the motivated or unmotivated percent chance was zero are considered vetoes. On the other hand, we define as lower bound of the set the case in which more alternatives can possibly be vetoed: all those whose maximum probability (maximum between motivated or unmotivated) was lower than 50.

Consideration set. Measures of consideration vary slightly across the first three waves and more decidedly in Wave 4.

In particular Wave 1 elicited whether respondents, and if so for how long, had been devoting thought and time to the high school track decision prior to 8^{th} grade (e.g., by reasoning for themselves about the choice or by gathering information on available curricula or future prospects implied by different choices). Respondents were additionally asked whether, and if so for how long, they had been talking about the high-school track choice with their relevant others, i.e. parents, older siblings, same-age friends or relatives, older friends or relatives currently in high school, adult friends or relatives out of school, and their teachers. Respondents could indicate that they had started thinking about the high school choice as early as elementary school. This question was supported by evidence from qualitative studies (e.g., Istituto IARD (2001), Istituto CISEM-IARD (2009)) and from in-depth interviews carried out during the design phase of the VI-S suggesting that many families concentrate their choice effort during the first school term of 8^{th} grade, especially during the 2-3 months immediately preceding the pre-enrollment deadline, but also that a small but sizable fraction of children and families enter eighth grade better informed and with better formed ("concentrated") preferences over high-school tracks and their future paths than the majority.

Waves 2 and 3 ask a similar question about the alternatives considered (i.e. thought about, discussed with someone else, and/or researched), but as for the temporal window they ask to focus only on the period between the previous survey and the one being currently filled in at the moment. The different temporal windows allow for the definition not only of a set at the moment of the survey, but also for a cumulative measure from Wave 1 to 3.

Wave 4 instead asks an open question about the alternatives considered. Given the substantial difference between the Waves 1 to 3 and Wave 4 measures, in the at-the-moment-of-choice consideration set we include only the information from Wave 4, disregarding the information coming from Wave-3 respondents who had already pre-enrolled.

Top-three alternatives and Ranked-first alternative. Before the choice respondents were asked to rank all alternatives from 1 to 10[13], and each of the three preferred options was also associated with the probability that this would be the actual choice if the choice had to be done on that day. In Waves 2 and 3 ties were allowed.

At choice respondents report their ranked alternatives as written down on the official pre-enrollment form.

[13]In Wave 1, only the top 3 choices were ranked. In the following waves, respondents were presented a list of all the alternatives and had to assign a rank to each of them from 1 to 10, with 1 being the preferred option.

5 Heterogeneous Choice Sets

5.1 Descriptive Statistics

In our analysis of choice set definition we will consider the main drivers of choice set inclusion and evolution, but many forces are at play. For example, students may be influenced by their peers' behavior or by the expectations they have about it (refer to Chapter 2 of this Thesis); children may listen to teachers' advice, but may also talk to older siblings or look up at their experiences. All these sources may contribute in a negative or positive way towards the inclusion of an alternative in the choice set.

Table 6 reports summary statistics about the number of curricula that were considered or suggested or discussed, both positively and negatively, at the time of choice. We can see that median numbers of considered or suggested alternative are low, but still they are relevant measures for understanding how the choice set formation process and the family interaction happen. In particular we see that mothers tend to suggest against alternatives more than fathers, but as we see in Table C.4 in the Appendix (where we present the same summary statistics split by gender) this hides the fact that while mothers suggest against on average 1.72 curricula and fathers 1.47, both of them on average suggest against more alternatives to male children.

Table C.5 in the Appendix presents similar at-the-moment-of-choice summary statistics across curricula, with the numbers representing the average share of alternatives (where 100% refers to the 10 alternatives available), and Table C.6 in the Appendix presents the same information while grouping the curricula by track. Among the "suggested" variables, it is common to have as most suggested curriculum the Math&Science one in the General track, the Technology curriculum in the Technical track, and the Services curriculum in the Vocational track, thus mirroring the distribution of the most chosen curricula in the sample (as displayed in the first rows of the table). A similar pattern can be seen for whether or not the curricula were present in the ranking (either generally or among the top three choices) in both Waves 3 and 4. Awareness about the existence of the different alternatives is very high at this point in time. Again, crossing parents' and students' gender may reveal important patterns. In Table C.7 in the Appendix we can see how female respondents report on average more suggestions, apart from the case of the Technical curriculum in the Technical track. Looking at other measures more related to the child's active participation, we see a slightly different pattern. In fact, most of the

Table 6: Positive and negative forces at play as reported at the time of choice – Waves 3 and 4, Child. Number of Curricula (range: 0 to 10).

Factors	**Median**	**Mean**	**StdDev**	**Min**	**Max**	**N**
Positive forces						
Considered at choice[a,b]	2	1.79	.87	1	4	227
Suggested by mom[b]	1	1.17	1.27	0	6	241
Suggested by dad[b]	1	1.06	1.18	0	6	241
Suggested by teacher (orientation)[b]	1	.75	1.02	0	10	241
Suggested by other teacher[b]	0	.46	.71	0	4	241
Present in ranking[b]	10	8.55	2.96	1	10	227
Present in ranking[c]	10	8.97	2.66	1	10	203
Aware of it[c,d]	10	9.56	1.10	5	10	216
Thought about it in the previous month[c]	1	.81	.71	0	3	216
Talked about it in the previous month, with mom[c]	0	.46	.62	0	3	216
Talked about it in the previous month, with dad[c]	0	.33	.55	0	2	216
Talked about it in the previous month, with both parents[c]	0	.35	.58	0	3	216
Talked about it in the previous month, with teacher[c]	0	.20	.46	0	2	216
Negative forces						
Mom suggested against[b]	1	1.72	2.38	0	9	241
Dad suggested against[b]	0	1.47	2.27	0	9	241
Teacher (orientation) suggested against	0	.76	1.92	0	9	241
Other teacher suggested against	0	.46	1.45	0	9	241
Not allowed by parents[b]	0	1.46	2.13	0	8	241
Child did not want to consider it[b]	7	6.07	2.99	0	10	241

[a]: Open question. Student had to write down the name of schools considered for the choice and their respective curricula.
[b]: As of wave 4, after pre-enrollment decision has been submitted. N = 241.
[c]: As of wave 3, only for those who declare that their pre-enrollment decision has been submitted. N = 216.
N = 103 observations who answered both to wave 3 and 4.
[d]: "Awareness" refers to having declared that one curriculum is either known or the child has heard of it.

thinking and talking seems to be concentrated on the Languages and the Social Sciences curricula in the General track, and on the Economic curriculum in the Technical track; the Vocational track displays a behavior similar to what already commented. In the case of Languages and of Economic curricula these numbers are mostly driven by female respondents, as reported in Table C.7; both options are in fact more commonly chosen by girls. The Social Sciences curriculum is also more chosen by girls than by boys, but it looks like in the last pre-choice period this was the curriculum on which male students concentrated more their thinking and talking effort; this may be explained by the fact that the Social Sciences curriculum was one of the two new introductions on that academic year, together with the Music&Choral option. The schools that were mostly discouraged are the Art or the Musical&Choral curricula in the General track, and the Professional Training in the Vocational track, with results more heterogeneous by gender in this case; these alternatives are also the ones most often vetoed by parents to both male and female children.

In this paper we argue that the choice is influenced not only by agents' preferences but also by the bargaining process within the families. Table 7 presents how children perceived the choice process in their family. Answering to the question "Which of the

Table 7: Share of answers to the question "Which of the following best describes the way in which the choice of the best high school curriculum for you has been carried out in your family?" – Wave 4, Child.

Style of choice			
Style A			
Common decision (%)		*Who had the last word?*[a] (%)	
Talked and reached a common agreement	36	Child	67
		Father	12
		Mother	10
		Other relative	3
Style B			
One person decided after listening to others: who? (%)		*Of which, listened to... (%)*	
Child	50	Father	60
		Mother	69
		Other relative	32
		Teacher	40
Father	2	Child	50
		Mother	50
		Other relative	25
		Teacher	25
Mother	1	Child	-
		Father	-
		Other relative	-
		Teacher	-
Parents	7	Child	62
		Other relative	23
		Teacher	31
Other relative	0		
Teacher	0		
Style C			
One person decided without listening to others: who? (%)			
Child	3		
Mother	0.5		
Father	0.5		
N	187 (100%)		

following best describes the way in which the choice of the best high school curriculum for you has been carried out in your family?" in the last wave of the survey, the most common style is letting the child decide (50% of the cases) after listening to the mother and/or the father. Thirsty-six percent of the sample reports having discussed and reached a common decision, where the child in most of the cases was the one who had the last word. Situations in which both parents together (7%), the father alone (2%) or the mother alone (1%) decide are marginal, and in all these cases the child was the figured to which they had mostly listened to, according to the child's report. In 3% of the cases children declare having chosen completely alone. Table C.8 in the Appendix presents the results split by gender. Figure C.1 in the Appendix presents how often each of these styles (i.e. common decision; one person decided after listening to others; one person decided without listening to others) were ranked as first, second, or third favorite way of reaching a decision. The most common mix was to rank as preferred option a situation in which child and parent discuss together until finding an agreement, while the second favorite is when one person only listens to others' reasons but then chooses independently.

5.2 Realized Heterogeneous Choice Sets

We now present the estimation of the discussed choice sets using the survey measures presented in section (4.5). For at-choice sets we do not distinguish between children and parents, as we consider realized sets as a family outcome.

Size. Table 8 presents the number of alternatives included in each of the choice sets at the moment of choice, out of the 10 possible options. The choice set at the moment of choice contains only the selected alternative, therefore the choice set of each agent contains only one option. The set of stated preferred alternatives counts the number of curricula among the (up to) three ranked schools in the pre-enrollment form, and it shows that on average students tend to list schools belonging to the same curriculum but may also select other alternatives (if all ranked schools belonged to the same curriculum, the mean would be 1). The consideration set shows how almost two options on average were actively considered for the final choice, thus more than those listed in the pre-enrollment form. The awareness set includes almost the full set of available alternatives, while the agency set deserves a more detailed discussion as follows.

In this table we include three different definitions of agency set. One set, labeled as "explicit veto", is defined taking into consideration only the veto reported by the child

Table 8: At-the-moment-of-choice choice set – Wave 3, if Pre-Enrolled, and Wave 4, Family Outcome.

	Family outcome					
	Mean	**Std Dev**	**p10**	**p50**	**p90**	**N**
Chosen alternative(s)						
Ranked-first alternative [a]	1	0				354
Top-three alternative(s) [a]	1.28	.56	1	1	2	354
Consideration set	1.67	.92	1	1	3	241
Feasibility sets						
Agency sets						
Implicit parental veto, lb[b]	7.66	2.78	3	9	10	238
Implicit parental veto, ub[b]	8.03	3.11	3	10	10	239
Explicit parental veto	8.80	1.94	5	10	10	241
Awareness set	9.95	.34	10	10	10	238
Universal choice set	10					

We prioritize information from the child.
When it is missing, we check whether the parent answered in Wave 3 & reported an early pre-enrollment.
[a]: pooling information from Wave 4 and Wave 3 (children) if students pre-enrolled early.
[b]: *lb*: lower bound; *ub*: upper bound.

in Wave 4. On average slightly more than one alternative was explicitly vetoed by the parents. However, it is reasonable to assume that vetoes are the result of an interaction between child and parents in which the latter felt the need to exclude one option from the feasibility set. It is possible that such interaction never realized if the child perceived that a particular option would have not been accepted by the parents and therefore did not dare ask about it, or if the child was not so interested in that option. We therefore define as "implicit vetoes" those reconstructed from a low probability that the parents would accept such an option for their child. We define the upper bound as excluding all the options for which the child reported a probability equal to 0 that the parent(s) would accept that choice either with our without motivation. The lower bound instead excludes the options for which, between the probability of accepting such an alternative with or without motivation, the maximum is strictly lower than 50. We do not constrain these sets in any way; they are only nested in the universal choice set and there is no rule about including the chosen alternative(s). We see that implicit vetoes are on average more than the explicit ones, resulting in smaller implicit agency sets (lower and upper bounds).

Overall, from this table we can conclude that, while at pre-enrollment there is almost no evidence of limited awareness of the alternatives, there is substantial evidence of limited agency and limited consideration. Agency in particular is affected by both explicit constraints and implicit ones.

Tables C.9 and C.10 in the Appendix refer to the same choice set estimation, but report the summary statistics for included alternatives in each set for specific subgroups defined according to some variables: child's gender, child's seventh-grade GPA, and parental education as reported in Wave 1. In Table C.9 we can see that the mean number of included alternatives is higher for female respondents for almost all the sets. Students with a lower GPA pre-enroll listing alternative more concentrated on one curriculum and consider less alternatives; moreover, they also report fewer parental vetoes (both implicit and explicit). Table C.10 presents the same decreasing pattern for the number of options included in the agency set for parents' education: the higher the educational level, the lower the mean number of feasible alternatives, meaning that more educated parents tend to impose more vetoes, or children of more educated parents tend to report them more.

Parental education has been linked to parenting style (Doepke and Zilibotti (2019)); in our case, having fewer feasible options when parental education is higher might mean that parents are more involved in the choice process of their child and may impose more restrictions (as compatible with the authoritarian, authoritative, or intensive styles), while parents with lower education may be uninvolved (in line with the permissive or the neglectful styles). Further investigation is needed to establish a clearer connection.

Composition. Table 9 reports the composition of each set at the moment of choice in terms of the average number of tracks covered by each set, instead of the number of curricula; it is a measure of variety of alternative inclusion. We can see that while families are aware of all the tracks, still they focus their consideration effort in mostly one, and also explicit vetoes seem to be concentrated more in one track. At the same time the fact that among the top-three alternatives (the application set) the average number of tracks is bigger than one means that in the pre-enrollment form students not only apply to different curricula, but they also apply to schools belonging to different tracks. Table C.11 in the Appendix presents the composition of each set at the moment of choice in terms of ratio of curricula covered by each set within each track.

Table 9: Composition of each set at the moment of choice – Wave 3, if Pre-Enrolled, and Wave 4, Family Outcome. Average number of tracks covered within each set (range: 1 to 3).

	At Choice					
Set	**Mean Tracks**	**Std. Dev.**	**p10**	**p50**	**p90**	**N**
Chosen alternative(s)						
Ranked-first alternative(s)	1	0				354
Top-three alternative(s)	1.12	.34	1	1	2	354
Consideration set	1.22	.49	1	1	2	241
Feasibility sets						
Agency sets						
Implicit parental veto, lb[a]	1.05	1.35	0	0	3	238
Implicit parental veto, ub[a]	2.96	.33	3	3	3	239
Explicit parental veto	2.82	.51	2	3	3	241
Awareness set	2.99	.06	3	3	3	238

[a]: *lb*: lower bound; *ub*: upper bound.

Heterogeneity. Table 10 presents the results from a Poisson regression of choice-set size on agents' characteristics.

Students' gender affects reporting a higher number of curricula on the application form, considering more alternatives, and are subject to less implicit vetoes. As for explicit vetoes, students hear more options vetoed when parents are living together instead of in different households. While the mother's home-making status does not seem to matter, having a father with a blue-collar job increases the size of the agency sets as defined by the explicit vetoes, meaning that more options are permitted, similarly to the case of students that have a GPA in the lower 25^{th} percentile of the sample distribution. Having older siblings reduces the probability that the top three alternatives are from different curricula, suggesting that families may draw from this experience to extract information. Awareness at choice is very concentrated (almost everybody knows of all the options) and it is not influenced by these family characteristics.

Table C.12 in the Appendix presents the same regression over the same sets and the same covariates but using as dependent variable the number of tracks included in each choice set instead of the number of curricula. In the case of track inclusion being female shrinks the agency set (implicit); having older siblings leads families to apply to alternatives from the same track; being a foreign-born student leads you to consider alternatives more concentrated in one or two tracks instead of from all three, while living

Table 10: POISSON REGRESSIONS OF THE AT-THE-MOMENT-OF-CHOICE CHOICE SET INCLUSION ON CHILD'S AND PARENTS' CHARACTERISTICS – WAVE 3, IF PRE-ENROLLED, AND WAVE 4, FAMILY OUTCOME. SIGNIFICANCE LEVEL OF COEFFICIENTS REPORTED

	Family outcome						
	Ranked-First Alt.	**Top-Three Alt.**	**Consid. Set**	**Agency Set, implicit lb**	**Agency Set, implicit ub**	**Agency Set, explicit**	**Awareness Set**
After the choice							
Female student	-	.124**	.166**	.039	.143**	.054	-.004
		(.053)	(.083)	(.059)	(.062)	(.036)	(.003)
Foreign-born student	-	.008	-.009	.065	.028	-.070	-.022
		(.105)	(.203)	(.095)	(.105)	(.068)	(.016)
Lives with both parents	-	.041	.147	.106	-.007	-.131*	-.000
		(.107)	(.124)	(.084)	(.096)	(.078)	(.002)
Stay-at-home mother	-	-.077	-.018	.098	.100	-.037	-.007
		(.060)	(.099)	(.064)	(.062)	(.042)	(.005)
Blue-collar father	-	-.012	.052	.004	-.081	.065*	-.002
		(.062)	(.117)	(.072)	(.085)	(.037)	(.006)
Has older siblings	-	-.106*	.047	-.073	-.025	-.047	.001
		(.057)	(.094)	(.055)	(.055)	(.035)	(.004)
7^{th}-grade GPA,	-	-.029	-.081	.031	.107	.095**	.001
lower 25perc		(.064)	(.110)	(.075)	(.078)	(.044)	(.005)
7^{th}-grade GPA,	-	-.024	.054	.031	.147**	.023	-.002
upper 25perc		(.066)	(.101)	(.060)	(.062)	(.041)	(.004)
Sample size	239	239	156	194	195	156	194

lb: lower bound; *ub*: upper bound.

Significance levels: [***] significant at 1%; [**] significant at 5%; [*] significant at 10%.

Predictors: *female student:* dummy=1 if student is female; *foreign-born student:* dummy=1 if student is foreign-born; *lives with both parents:* dummy=1 if student lives with both parents; *stay-at-home mother:* dummy=1 if student has a stay-at-home mother; *blue-collar father:* dummy=1 if student's father works in a blue-collar occupation; *has older siblings:* dummy=1 if student has older siblings (between 1 and 3); *7^{th}-grade GPA, lower 25 percentile:* dummy=1 if student's GPA in the 7th grade end-of-year report (between 6 and 10) is in the bottom quartile of the distribution; *7^{th}-grade GPA, upper 25 percentile:* dummy=1 if student's GPA in the 7th grade end-of-year report (between 6 and 10) is in the upper quartile of the distribution.

with both parents has a positive effect on the consideration set. Having a father with a blue-collar job and having a GPA in the lower 25^{th} percentile of the sample distribution increase the chances of including more tracks in the (implicit and explicit) agency sets.

From these analyses we can notice how having a father with a blue-collar job and having a GPA in the lower 25^{th} percentile of the sample distribution tend to impact the size and composition of the agency set, and how being foreign-born negatively affects the composition of the consideration set; this is consistent with lower parental involvement in school choice among families from a lower socio-economic background and a higher probability of "weaker" students of choosing less academic tracks, thus usually excluding the General track from the choice sets.

6 Evolution of Heterogeneous Choice Sets

6.1 Descriptive Statistics

The surveys administered before the pre-enrollment choice provide a lot of information on the evolution of the choice sets. In particular, as described in section (4.5), they explore the dimensions related to the information gathering process (through independent search, through thinking on one's own, through talking with others), the awareness about existing alternatives, and their ranking. The most interesting dimensions in this pre-decision period is about the possibility that some options could be vetoed by parents, either explicitly or implicitly. Before moving on with the discussion, we present a few interpretations of this measure.

When children are asked to provide the probability that parents would accept an option in probabilistic terms, we interpret this probabilistic formulation as expressing the uncertainty around both parenting styles and parental preferences. On the other hand, parents should have no uncertainty about their present parental preferences; the probabilistic formulation is this case depends on the style of interaction with the child, and possibly hints at awareness about potential informational shortcomings. In principle we could interpret the "no motivation" probability as baseline preference of the parent, and the difference between that and the "with motivation" probability as an indicator of parenting style[14]: do parents leave room for being convinced or do they know that whatever their child says they will not change their minds? In the latter case, the authoritarian parents know that their preferences will not change to compromise with their child. Figures from C.2 to C.5 in the Appendix present the frequencies of answers to this question, by wave and agent. The more time passes, the more probabilities tend to be polarised towards either 0 (in particular in the "non-motivated" case) or 100 (in the "motivated" case).

Figures C.6 to C.9 in the Appendix summarise the answers to this same question in Wave 1 only, assuming that high probabilities express confidence about acceptance, and low probabilities express confidence about rejection. Comparing Figure C.6 and C.8 we can see that children think that their ability to justify an alternative is valuable in order to make parents accept it; from the comparison of Figures C.7 and C.9 it also looks like parents may be keen on listening to the motivations of their children. This suggests that overall the prevalent parenting style in the sample is less likely to be the authoritarian

[14]Note that in the data the "no motivation" probabilities can be either smaller or larger than the "with motivation" probabilities.

one.

6.2 Before-the-Choice Heterogeneous Choice Sets

Some of the sets are measured in the same way as their at-choice counterparts, but some are not. The most important difference between the two time periods is that some of the before-the-choice sets are probabilistic, in particular the agency set and the preferred alternative. The agency set (in terms of implicit vetoes only) is probabilistic because there is some uncertainty related to parental preferences and parenting styles on the child's size and related to family interactions and information on the parents' side; the preferred choice(s) set is also probabilistic because it involves thinking about future uncertain outcomes. Second, because of the survey design we estimate the consideration set both at the time of the survey and cumulatively since the beginning of the thought process. Third, in this context we consider the child's and the parents' sets separately, as we assume that both of them are participating in the process and still have not coordinated or fully bargained on all the options.

Size. Tables 11 and 12 present the summary statistics for the average number of alternatives included in each set independently for each wave, respectively for children and parents before the choice (the pre-enrollment form had to be submitted at the end of February). We use information from Wave 1 (elicited in October) and Wave 2 (elicited before the Christmas break); when information from Wave 2 was not available, we used answers from Wave 3 (elicited in January) if available and if the agent reported not having pre-enrolled in high school yet. We report information only pertaining to the agents for which we were able to estimate the sets in both waves. In Tables 11 and 12 we report also at-choice choice sets estimated on the matched subsample of agents for which Wave 1 and Wave 2 sets have been estimated. Given that the at-choice sample is relatively smaller, Tables C.13 and C.14 in the Appendix present summary statistics only for the respondents for which we estimated the choice sets in all the three periods (Waves 1, 2 and at choice), i.e. we matched answers across all the three panels of each table.

For both parents and children we see that the size of each set grows over time from Wave 1 to Wave 2[15]. There is also substantial evidence of limited consideration and

[15] One caveat about measurement is the following. Wave-1 preferred choices were elicited differently from Wave 2. See section (C.3) in the Appendix for more detail. This means that Wave 2 (and 3) allowed for ties in rankings. Table C.15 in the Appendix provides information about the distribution of these ties.

Table 11: Before-the-choice choice set – Waves 1 and 2, Child. Number of alternatives (Range: 0 to 10). Matched Answers Across Waves, with At Choice as Comparison.

Wave 1

Set	Mean	Std. Dev.	p10	p50	p90	Mean Prob.	Std. Dev.	N
Stated preferred alternative(s)								
Ranked-first alternative(s)	1	0	-	-	-	71.56[a]	24.76	287
Top-three alternative(s)	2.57	.67	1	3	3	43.61[b]	19.97	287
Consideration set(s)								
Active consideration set	3.34	.99	2	3	5			287
Feasibility sets								
Agency sets								
Implicit parental veto, lb[c]	4.72	2.75	2	4	10	63.63	20.53	253
Implicit parental veto, ub[c]	5.86	3.02	2	5	10	53.28	22.97	315
Awareness set	8.76	1.62	6	9	10			345

Wave 2

Set	Mean	Std. Dev.	p10	p50	p90	Mean Prob.	Std. Dev.	N
Stated preferred alternative(s)								
Ranked-first alternative(s)[d]	1.13	.59	1	1	1	75.25[a]	28.30	287
Top-three alternative(s)[d]	3.47	1.69	3	3	4	31.22[b]	13.70	287
Consideration set(s)								
Active consideration set	4.08	1.69	3	4	5			287
Cumulative consideration set, ub[c]	4.88	1.63	3	4.5	6			312
Feasibility sets								
Agency sets								
Implicit parental veto, lb[c]	4.80	2.83	1	4	10	67.94	21.66	253
Implicit parental veto, ub[c]	6.24	2.92	3	6	10	57.46	25.42	315
Awareness set	9.49	1.12	8	10	10			345

At Choice

Set	Mean	Std. Dev.	p10	p50	p90	N
Chosen alternative(s)						
Ranked-first alternative(s)	1	0				177
Top-three alternative(s)	1.26	.55	1	1	2	177
Consideration set	1.67	.93	1	1	3	117
Feasibility sets						
Agency sets						
Implicit parental veto, lb[c]	7.66	3.10	3	10	10	193
Implicit parental veto, ub[c]	6.57	3.18	10	10	10	164
Explicit parental veto	8.875	1.91	5	10	10	128
Awareness set	9.94	.39	10	10	10	173

[a]: Mean probability that the first-ranked alternative would be chosen today.
[b]: Mean probability that the first three ranked alternatives would be chosen today.
[c]: *lb*: lower bound; *ub*: upper bound.
[d]: Ties allowed.

Table 12: Before-the-choice choice set – Waves 1 and 2, Parent. Number of alternatives (Range: 0 to 10). Matched Answers Across Waves, with At Choice as Comparison.

				Wave 1				
Set	**Mean**	**Std. Dev.**	**p10**	**p50**	**p90**	**Mean Prob.**	**Std. Dev.**	**N**
Stated preferred alternative(s)								
Ranked-first alternative(s)	1	-				66.65[a]	25.83	264
Top-three alternative(s)	2.78	.70	2	3	3	39.17[b]	16.29	264
Consideration set(s)								
Active consideration set	3.57	1.08	2	4	5			264
Feasibility sets								
Agency sets								
Implicit parental veto, lb[c]	5.45	2.65	2	5	10	61.27	20.89	235
Implicit parental veto, ub[c]	6.20	3.09	3	6	10	53.01	21.83	274
Awareness set	8.88	2	6	10	10			302
				Wave 2				
Set	**Mean**	**Std. Dev.**	**p10**	**p50**	**p90**	**Mean Prob.**	**Std. Dev.**	**N**
Stated preferred alternative(s)								
Ranked-first alternative(s)[d]	1.18	.61	1	1	2	12.87[a]	25.97	264
Top-three alternative(s)[d]	3.92	2.40	3	3	10	[b]		264
Consideration set(s)								
Active consideration set	4.41	2.34	3	4	10			264
Cumulative consideration set, ub[c]	5.32	2.07	3	5	10			265
Feasibility sets								
Agency sets								
Implicit parental veto, lb[c]	5.35	2.85	2	5	10	63.67	21.56	235
Implicit parental veto, ub[c]	6.48	3.15	3	7	10	56.88	23.20	274
Awareness set	9.26	1.78	8	10	10			302
				At Choice				
Set	**Mean**	**Std. Dev.**	**p10**	**p50**	**p90**			**N**
Chosen alternative(s)								
Ranked-first alternative(s)	1	-						166
Top-three alternative(s)	1.28	.56	1	1	2			166
Consideration set	1.60	.83	1	1	3			109
Feasibility sets								
Agency sets								
Implicit parental veto, lb[c]	6.62	3.20	4	10	10			154
Implicit parental veto, ub[c]	7.63	3.10	10	10	10			174
Explicit parental veto	8.96	1.87	5	10	10			115
Awareness set	9.93	.40	10	10	10			162

[a]: Mean probability that the first-ranked alternative would be chosen today.
[b]: Mean probability that the first three ranked alternatives would be chosen today.
[c]: *lb*: lower bound; *ub*: upper bound.
[d]: Ties allowed.

limited agency over time; moreover, children's choice sets are smaller than their parents'. This means that, in particular for agency, students' perceptions of their parents' vetoing behavior imply on average more limited decision agency (i.e. smaller agency sets) than their parents' perceptions. Nevertheless, students' decision agency tend to increase on average over the choice process, according to both students' and parents' perceptions.

Tables from C.16 to C.23 in the Appendix present the distribution of choice set sizes by family characteristics (child's gender, child's seventh-grade GPA, and parental education) for both children and parents in Waves 1 and 2. We can see that in Wave 1 female students tend to have larger choice sets on average except for smaller agency sets, while in Wave 2 choice sets of female students are all smaller except for awareness; the same is true for parents of female children in Wave 2. As for child's GPA, in Wave 1 students with a GPA in the bottom 25^{th} percentile have smaller sets, while in Wave 2 they only have smaller agency sets, and the same is true for parents of these children. Looking at parents, for parental education of both mothers and fathers the patterns are less clear.

Figure 1 graphically compares the average size of the different choice sets for both children (left panel) and parents (right panel) in Wave 1 and 2, before the choice. Overall the trends seem to be the same, with increasing average sizes; parents start from higher levels in Wave 1.

Composition. Tables 13 and 14 present the composition of each set before the choice in Waves 1 and 2 in terms of the average number of tracks covered by each set, instead of the number of curricula. It is interesting to note that for both preferred alternatives and the consideration set we see that Waves 1 and 2 cover more tracks than their at-choice counterparts for both parents and children. Thus, during the decision-making process agents tend to consider more diverse alternatives. The agency sets as defined by implicit vetoes are similar in the two before-the-choice waves in particular for children. Table C.24 in the Appendix presents the composition of each set at the moment of choice in terms of ratio of curricula covered by each set within each track.

Figure 1: Evolution of choice set size before the choice – Child & Parent, Mean. Matched Answers Across Waves.

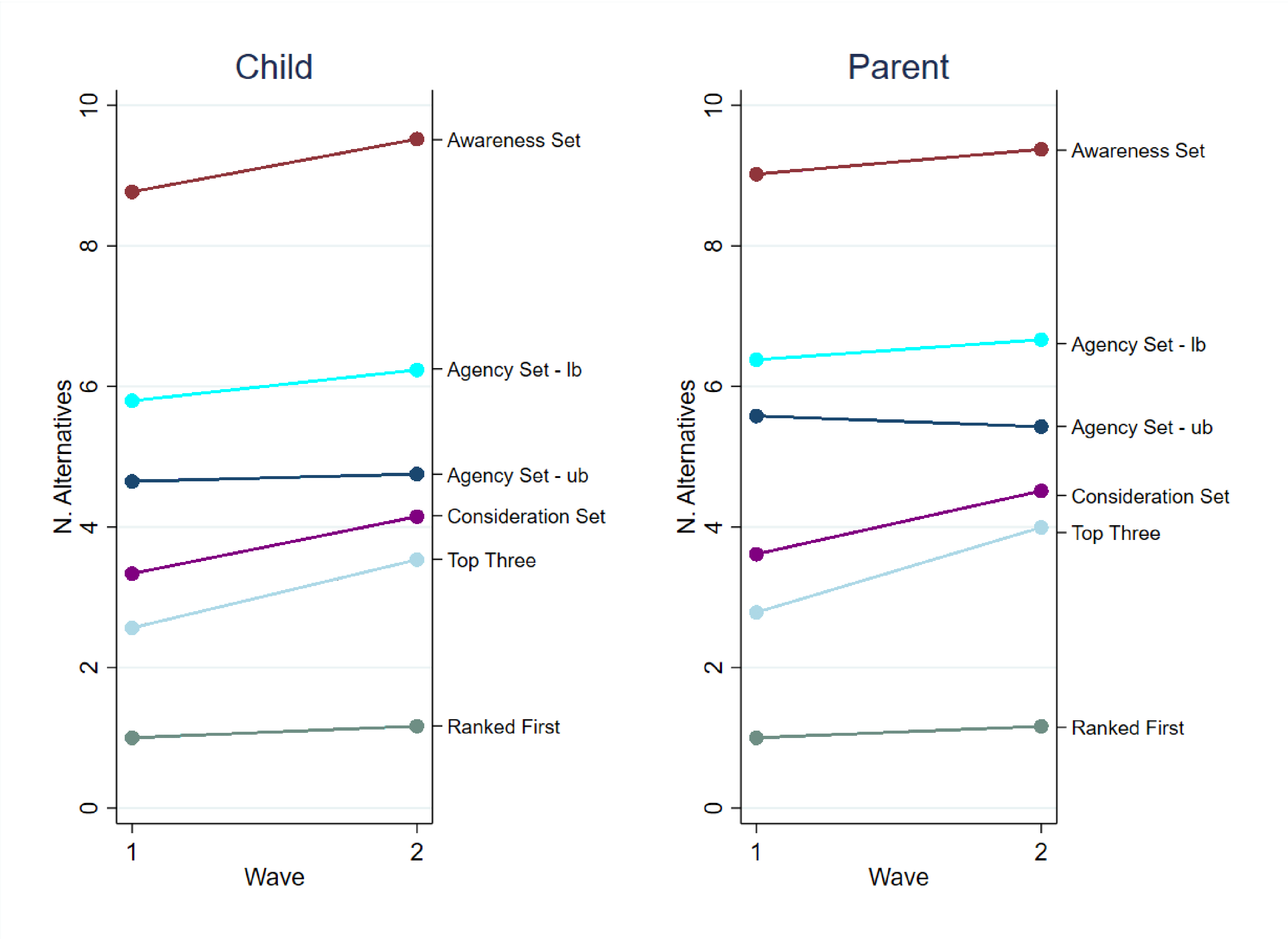

Table 13: COMPOSITION OF EACH SET BEFORE THE CHOICE – WAVES 1 AND 2, CHILD. AVERAGE NUMBER OF TRACKS COVERED WITHIN EACH SET (RANGE: 1 TO 3). MATCHED ANSWERS ACROSS WAVES, WITH AT CHOICE AS COMPARISON.

Wave 1

Set	**Mean**	**Std. Dev.**	**p10**	**p50**	**p90**	**N**
Stated preferred alternative(s)						
Ranked-first alternative(s)[a]	1	0				287
Top-three alternative(s)[a]	1.56	.60	1	1	2	287
Consideration set	1.78	.71	1	2	3	287
Feasibility sets						
Agency sets						
Implicit parental veto, lb[b]	1.84	.82	1	2	3	253
Implicit parental veto, ub[b]	2.22	.80	1	2	3	315
Awareness set	2.86	.39	2	3	3	345

Wave 2

Set	**Mean**	**Std. Dev.**	**p10**	**p50**	**p90**	**N**
Stated preferred alternative(s)						
Ranked-first alternative(s)[a]	1.04	.22	1	1	1	287
Top-three alternative(s)[a]	1.73	.68	1	2	3	287
Consideration set	1.93	.77	1	2	3	287
Feasibility sets						
Agency sets						
Implicit parental veto, lb[b]	1.83	.84	1	2	3	253
Implicit parental veto, ub[b]	2.25	.79	1	2	3	315
Awareness set	2.95	.27	3	3	3	345

After the Choice[c]

Set	**Mean**	**Std. Dev.**	**p10**	**p50**	**p90**	**N**
Chosen alternative(s)						
Ranked-first alternative(s)	1	0				177
Top-three alternative(s)	1.08	.30	1	1	1	177
Consideration set	1.17	.44	1	1	2	117
Feasibility sets						
Agency sets						
Implicit parental veto, lb[b]	.78	1.21	0	0	3	147
Implicit parental veto, ub[b]	2.95	.37	3	3	3	170
Explicit parental veto	2.84	.48	2	3	3	126
Awareness set	2.99	.08	3	3	3	173

[a]: Ties allowed.
[b]: *lb*: lower bound; *ub*: upper bound.
[c]: Family outcome, matched answers with Waves 1 & 2.

Table 14: Composition of each set before the choice – Waves 1 and 2, Parent. Average number of tracks covered within each set (range: 1 to 3). Matched Answers Across Waves, with At Choice as Comparison.

Wave 1

Set	Mean	Std. Dev.	p10	p50	p90	N
Stated preferred alternative(s)						
Ranked-first alternative(s)[a]	1	0				264
Top-three alternative(s)[a]	1.70	.67	1	2	3	264
Consideration set	1.88	.74	1	2	3	264
Feasibility sets						
Agency sets						
Implicit parental veto, lb[b]	2.15	.76	1	2	3	235
Implicit parental veto, ub[b]	2.33	.77	1	3	3	274
Awareness set	2.86	.43	2	3	3	302

Wave 2

Set	Mean	Std. Dev.	p10	p50	p90	N
Stated preferred alternative(s)						
Ranked-first alternative(s)[a]	1.07	.29	1	1	1	264
Top-three alternative(s)[a]	1.75	.74	1	2	3	264
Consideration set	1.94	.78	1	2	3	264
Feasibility sets						
Agency sets						
Implicit parental veto, lb[b]	1.97	.83	1	2	3	235
Implicit parental veto, ub[b]	2.25	.81	1	2	3	274
Awareness set	2.88	.41	3	3	3	302

After the Choice[c]

Set	Mean	Std. Dev.	p10	p50	p90	N
Chosen alternative(s)						
Ranked-first alternative(s)	1	0				166
Top-three alternative(s)	1.10	.32	1	1	1	166
Consideration set	1.16	.44	1	1	2	109
Feasibility sets						
Agency sets						
Implicit parental veto, lb[b]	.77	1.21	0	0	3	136
Implicit parental veto, ub[b]	2.94	.42	3	3	3	154
Explicit parental veto	2.87	.43	3	3	3	113
Awareness set	2.99	.08	3	3	3	162

[a]: Ties allowed.
[b]: *lb*: lower bound; *ub*: upper bound.
[c]: Family outcome, matched answers with Waves 1 & 2.

Heterogeneity. Tables 15 and 16 present the results from Poisson regressions of choice-set sizes on agents' characteristics.

In Table 15 we can see that for children in Wave 1 consideration set size is positively affected for female students; having a father with a blue-collar job increases the size of the agency set, while having older siblings and having a GPA in the bottom 25^{th} percentile decrease it. In Wave 2 instead GPA affects the number of options that the child lists as favorite (a lower GPA increases its size, a higher GPA decreases it) or in the top three (a higher GPA decreases its size); agency size is positively affected by having a father with a blue-collar job, and negatively by being foreign-born or having a low GPA; last, awareness is positively affected by having older siblings and having a lower GPA. The fact that having an older sibling shrinks the agency set and over time increases the awareness set is indicative of the fact that information within the family may be shared and that younger children learn from their siblings' knowledge.

Table 16 repeats the analysis on the parents' sample. In this case we can see that in Wave 1 child's gender affects negatively consideration and awareness, and in Wave 2 negatively the size of the ranked-first set and the agency set. If the father has a blue-collar job then the size of the application (top-three alternatives), the consideration and the agency sets are all negatively affected. Moreover, if the child has a low GPA then the parents' consideration set and agency sets are negatively impacted. In Wave 2 we see that having co-residing parents decreases the application set; being a home-maker mother decreases the awareness set, which is in turn increased if in the family there are other children (again, signaling this extra information channel). Also in this second wave if the child has a low GPA then the parents' agency sets are negatively impacted, while the ranked-first and the top-three alternatives sets are smaller if the child has a high GPA.

Tables C.25 and C.26 in the Appendix present the same regressions over the same sets and the same covariates for both parents and children but using as dependent variable the number of tracks included in each choice set instead of the number of curricula. Also in this case we can see from Table C.25 that being a female student or having a high GPA tends to concentrate your decisional effort, so that the number of tracks covered in the top-three alternatives or in the consideration set is smaller; also being foreign-born tends to decrease these sets, together with awareness in Wave 1. As for parents (Table C.26), having a female child tends to decrease the size of the awareness set in Wave 1 and of almost all the sets in Wave 2. The child's GPA is also important, as parents of better performing students tend to have more concentrated preferences on the considered and

Table 15: Predictors of the number of curricula included in each child's set before the choice – Waves 1 and 2, Child.

	Child					
	Ranked-First Alt.	**Top-Three Alt.**	**Consid. Set**	**Agency Set, lb**	**Agency Set, ub**	**Awareness Set**
Wave 1						
Female student	-	.024	.083**	.008	.009	.015
		(.033)	(.035)	(.060)	(.076)	(.021)
Foreign-born student	-	-.087	-.130	-.114	-.225	-.081
		(.086)	(.086)	(.132)	(.152)	(.058)
Lives with both parents	-	.046	.074	-.161	.148	-.026
		(.041)	(.047)	(.105)	(.113)	(.029)
Stay-at-home mother	-	-.028	-.070	.037	.075	-.001
		(.039)	(.044)	(.070)	(.087)	(.026)
Blue-collar father	-	.007	-.019	-.018	.157*	.019
		(.040)	(.046)	(.078)	(.095)	(.025)
Has older siblings	-	.040	.054	-.036	-.142*	-.008
		(.032)	(.038)	(.061)	(.078)	(.021)
7^{th}-grade GPA,	-	-.041	-.060	-.144*	-.126	-.004
lower 25perc		(.039)	(.041)	(.078)	(.113)	(.027)
7^{th}-grade GPA,	-	-.014	.031	-.037	-.051	-.021
upper 25perc		(.037)	(.045)	(.069)	(.087)	(.026)
Sample size	246	246	246	270	225	282
Wave 2						
Female student	.032	-.034	-.022	-.028	-.117	.008
	(.075)	(.062)	(.053)	(.056)	(.075)	(.015)
Foreign-born student	.196	.025	-.003	-.159	-.236*	-.046
	(.193)	(.113)	(.104)	(.124)	(.143)	(.040)
Lives with both parents	.041	-.057	-.005	-.055	.004	-.012
	(.120)	(.078)	(.067)	(.097)	(.124)	(.025)
Stay-at-home mother	-.064	.022	.025	-.015	-.075	-.020
	(.092)	(.071)	(.059)	(.065)	(.093)	(.018)
Blue-collar father	.023	.034	.042	.137**	.136	-.002
	(.097)	(.081)	(.069)	(.069)	(.093)	(.018)
Has older siblings	.076	.014	.051	.055	.003	.031**
	(.069)	(.061)	(.052)	(.056)	(.075)	(.014)
7^{th}-grade GPA,	.167*	.140	.076	-.064	-.271**	.031*
lower 25perc	(.098)	(.087)	(.075)	(.075)	(.119)	(.017)
7^{th}-grade GPA,	-.086*	-.115**	-.051	.092	.062	.001
upper 25perc	(.045)	(.045)	(.045)	(.062)	(.081)	(.018)
Sample size	246	246	246	270	225	282

lb: lower bound; *ub*: upper bound.

***

Significance levels: [***] significant at 1%; [**] significant at 5%; [*] significant at 10%.

Predictors: *female student:* dummy=1 if student is female; *foreign-born student:* dummy=1 if student is foreign-born; *lives with both parents:* dummy=1 if student lives with both parents; *stay-at-home mother:* dummy=1 if student has a stay-at-home mother; *blue-collar father:* dummy=1 if student's father works in a blue-collar occupation; *has older siblings:* dummy=1 if student has older siblings (between 1 and 3); *7^{th}-grade GPA, lower 25 percentile:* dummy=1 if student's GPA in the 7th grade end-of-year report (between 6 and 10) is in the bottom quartile of the distribution; *7^{th}-grade GPA, upper 25 percentile:* dummy=1 if student's GPA in the 7th grade end-of-year report (between 6 and 10) is in the upper quartile of the distribution.

Table 16: Predictors of the number of curricula included in each parent's set before the choice – Waves 1 and 2, Parent.

	Parent					
	Ranked-First Alt.	**Top-Three Alt.**	**Consid. Set**	**Agency Set, lb**	**Agency Set, ub**	**Awareness Set**
Wave 1						
Female student	-	.010	-.066*	-.030	.070	-.043*
		(.033)	(.040)	(.063)	(.064)	(.023)
Foreign-born student	-	.048	-.049	-.021	-.152	-.084
		(.068)	(.062)	(.134)	(.164)	(.065)
Lives with both parents	-	-.030	-.014	-.036	.053	.024
		(.040)	(.052)	(.106)	(.100)	(.030)
Stay-at-home mother	-	.073**	.013	.106	.023	-.017
		(.034)	(.046)	(.071)	(.075)	(.032)
Blue-collar father	-	-.093**	-.098**	-.204**	-.102	-.034
		(.041)	(.047)	(.095)	(.104)	(.034)
Has older siblings	-	.001	-.016	.029	.004	-.012
		(.031)	(.040)	(.063)	(.067)	(.025)
7^{th}-grade GPA,	-	.001	-.088*	-.208**	-.304***	-.041
lower 25perc		(.038)	(.048)	(.086)	(.093)	(.033)
7^{th}-grade GPA,	-	-.025	-.006	.005	-.041	.023
upper 25perc		(.039)	(.049)	(.071)	(.068)	(.024)
Sample size	228	228	228	237	210	254
Wave 2						
Female student	-.142**	-.060	-.090	-.045	-.186***	-.037
	(.069)	(.079)	(.069)	(.065)	(.071)	(.024)
Foreign-born student	-.080	.370**	.266	.087	-.237	.001
	(.080)	(.171)	(.169)	(.128)	(.187)	(.047)
Lives with both parents	-.080	-.191*	-.133	-.045	-.072	-.026
	(.058)	(.112)	(.103)	(.097)	(.100)	(.040)
Stay-at-home mother	.011	-.047	-.044	.040	.081	-.064*
	(.081)	(.099)	(.087)	(.077)	(.088)	(.035)
Blue-collar father	-.068	-.078	-.063	-.142	-.137	-.005
	(.070)	(.097)	(.087)	(.090)	(.104)	(.035)
Has older siblings	-.014	.055	.072	.002	-.049	.044*
	(.083)	(.075)	(.066)	(.063)	(.072)	(.024)
7^{th}-grade GPA,	.009	.020	-.022	-.148*	-.255**	-.027
lower 25perc	(.087)	(.106)	(.094)	(.087)	(.105)	(.034)
7^{th}-grade GPA,	-.140**	-.137*	-.061	-.067	.091	.033
upper 25perc	(.068)	(.079)	(.067)	(.072)	(.076)	(.023)
Sample size	228	228	228	237	210	254

lb: lower bound; *ub*: upper bound.

Significance levels: [***] significant at 1%; [**] significant at 5%; [*] significant at 10%.

Predictors: *female student:* dummy=1 if student is female; *foreign-born student:* dummy=1 if student is foreign-born; *lives with both parents:* dummy=1 if student lives with both parents; *stay-at-home mother:* dummy=1 if student has a stay-at-home mother; *blue-collar father:* dummy=1 if student's father works in a blue-collar occupation; *has older siblings:* dummy=1 if student has older siblings (between 1 and 3); *7^{th}-grade GPA, lower 25 percentile:* dummy=1 if student's GPA in the 7th grade end-of-year report (between 6 and 10) is in the bottom quartile of the distribution; *7^{th}-grade GPA, upper 25 percentile:* dummy=1 if student's GPA in the 7th grade end-of-year report (between 6 and 10) is in the upper quartile of the distribution.

top-three ranked alternatives; moreover, in Wave 2 track awareness is at the same time decrease by being a stay-at-home mother and increased by being a blue-collar father.

7 Next Steps: Parenting Styles

We want to characterize families in terms of parenting style, as defined in Doepke and Zilibotti (2019), and see how this influences choice set sizes and compositions.

To carry out this labeling we rely on multiple survey measures. The first one is related to the number of vetoes imposed to the child, both explicitly and implicitly, as already defined; we consider the imposition of a veto as a trace of (at least some) authoritarian parenting. Second, we use the information on how the choice was made within the family (as seen in Table 7) to distinguish authoritarian families (where child and parent(s) report choosing together) from permissive or neglectful (where the child chooses alone, without listening to parents and/or having alternatives vetoed). Third, we use a survey question on how some factors should influence the choice and their relative weight as perceived by the child (the question is presented in section (C.3) in the Appendix, Table C.4).

While permissive and neglectful styles should be mutually exclusive, it is possible that families show signs of both authoritarian and authoritative behaviors, thus labeled as intensive or over-parenting. In this analysis we aim to detect evidence of these styles within each family, possibly finding practices related to different classes of parenting.

Table 17 documents some preliminary evidence on the share of families that present at least some traces of one of the above-mentioned parenting styles.

Table 17: Evidence of Traces of Parenting Styles – Before & At choice.

Evidence of...	**Measure**	**% families**	**N**
Authoritarian parent	At least one explicit[a] veto	43.15	241
	At least one potential[b] veto	2.73-86.55[c]	238
Authoritative parent	Child & parent(s) choose[a] together	35.83	187
Permissive parent	Child chooses[a] alone, after listening to parent(s)	37.43	187
Neglectful parent	Child chooses[a] alone, without listening to parent(s) last	14.97	187
	Child chooses alone, without listening to parent(s) last & no explicit[a] vetoes	8.02	187

[a]: Elicited in Wave 4 as reported by the child only.
[b]: Elicited in Wave 3, if already pre-enrolled, as reported by the child or the parent.
[c]: Bounds obtained from the two definitions of implicit parental vetoes (upper and lower bound).

8 Conclusion and Agenda

In this paper we document the size, composition and factors driving the heterogeneity of the different choice sets for the different agents involved, both during the decision-making process and at choice. We find that agents tend to expand their application, consideration, agency and awareness sets over time before the choice, but at the moment of submitting the pre-enrollment form families tend to have more concentrated preference on fewer alternatives ranked as favorite and considered for the choice. Over time there is substantial evidence of limited consideration and limited agency, while awareness is increasing over time and there is no evidence of limited awareness at choice. We also detail how student and family characteristics affect the size of these sets and their composition in terms of number of tracks covered.

In our agenda, first we want to conduct a validation exercise. We want to investigate how parental percent chances of accepting an alternative, whether with or without motivation (i.e. the measure used to construct the implicit vetoes), map into parental preferences and the child's perception of these preferences; and the same can be done starting from children's percent chances and their relationship with children's preferences and parental perceptions of children's preferences. We aim to prove that this is a strong and reliable measure.

Second, we want to explore the role of parental background on choice set inclusion and vetoing. In particular we plan to outline choice set inclusion predictors in terms of parental education and define whether this measure holds also for curriculum-specific vetoing behaviors.

Third, we are working on providing a solid foundation for mapping our survey measures into parenting styles. We want to explore more widely how they can be precisely measured in this setting and how they influence choice set size and composition. We will go deeper into the forces that shape the choice sets and in particular their evolution over time, both before the final choice and at its realization.

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Appendix to Chapter 1

A.1 Extended Literature Review

With the innovation process marching at high speed and a wide diffusion of technology, we live in an era of possibilities. Yet, the driving question of our age should not be "what can we do?", but rather "what do we want to become?", the so-called Human Enhancement question (Harari (2014)). To understand which are the possible paths that we can undertake, it is useful to have a look at where we stand now.

In this section I first give an overview of the current Internet and screen-use diffusion among younger generations, then I move on to the medical and psychological research on technology use, focusing on smartphones. I concentrate then on more economic topics, in particular the effect on time use and performance. Finally I briefly review other fields related to this project, i.e. task-based goal setting, peer effects, and family role in defining smartphone use.

The current picture. According to OECD (2019), in 2015 on average across OECD countries a typical 15-year-old spent more than two hours online every weekday after school (a 40-minute increase since 2012), and more than three during weekend days. Moreover, teenagers reported using the Internet since the age of 10, and according to Gottschalk (2019) the year of first exposure to technology is decreasing: preschoolers become familiar with digital devices before they are exposed to books. "Extreme Internet users" are those who spend more than 6 hours per day online, and according to PISA across OECD countries on average 26% of students fall into this category. Time spent online often requires active engagement from the users, especially through the creation of private profiles on digital platforms; in 2019 Ofcom reported that in the UK about 70% of kids aged 12-15 have a social media profile, and in the US around 97% of teenagers between 13 and 17 use at least one social media platform. The numbers I mentioned are not bad *per se* until we understand how this time is used and from which other activities it is subtracted. As OECD (2018) reports, greater social media use is associated with poorer sleep, a rise in cyber-bullying in some countries, and body image concerns. Although there is no scientific research that is able to define an optimal amount of screen use, there is some evidence of a “Goldilocks effect”, meaning that moderate engagement in online and digital activities may be beneficial for subjective well-being, while both too much and too little activity may be harmful.

The teenagers I am talking about belong to the so-called “Generation Z” and they are the first digital natives. As Morace (2017) describes, they are competitive individuals in need of feedback, looking for human interactions both online and offline. Having been exposed to their peers both around the world and across social classes through the possibilities offered by Internet, they accept diversity as the norm and flexibility as a challenge, and have a strong desire to contribute and create, as Miller (2018) points out. While always looking for new stimuli and trying to live the world of adult behaviors without having reached maturity (the *adulting* phenomenon), their basic needs are still the ones we all know: a healthy mental and physical development which includes good quality regular sleep, and quality time spent with family and friends (OECD (2019)). Therefore, it would be worth assessing whether screen time affects these two elements and thus impacts well-being, instead of looking for a direct connection between digital activities and mental health. The Goldilocks effect may be in place in the cases where teenagers are able to balance the online and offline aspects of their lives, without sacrificing e.g. sleep for Internet time.

A medical perspective. In the past decades, medicine has been trying to uncover the potential of our brains. As our environment and needs change, the brain undergoes a dynamic process of never-ending transformation; this property is called neuroplasticity, i.e. the ability to rewire neural pathways and synapses in the brain. George (2013) analyses what happens upon brain stimulation; he claims that things that grab our attention attract the part of the brain that is supposed to scan the environment for danger, and the brain is programmed to respond to these stimuli. Unfortunately, these distractions interfere with memory and thinking.

Along these lines, Dalton (2013) studies how the use of Internet and technological tools is changing our brains. Using MRI images he sees that the Internet is altering the frontal lobes of our brains and impacting working memory. In a series of tests conducted on groups performing heavy multitask *versus* people who did not, disappointing outcomes appeared for the first group: multitaskers performed worse on cognitive tests, showing lower control over working memory and a decreased ability to concentrate. Extensive exposure to technologies causes fragmented attention, and the constant stimulation prevents the learning process. Moreover, superficial reading minimizes comprehension and thus hinders the ability to critically evaluate information; Millennials are exposed to this risk, but they compensate the lack of in-depth analysis with gathering a lot of information instead as also Firth et al. (2019) confirm. The latter study tackles the same issue by providing findings from psychological, psychiatric and neuroimaging research. It supports the idea that extensive media multi-tasking during childhood and adolescence may predict attentional deficits and impact cognitive development through a reduction in academic and social engagement and creative thinking. Moreover, it underlines how social structures may be affected by the introduction of immediate and quantifiable feedback (e.g. likes, followers) which may negatively impact self-esteem and anxiety by providing an objective metric for social success.

Attention-shifting. The term “grasshopper mind”, introduced by Seymour Papert, denotes a brain that continuously shifts its focus jumping from one point to the next, distracted from the original task. This expression has been used to describe the young generations, especially those who grew up giving the new digital technologies for granted and started using tablets before learning how to read. Wolf (2018) analyses this phenomenon extensively, reporting how the human brain is keen to novelty for evolutionary purposes, because what is new could be dangerous and needs to attract our attention; however, attention-flitting, task-switching behaviors since childhood may make the brain constantly on the verge of hyper-attention, as hormones like cortisol and adrenaline are those associated with fight and stress, and this may lead to being dependent from digital technologies that constantly flood the brain with the streams of novelty it needs.

More broadly speaking, the topic of attention shifting online has been investigated by Lorenz-Spreen et al. (2019), who document how collective attention has accelerated in the last years. By using categorized contents such as hashtags on Twitter, they estimate the amount of collective attention dedicated to a topic and find evidence of increasingly steeper gradients and shorter intervals of collective attention given to each cultural item. They suggest that the increasing accessibility of information on one side and the constraints in terms of cognitive and time limitations of users on the other lead to a redistribution of the available resources across time towards more rapid changes.

The psychology behind media usage. The study by Horwood and Anglim (2019) is a good starting point for the recognition of effects on the psychological sphere, as it detects patterns determining problematic smartphone usage. In particular, the authors find that using the smartphone for entertainment purposes is negatively correlated with subjective well-being, differently from communication purposes that are unrelated or slightly positively so with well-being.

Hunt et al. (2018) aim to measure the relationship between the use of three specific social media platforms and well-being in terms of social support, fear of missing out ("FOMO"), loneliness, anxiety, depression, self-esteem, autonomy and self-acceptance. They set up a randomized treatment limiting for four weeks the use of Facebook, Instagram, and Snapchat at ten minutes per day per platform, checking the compliance by looking at weekly screenshots of the iPhone battery use report. They observe that experimentally limiting social media usage on the smartphone had a significant impact on well-being: both loneliness and depressive symptoms declined in the experimental group, while both fear of missing out and anxiety declined in both groups (probably as a result of an increased self-monitoring triggered by the experiment). No effects have been detected on social support, self-esteem, or psychological well-being.

As Bianchi and Phillips (2005) state, problematic behaviors associated with mobile phones are due to lack of self-control and/or societal control, and they are likely to be stemming from pre-existing factors. While reminding that addictive behaviors may be a symptom of an impulse control deficit or depression, they also carry out a psychological analysis and identify some personality traits that predict certain behaviors, finding that extraversion and lower self-esteem predict problem use of mobile phones. Hawi and Samaha (2017) find a correlation between social media addiction and life satisfaction, and posit that self-esteem is the link between these two. Pera (2020) concludes that depression and anxiety symptoms are associated with problematic smartphone usage and can generate psychological distress, poor sleep quality, and diminished academic performance. Oulasvirta et al. (2012) support the claim that smartphones are creating a checking habit in users, i.e. a brief and repetitive inspection of dynamic content quickly accessible on the device that allows for informational "rewards". Wilmer and Chein (2016) instead suggest that, more than seeking a rewarding stimulus, mobile technology habits such as frequent checking are driven most strongly by uncontrolled impulses, and indeed Schnauber-Stockmann and Naab (2019) assess how repetition of an app-related behavior (e.g. opening it, checking notifications) increases the strength of the habit regardless of the reward.

Vanman, Baker, and Tobin (2018) focus specifically on Facebook and look at the effects of a short-term abstention on stress and well-being using both survey measures and health outcomes. People randomized into the treatment group had lower cortisol levels after the five days of the experiment, hence hinting at lower physical stress, even though they reported a lower subjective well-being compared to the control group. A possible mechanism relies on the fact that while the experience of a detox has indeed been less stressful, on the other hand people in five days may feel more cut off from their social network and therefore the psychological perception of lower well-being has been magnified.

Given the endogeneity in such behavior adoption, it is at the moment difficult to answer the question "are behavioral problems and personality traits predictive of screen time, or does screen time predict behavioral tendencies?". Most of the literature has focused on detecting negative outcomes, and moreover recent phenomena like "screen-stacking" (media multitasking, i.e. using more technological devices at the same time) have not been studied and may have important behavioral and cognitive repercussions, for example for attention spans and stress management.

The crowding-out effect on time and (lasting) habits. Our modern society in the past decades has been revolutionized many times thanks to the introduction of new technological items, and Gottschalk (2019) reviews many important studies conducted over medias of different kinds, allowing us to make some considerations about the present issue. For example, when it comes to television it is difficult to draw a sharp line between bad and good outcomes; in fact, it seems that time spent in front of a TV may be detrimental for the child if this time is subtracted from other social or health-promoting activities, while watching high-quality content may improve academic outcomes, in particular if parents engage in this activity as well. Could it be the same for our smartphones?

Mosquera et al. (2018) assess the value that agents assign to the use of Facebook, by paying participants not to use the platform for a week. According to the authors' findings, the treatment group did not look for online substitutes such as other social media, neither did they look for news from other sources. Notwithstanding the fact that being off Facebook for a week encouraged engagement in more healthy activities and decreased depression symptoms, still users increase their reported value of Facebook after the end of the experiment. In fact, after a week restriction the value of using Facebook increased by 15%, with a larger increase for women.

Blocking the use of Facebook is the tool applied also in the paper by Allcott, Braghieri, et al. (2019), but the focus of the analysis is broader than just subjective well-being and time use. The experiment mandates a randomization among US users recruited through Facebook ads such that treated individuals were incentivised to deactivate their Facebook accounts for a period of four weeks ending just after the November 2018 midterm elections. In line with Mosquera et al. (2018), non-Facebook social media usage decreased together with other online activities, while watching television and spending time with family and friends increased. News knowledge and attention to politics were negatively affected, while small improvements can be recovered from self-reported happiness, life satisfaction, and anxiety. Interestingly, the authors also find effects in the long run; several weeks after the end of the treatment, treated individuals' reported usage of the Facebook mobile app was 11 minutes (22 percent) lower than the control group. At odds with Vanman, Baker, and Tobin (2018) and Allcott, Braghieri, et al. (2019), post-experiment demand for Facebook declined, and indeed 5% of the treatment group still had their accounts deactivated nine weeks after the end of the experiment. This difference could be driven by the different length of the experiment which allowed for some habit formation, while in the previous two studies one week was not enough to trigger behavioral or psychological changes if Facebook was addictive for these users. Along these lines, Allcott, Gentzkow, and Song (2021) study self-control problems by experimentally limiting smartphone screen time of six social media and web platforms under different design and incentive schemes. Treated individuals were able to successfully decrease their smartphone time even after the end of the intervention. More positive effects were found for people who reported being more interested in reducing their smartphone use and higher addiction measures at baseline. Similarly, Hoong (2021)'s results are also driven by consumers who wish for a change in their habits. The author randomly encourages US Facebook users to voluntarily adopt app time limits, and finds that encouragement to adopt application limits significantly reduces smartphone and Facebook use, even persistent after the end of the experiment; this decrease is experienced by users that at baseline had declared a higher usage than desired. The author also documents how some participants were willing to set app limits even without incentives, thus highlighting a latent demand for commitment devices of this kind.

The fact that digital platforms are design to attract attention and constantly call the consumer back is no secret[16]. For example Billari, Giuntella, and Stella (2018) find a large and negative impact of high-speed Internet on sleep duration and quality, in particular for younger adults. Ichihashi and Kim (2021) analyse competition for consumer attention looking at social media platform, and even suggest that restricting consumers' usage of these platforms may reduce incentives to increase addictiveness of certain features.

On top of quantitative time allocation, further qualitative changes should be examined. Rotondi, Stanca, and Tomasuolo (2017) assess how the intrusiveness of the smartphone has the power of reducing the quality, and hence the value, of face-to-face social interactions. Using a sample of Italian individuals, they find evidence that smartphone usage negatively affects this kind of interactions. In particular, they find that the positive association between time spent with friends and satisfaction stemming from it is significantly less strong for individuals who use the smartphone. The intrusiveness of this device is determined by the fact that, unlike monological communication technologies such as the television, the mobile phone allows for an exclusive use and its interactive communication flow requires constant connection. The authors argue that the negative effects found on well-being may arise from the change in sensory perception that happens in response to this continuous flow which generates a private space for other simultaneous digital interactions.

How technology affects performance: an economic approach. Educational outcomes can be influenced through multiple channels. Having technological tools available may indeed boost learning under specific conditions, for example in Attanasio, Bird, et al. (2019) where a tablet-based program for financial literacy in Colombia proved effective thanks to the gamified and simplified presentation of contents. Nonetheless, learning on screen can be detrimental; Mangen, Walgermo, and Brønnick (2013) show that students who read texts in print scored significantly better on a reading comprehension test than students who read texts digitally. They argue that this result may happen for many reasons, in particular the fixity of the printed text may help reconstructing the spatial representation of the content, which supports memory and comprehension, together with the lighting conditions of the screen that cause visual fatigue.

In this analysis I do not want to determine whether using digital tools is useful for academic purposes or not, but rather whether having digital distractions available can be detrimental for the learning process. Payne-Carter, Greenberg, and Walker (2017) conduct

[16] See for example www.sciencefocus.com (October 29 2018).

an experiment that randomly allowed students access to laptop and tablet computers during an introductory economics course in a military academy. They find that being allowed to use laptops and tablets in class decreased the final exam score by 18 percent of a standard deviation, compared to students who were not allowed to use these devices in class. These negative effects are stronger for male students and for those who entered the course with a high GPA. In line with this, also Barbetta, Canino, and Cima (2019) in the evaluation of the impact of Twitter on reading and comprehension skills find that those harmed the most are the students which are more likely to perform better. On top of the explanation that these devices are a source of distraction, Payne-Carter, Greenberg, and Walker (2017) argue that their result could be driven by the fact that teachers are less effective in classes where students are allowed to use a laptop because this condition may change their attitude, but it is also possible that if students switch from taking notes manually to writing on their laptops, then this may have detrimental effects in line with what argued by Mangen, Walgermo, and Brønnick (2013). Using laptops in class for academic *versus* non academic purposes has been investigated by Ravizza, Uitvlugt, and Fenn (2017), who look at students' perception of laptop Internet use and classroom performance. Thanks to a monitoring technology, they are able to measure actual laptop Internet use in class and find that nonacademic use is associated to lower performance on the final exam.

Looking specifically at mobile phones, Amez and Baert (2020) review many studies that focus on the relationship between smartphones and educational achievements, detecting a predominance of negative effects but mostly in observational studies. After highlighting how students perceive their smartphones as a source of entertainment and not as a study tool (Lepp et al. (2013)), they point out that the time spent on smartphone use is time lost for study activities, and moreover physical proximity may lead to task-switching behaviors. This may be induced by distractions coming from notifications (Junco and Cotten (2012)), the lack of focus deriving from FOMO (Chen and Yan (2016)) or addiction, or the fact that bored students may find a fast source of amusement (Hawi and Samaha (2016)).

Teachers have started taking actions in order to regain their classes' attention. Starting from the evidence presented by Katz and Lambert (2016) that turning off mobile phones during lectures is correlated with higher test scores, Whittington (2019) finds that cell phone use during class is a consistent negative predictor of performance for undergraduate students, particularly if used for non-course-related purposes. He therefore conducted an experiment in the first-year classes he taught in introductory psychology, randomly assigning half of the sections to a device-free environment. Students in these classes were asked to put their devices in a paper wrap to be exposed on their desks during the lectures. By comparing academic outcomes of a group who participated to this experiment for the whole semester *versus* the control group who joined only in the second half, the author finds significantly higher scores on midterm exams and higher levels of course satisfaction and classroom connection for the device-free classes. However, the design has some drawbacks, including the fact that randomization was not at the individual level and class sections were taught by the study author who may have unintentionally biased the experiment (also because negative effects of cell phones on academic achievements had been discussed in class as part of the program). Moreover, this design does not eliminate the physical presence of the smartphone from the desk, which according to Ward et al. (2017) is distracting in itself: one's own smartphone presence may drain limited capacity cognitive resources in order to exert attentional control, thus decreasing the amount of brain power that can be devoted to tasks. The authors further suggest that a voluntary disconnection may be beneficial, as this both reduces digital distractions and redefines salience of technological devices, thus increasing the available working memory. Felisoni and Godoi (2018) monitor students' smartphone behaviors through monitoring apps that report the amount of screen time. They estimate that screen time is more harmful if it happens during class, as opposed to free time or weekends; moreover, GPA is correlated with self-efficacy survey measures, but both of them are negatively correlated with smartphone use. In a crowded class, smartphone usage may be harmful also to the other people. Starting from Campbell (2006)'s survey results that ringing is irritating and distracting for both students and faculty members, in a lab setting End et al. (2010) determine whether the cell phone ring is distracting through a note-taking experiment on students, and find that indeed treated participants lose some pieces of information if disrupted at that moment.

For these reasons and many others related not only to distractions but also to e.g. to cheating, some schools have started adopting rules about mobile phone usage during lecture hours. Beland and Murphy (2016) estimate the effect of school bans of mobile phones on student test scores by studying the history of school policies in four English cities combined with administrative data on academic performance. Differences in implementation dates of mobile phone bans allow the authors to estimate a 6.41% of a standard deviation increase in test scores following a phone ban. However, in order for this policy to be effective a wide compliance is needed; this effect is mostly driven by the disadvantaged and low-achieving students. Kessel, Hardardottir, and Tyrefors (2020) partly replicate Beland and Murphy (2016)'s study in Sweden and increase the participation rate of schools to their surveys, finding no impact of mobile phone bans on student performance. On the other hand, Abrahamsson (2020) studies the effects of banning smartphones from Norwegian middle schools on students' educational outcomes, using a quasi-experimental design. She finds results mostly for female students, with an increase in middle- school GPA and a higher chance of attending an academic high school track. There has been an increase in attention towards the topic of bans[17], even though it is not clear whether this sort of policies may have decreasing effects over time as happens in other contexts[18].

Pure distractions like checking one's emails are not the only source of attention disruption while studying or in class. Starting from the idea that multitasking decreases information recall, Sana, Weston, and Cepeda (2013) argue that students' continuous switching between academic and non-academic tasks in class hinders learning as it drains attentional resources[19]. They thus set up two experiments. In the first one, students asked to take notes in class on their laptop score worse in a comprehension test if they multitasked during the lectures; in the other experiment, they want to test the peer exposure component by asking students to take paper-and-pencil notes but while in view of multitaskers' laptops. Participants in sight of these distracted classmates scored lower in a test than participants not exposed to multitaskers. Ophir, Nass, and Wagner (2009) document that multitaskers tend to be more distracted by media, while people who do not frequently multitask are better able at focusing also in the face of distractions. DeJarnette (2018) evaluates whether interruptions at work cause productivity losses that persist over time; he documents the existence of an "effort momentum", i.e. after an interruption it takes some time to get back to the pre-interruption effort levels. Indeed Mark, Gudith, and Klocke (2008) estimate that it takes on average 23 minutes to gain back the level of focus workers had before a distraction.

On top of the modified ability to concentrate for long periods, another channel through which educational outcomes may be negatively affected is time allocation. In fact, it is

[17]See for example a BBC article about how schools should have consistent smartphone policies, especially after the pandemic: www.bbc.com (April 7 2021).

[18]See, among others, Abouk and Adams (2013) and the effect of text message bans while driving: fatal accidents are indeed reduced by bans if they are enforced as a primary offense, but the number of accidents seem to reconverge to the previous levels in about six months.

[19]See also this article presenting a book about the importance of uninterrupted focus: towardsdatascience.com (April 2 2021).

possible that having technological tools available decreases the time that students devote to studying. Belo, Ferreira, and Telang (2014) follow this approach and present a model about the trade-off coming from the use of technologies in education, namely the fact that digital devices are a powerful tool but a source of distraction at the same time. They do not focus on individual usage of Internet, but rather they exploit the introduction by the Portuguese government of broadband connection in schools; they use as outcome variable the grades of the ninth-grade national exams in Portuguese and Math and see which is the impact of the actual school-aggregated broadband usage. By using panel data and estimating first differences from 2005 to 2009, they find that average broadband use in schools reduces grades by 0.78 of a standard deviation, and the negative impact on scores happens regardless of gender, subject, and school quality. Nonetheless, students of schools that have a blocking policy concerning for example YouTube perform relatively better. Their considerations assume that distracting activities on the Internet (e.g. listening to music, playing games, and watching videos) are inherently bandwidth intensive, and a limitation of the study is that it is unclear which are the activities performed by students on the Internet at school; as in Payne-Carter, Greenberg, and Walker (2017), it is possible that a better Internet connection is not related to more distracted students but to less effective teachers.

Another contribution to the detrimental effect of digital distractions on performance comes from Marotta and Acquisti (2017). Their field experiment looks at workers on Amazon Mechanical Turk (MTurk) that complete tasks online in exchange for a monetary compensation. In order to block Internet distractions, the treatment group had to complete its MTurk tasks while activating an app that allowed users to block certain websites for fixed periods of time. Interestingly, there were two treatment groups: one that had a pre-set list of blocked apps and blocking windows, and one where people were asked to implement their own settings. The findings suggest that the group with exogenous settings experienced an increase in performance in a proof-reading task, while the treatment group that had to decide their own conditions failed at effectively self-committing. While these results may hold for mechanical tasks that require prolonged focus, it is not clear whether limiting distractions and online interruptions could be profitable for creative tasks that require other skills and a wandering mind.

In a similar framework, during a statistics MOOC Patterson (2015) randomly assigns students to four treatment groups, thus having: a control group, a group that pre-commits to daily time limits on distracting Internet activities, a group that gets a reminder triggered by distracted web browsing, and a group that uses a focus tool to block distracting websites for up to an hour when they are on the course website. The first treatment group is the one that sees significant improvements in course outcomes compared to all the other three; relative to the control, also course completion and time spent on the course website increases, with differences that are most pronounced in the first weeks and largest among students that according to observable characteristics are those predicted to do well. Collins and Eggers (2020) instead recruit a small sample of university students and ask them to install a software on their personal computers and mobile devices. After a monitoring period, students are randomized into the treatment, i.e. a maximum use of social media platforms of 10 minutes per day across all devices. The authors do not find any impact on well-being, life satisfaction, and mental health, nor on academic success, but they identify significant substitution effects: participants in the treatment group substituted their use of social media services for instant messaging apps.

Commitment, network, and role modeling. In the present paper the intervention consists of asking students to commit and stay away from their smartphones for several hours every day, and they do so voluntarily after being reminded daily by a notification coming from the app. Reminders and nudges could represent helpful tools in motivating students; previous research from behavioral economics suggests that students may not be able to attain their preferred long-run outcomes because of either psychological barriers, or adopting behaviors such as delaying studying, or engaging in distracting activities online (see Lavecchia, Liu, and Oreopoulos (2016)). On the other hand, providing students with nudges to help them improve attitudes and habits is not easy, as change requires sustained effort over a long period of time. Oreopoulos and Petronijevic (2019) have extensively studied this topic, implementing different interventions over multiple years in order to help students uncover their potential. Interventions were aimed at providing motivation for goal setting and adopting a growth mindset, together with some coaching programs that were either face-to-face or online with different intensities of communication. While none of these programs proved able to improve neither students' grades nor persistence, interventions using coaching did improve study habits and subjective well-being. Also Clark et al. (2018) study how goal setting can motivate college students to increase their effort and achieve better results. Focusing on self-set goals, the authors find that task-based goals are more effective than performance-based goals, the first ones being more measurable and controllable, and the second ones being more long-term, coherently with a model of present-biased and loss averse students. This could go in the direction of supporting the setting of my intervention: students do not commit to a performance target or to a long run change, but rather to sticking to a daily task. Moreover, in my implementation I do not explicitly state the objective of the task, while motivating students to participate every day in order to improve their academic performance may increase chances of engagement.

Related to attentional issues, Bronchetti et al. (2020) run field experiments to test the effect of reminders on task completion. They document how reminders increase the likelihood of task completion, but that take-up of reminders in their population is lower than 100% even when providing incentives to adopt the system. The willingness to pay for reminders increases with the increase in the bonus for task completion, but they also show that attention-increasing technologies are under-evaluated. This is in line with the idea that using my app may be beneficial for students but they may underestimate its value.

In the context of a university classroom, peers are fundamental for performance and I recognize their importance in trying to reconstruct the social network of students through survey measures. Networks shape our behaviors when it comes to productivity as well, as documented by Falk and Ichino (2006) who check in a real and controlled work environment how peers' presence increases productivity in a repetitive task. Cohen-Cole, Liu, and Zenou (2017) explore the relationship between academic performance, screens and peers. While they find that the academic performance of a student is negatively correlated with the time spent on screen-related activities, through their analysis they also determine that the academic performance of a student is positively affected by the academic performance of the peers and more importantly it is also negatively affected by the time the peers themselves spend on screen-related activities. Stinebrickner and Stinebrickner (2008) argue that educational outcomes are more influenced by good examples of time use rather than high ability students helping out their struggling low achieving peers, and find a negative effect on grades stemming from having a roommate that owns a video-game. Related to this result, Conley et al. (2017) bring strong evidence that friends' study time has a substantial effect on one's own study time, which is an important ingredient of academic achievement.

Last but not least, family and role modeling may have an important impact in determining the use of technologies. In the surveys I ask about family's attitude towards smartphone usage and I try to detect past exposure to rules and parental example. Spitzer

(2019) highlights how parenting affects the use of technology: children look up at their parents and tend to mimic their behaviors; from a young age children demand attentions, and when they do not receive them they may develop behavioral disorders. In a self-fulfilling spiral, children who misbehave and demand even more attention can increase the level of stress on parents, who in turn are even more likely to use digital devices and to interrupt the activities with their children. Palsson (2017) provides support for the idea that smartphones distract caregivers and increase injuries to children under 5 years old. The phenomenon of "phubbing" (a combination of "phone" and "snubbing", i.e. ignoring someone by paying attention to the smartphone) can be particularly harmful for the family, as documented by Pancani et al. (2020), and for the future well-being of children, as in Xie and Xie (2020). In this context, present smartphone use of students could be more heavily affected by past parental use rather than by present peers' attitude, and thus changing this behavior may be harder.

A.2 Distraction-blocking Apps

In the last years many companies across the world have started offering apps that at different levels are able to block distractions on one's smartphone or even make it a "dumb-phone", i.e. an old-fashioned mobile phone that allows only calls and text messages. The Internet is full of articles providing advice[20], or YouTube videos encouraging you to disconnect[21], or even books that are supposed to guide you in this process[22]. All these tools appeal at different segments of the population; while printed in-store material is more likely to appeal at an older target, apps and videos are more visible for younger users like those targeted in this intervention.

As for the apps, official statistics about users' profiles are not public, but one app with more than 500k downloads on Google Play App Store and an average evaluation of 4/5[23] has offered me via email a brief snapshot of their users as of 2019. This app helps people understand what a normal smartphone usage is. In the first place, they provide statistics about own usage and compare it to other users'. Then, they provide tools in order to manage, block and control the way the smartphone is used. As of end of July 2019, this app's users are 55% male and 45% female, with most of them in the age group 25-34 (33.5%), followed by 18-24 (27.5%), 35-44 (15.5%), 45-54 (12.5%) and 55-64 and 65+ (5.5% each). Most of their 600k users set a daily limit, meaning that they select apps on which they want to spend a maximum amount of time on a daily basis (almost always social media like Instagram and Snapchat), usually one hour. The average usage per day around the world varies, but usually both male and female users within the same country exhibit similar behaviors. Habit-monitoring tools are now available on most smartphones, with the option of setting productivity blocks and time limits.

[20] See, for example, some pieces of advice on fastcompany.com or app recommendations on wall-streetinsanity.com.

[21] See, for example, videos like youtube.com/digital-minimalism with more than one million visualizations.

[22] See, for example, "Off: Your Digital Detox for a Better Life" by Tanya Goodin and all her online material at tanyagoodin.com.

[23] As of October 20, 2020.

A.3 Institutional Setting, Intervention and Survey Descriptives

A.3.1 Bocconi Institutional Setting

Table A.1: First-semester first-year courses by program.

Program	**N courses**	**Credits**	**Topics**	**Midterm?**[a]
CLEAM	4	*Total:* 28		
		9	Microeconomics	y
		8	Mathematics	y
		10	Management	y
		1	Critical Thinking (seminar)	
CLEF	4	*Total:* 28		
		9	Microeconomics	y
		8	Mathematics	y
		10	Management	y
		1	Critical Thinking (seminar)	
CLEACC	4	*Total:* 31		
		9	Mathematics	y
		10	Management	y
		6	Private Law	
		6	Aesthetic theory	
BIEM	4	*Total:* 28		
		9	Microeconomics	y
		8	Mathematics	y
		10	Management	y
		1	Critical Thinking (seminar)	
BIEF	4	*Total:* 28		
		9	Microeconomics	y
		8	Mathematics	y
		10	Management	y
		1	Critical Thinking (seminar)	
BEMACS	3	*Total:* 24		
		8	Microeconomics	y
		8	Mathematics	
		8	Management	y
BIG	4	*Total:* 28		
		8	Microeconomics	y
		6	Mathematics	
		6	Public Law	y
		8	Political Science	y
BESS	4	*Total:* 29		
		7	Microeconomics	y
		9	Mathematics	
		7	Management	y
		6	Logic	y
BAI	4	*Total:* 31		
		8	Microeconomics	y
		8	Mathematics	y
		7	Algebra&Geometry	
		8	Computer Science	

These data refer to the first semester of the a.y. 2020/2021.
[a]: *y* means that the course scheduled a midterm examination.

Table A.2: Second-semester first-year courses by program.

Program	**N courses**	**Credits**	**Topics**	**Midterm?**[a]
CLEAM	5	*Total:* 31		
		8	Macroeconomics	y
		6	Computer Science	y
		7	Mathematics	y
		6	Private Law	
		4	Foreign Language	
CLEF	5	*Total:* 31		
		8	Macroeconomics	y
		6	Computer Science	y
		7	Mathematics	y
		6	Private Law	
		4	Foreign Language	
CLEACC	5	*Total:* 30		
		7	Microeconomics	y
		6	Computer Science	y
		4	Foreign Language	
		6	Methods&Research	
		7	Economic History	y
BIEM	5	*Total:* 31		
		8	Macroeconomics	y
		6	Computer Science	y
		7	Mathematics	y
		6	Private Law	y
		4	Foreign Language	
BIEF	5	*Total:* 31		
		8	Macroeconomics	y
		6	Computer Science	y
		7	Mathematics	y
		6	Private Law	y
		4	Foreign Language	
BEMACS	5	*Total:* 36		
		8	Computer Science	y
		8	Mathematics and Statistics	y
		4	Foreign Language	
		8	Accounting	y
		8	IT Law	
BIG	6	*Total:* 32		
		6	Macroeconomics	y
		6	Computer Science	y
		5	Foreign Language	
		6	Political Philosophy	y
		6	Quantitative Methods	y
		3	Marketing Research Skills	
BESS	5	*Total:* 33		
		7	Macroeconomics	y
		6	Computer Science	y
		9	Mathematics	y
		4	Foreign Language	
		7	Statistics	y
BAI	4	*Total:* 31		
		8	Computer Science	y
		7	Mathematics	y
		8	Probability	y
		8	Physics	y

These data refer to the second semester of the a.y. 2020/2021.
[a]: *y* means that the course scheduled a midterm examination.

A.3.2 The Intervention

Figure A.1: Number of active users and their average daily time on the app, by day – Fall (September 21-October 16 2020).

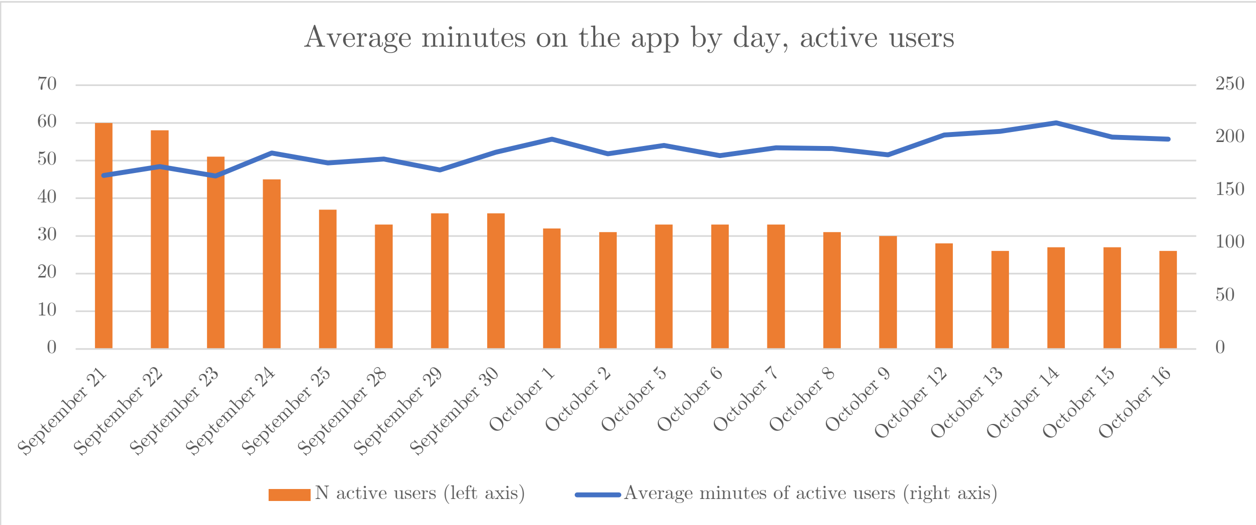


Figure A.2: Number of active users and their average daily time on the app, by day – Spring (February 15-March 12 2021).

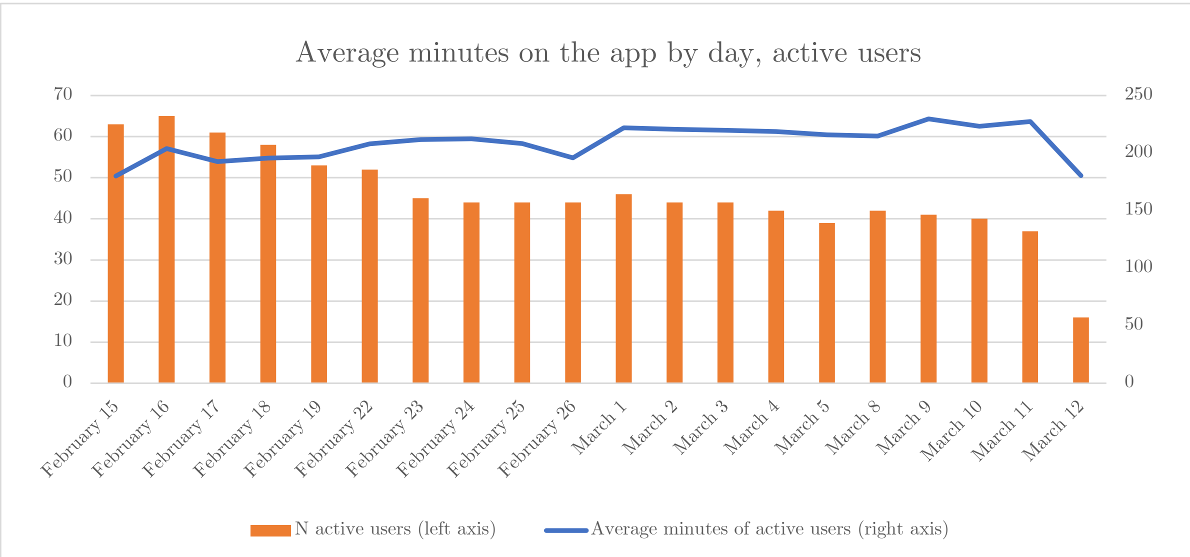


Table A.3: Total Active Participation to the Intervention.

	N	%
Only Fall 2020	64	40.51
Only Spring 2021	75	47.47
Persistent Participants (both)	19	12.03
N	158	

Table A.4: Summary statistics, overall (in hours) – Fall vs Spring.

Total Overall, Hours	**Fall 2020**	**Spring 2021**	**Persistent Participants**
Average total hours Fall	26.5		47
Min	0		0
Max	79		79
N	83		19
Average total hours Fall, if > 0	30.5		50
Min	0.02		1
Max	79		79
N	72		18
Average total hours Spring		34	47.5
Min		0	0
Max		80	80
N		94	19
Average total hours Spring, if > 0		40	53
Min		0.1	1
Max		80	80
N		80	17

Table A.5: Percentage of students that declared a certain app usage in the Post-Midterm survey *versus* the actual app usage – Fall (upper panel) vs Spring (lower panel).

Reported	**Actual**					
Fall						
	100%	**75-99%**	**50-74%**	**25-49%**	**<25%**	**Total row N**
100%	0	0	0	0	1.89	1
75-99%	0	18.87	3.78	3.78	7.55	18
50-74%	0	0	3.78	0	5.66	5
25-49%	0	0	0	1.89	9.43	6
<25%	0	0	0	1.89	41.51	23
Total column N	0	10	4	4	35	53
Spring						
	100%	**75-99%**	**50-74%**	**25-49%**	**<25%**	**Total row N**
100%	0	9.61	0	0	0	5
75-99%	0	46.15	1.92	0	0	25
50-74%	0	1.92	0	3.85	1.92	4
25-49%	0	1.92	1.92	0	1.92	3
<25%	0	0	0	1.92	26.92	15
Total column N	0	31	2	3	16	52

Figure A.3: Average daily time on the app of all users, by day – Fall (September 21-October 16 2020).

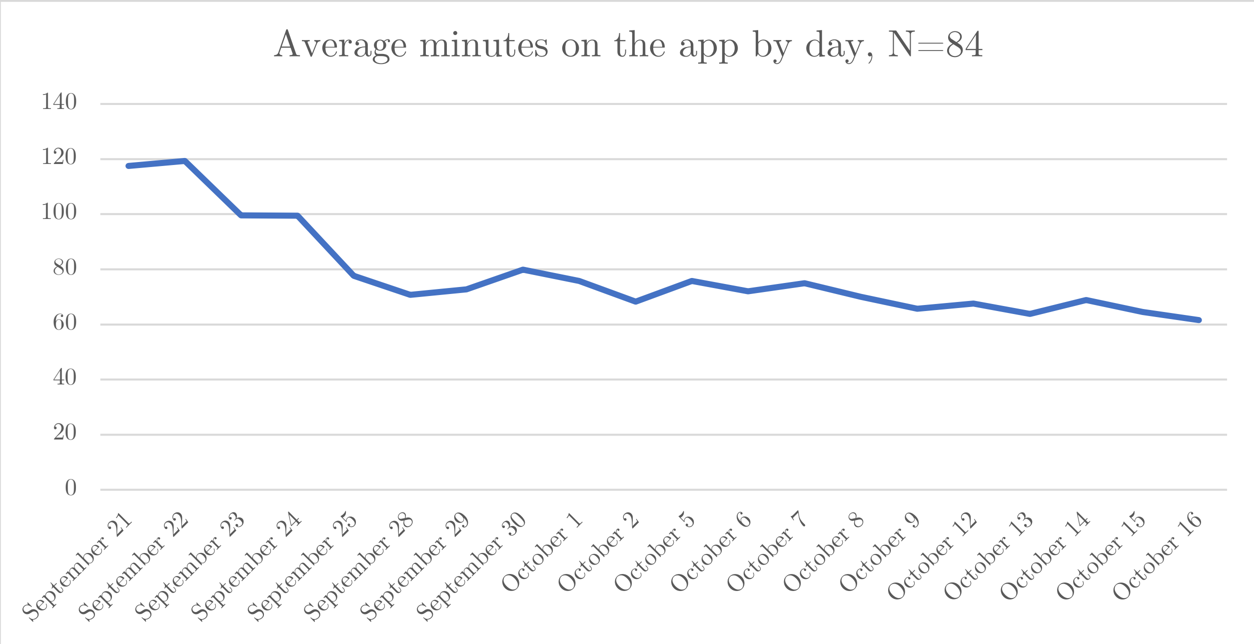


Figure A.4: Average daily time on the app of all users, by day – Spring (February 15 -March 12, 2021).

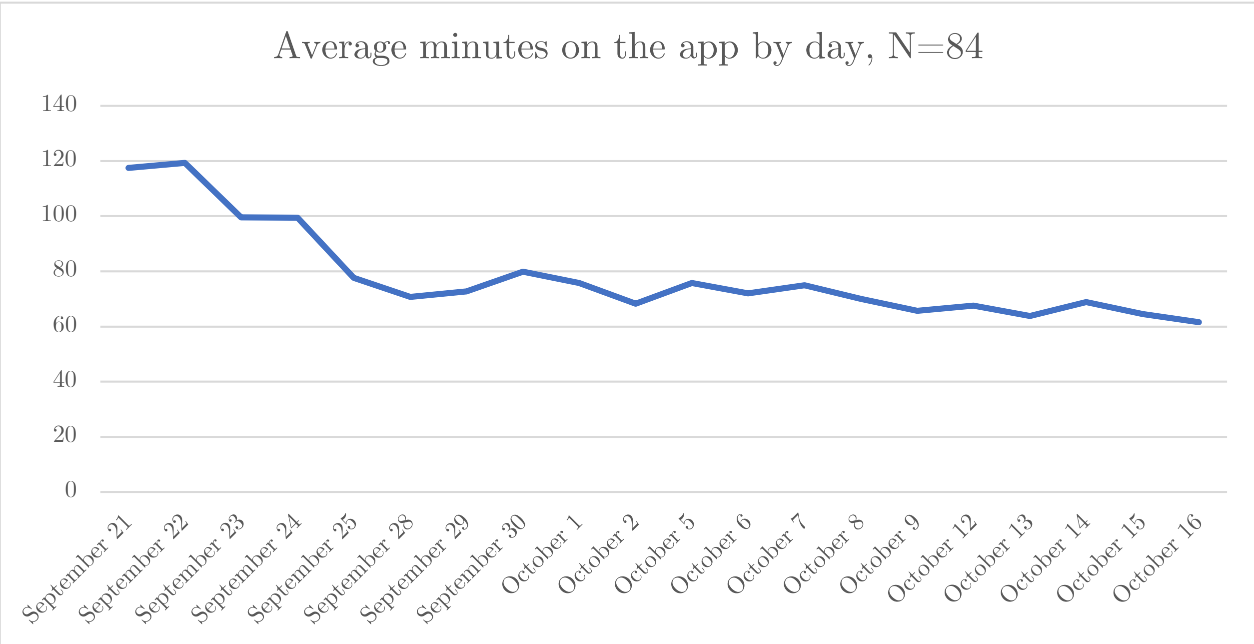
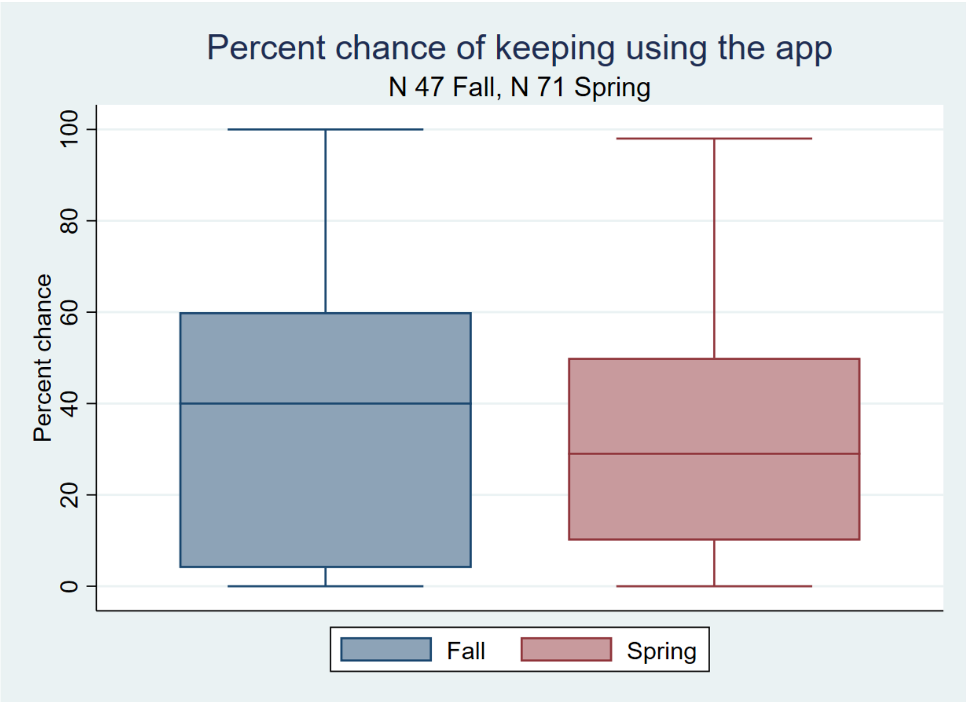


Figure A.5: Distribution of the reported percent chance of keeping using the app after the end of the intervention – Fall vs Spring.



All the box-and-whiskers plot in this Appendix provide the following information. The standard drawing presents a vertical plot, with y as the numerical axis and x as the categorical one; the plot may be rotated by 90°. The box spans from the 25th percentile (lower hinge) to the 75th percentile (upper hinge), reporting also the median with an inside-box line. The whiskers extend until the upper and lower adjacent values, which are the most extreme values within 1.5 times the interquartile range. Potential outliers are usually represented as round outside values.

Figure A.6: Distribution of the reported percent chance of keeping using the app after the end of the intervention, by whether students never used it afterward or indeed continued – Fall & Spring.

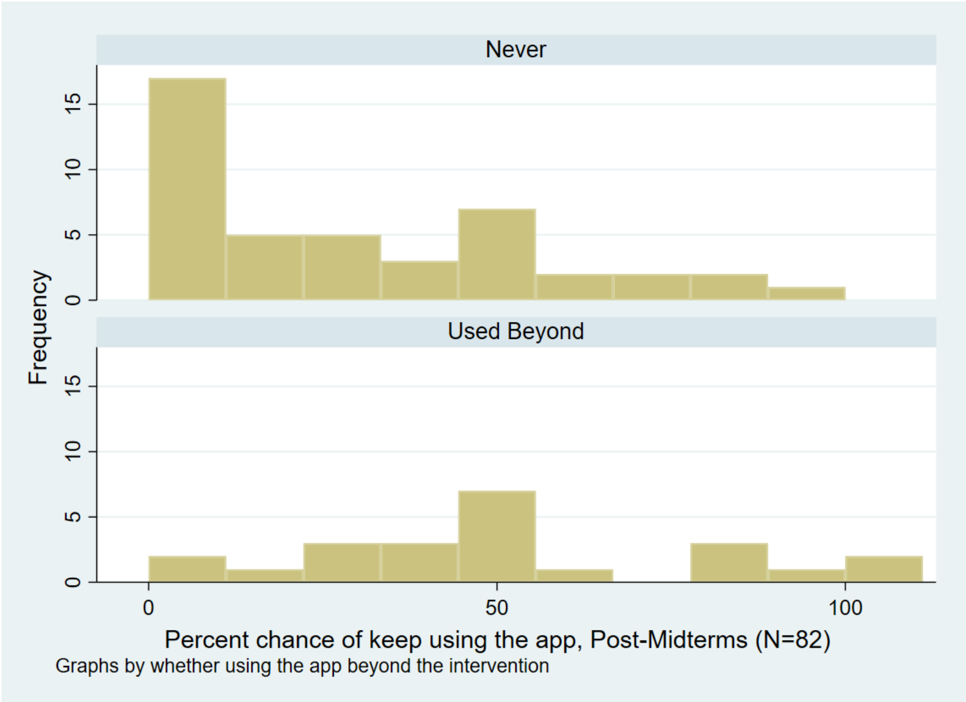
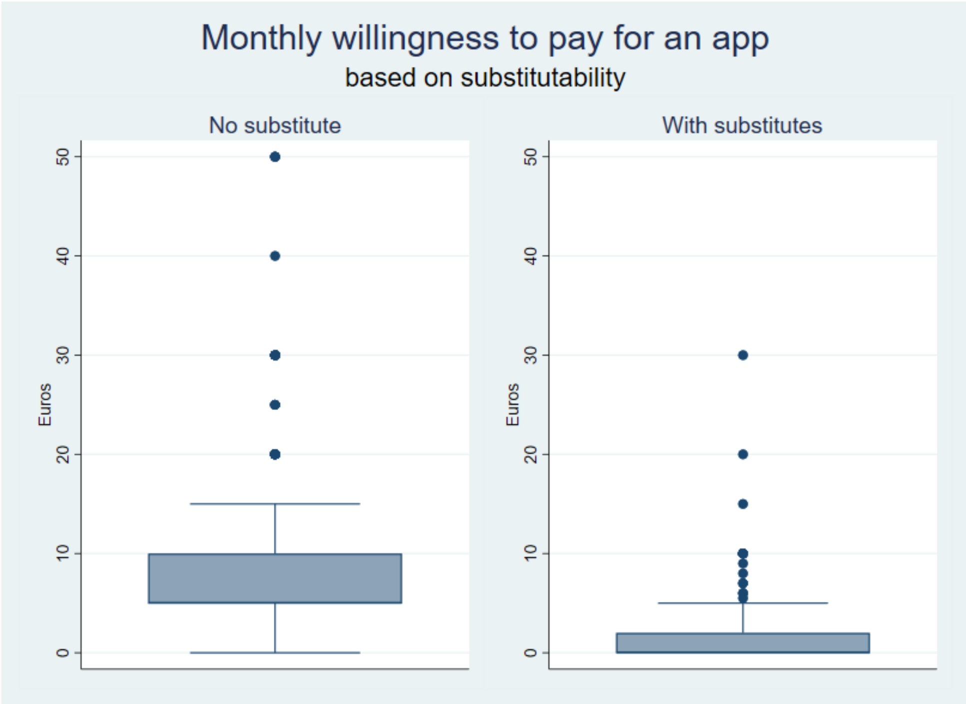


Figure A.7: Distribution of maximum willingness to pay on a monthly basis for an app that is used daily/weekly/less frequently – Post-Midterms, Fall.

This question was asked in Fall only.

Figure A.8: Distribution of maximum willingness to pay on a monthly basis for an app that can be hardly/easily substituted with non-smartphone tools – Post-Midterms, Fall.



This question was asked in Fall only.

Figure A.9: Average perceived difficulty of abstaining from some smartphone features while keeping the block active (slider: 0 to 100) – Post-Midterms, Fall & Spring.

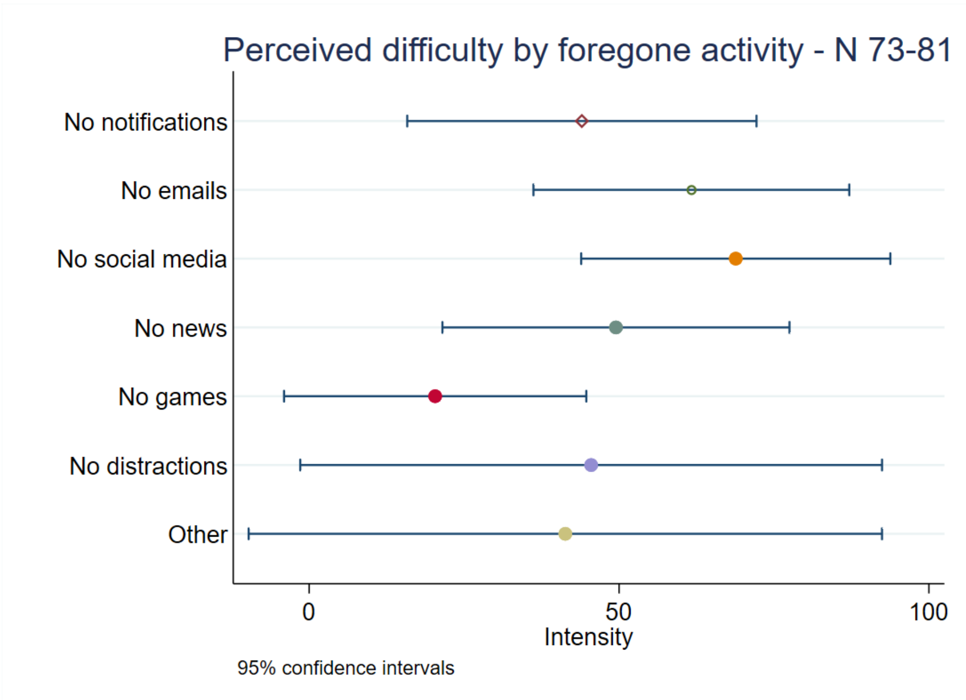


Figure A.10: Average perceived difficulty of the Intervention, by week (slider: 0 to 100) – Post-Midterms, Fall & Spring.

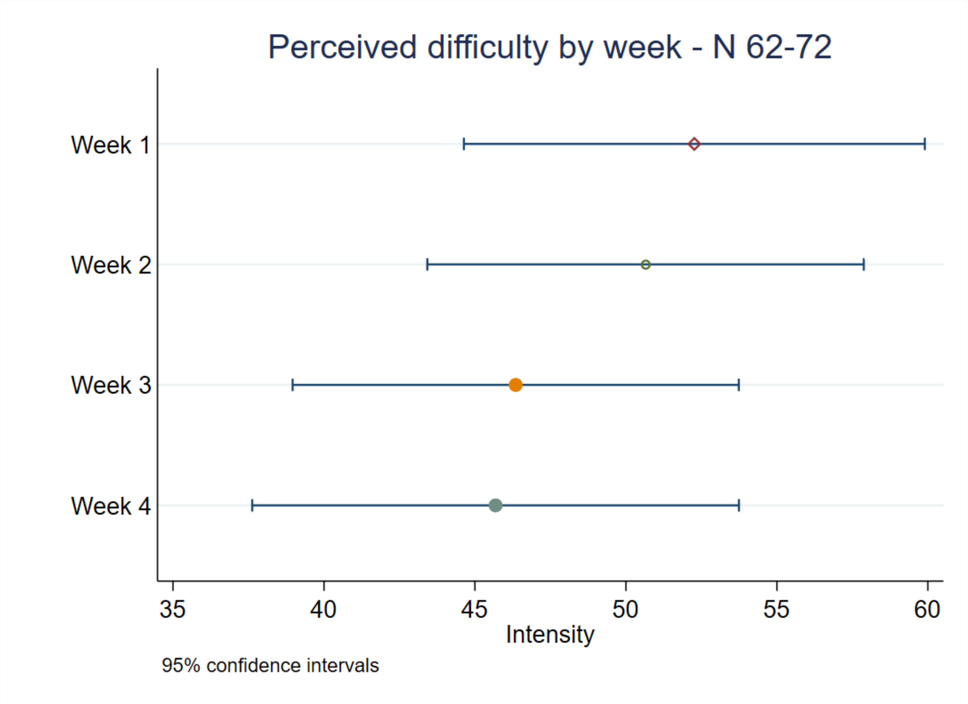


Figure A.11: Frequency of reported aspects perceived as the hardest while keeping the block active – Post-Midterms, Fall vs Spring.

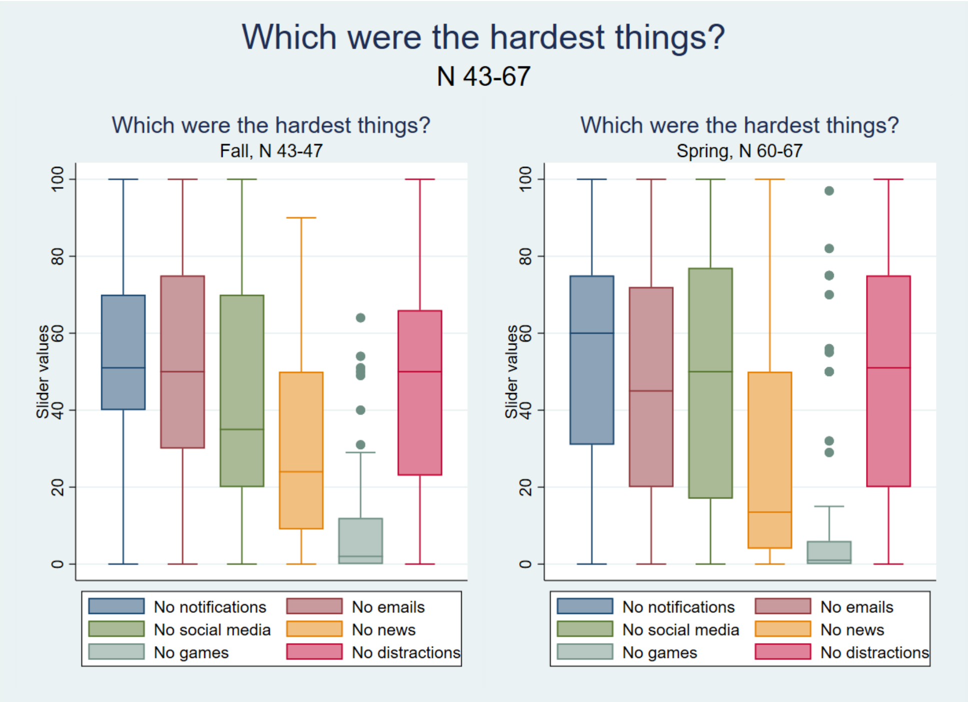


Figure A.12: Perceived difficulty of the intervention, by week – Post-Midterms, Fall vs Spring.

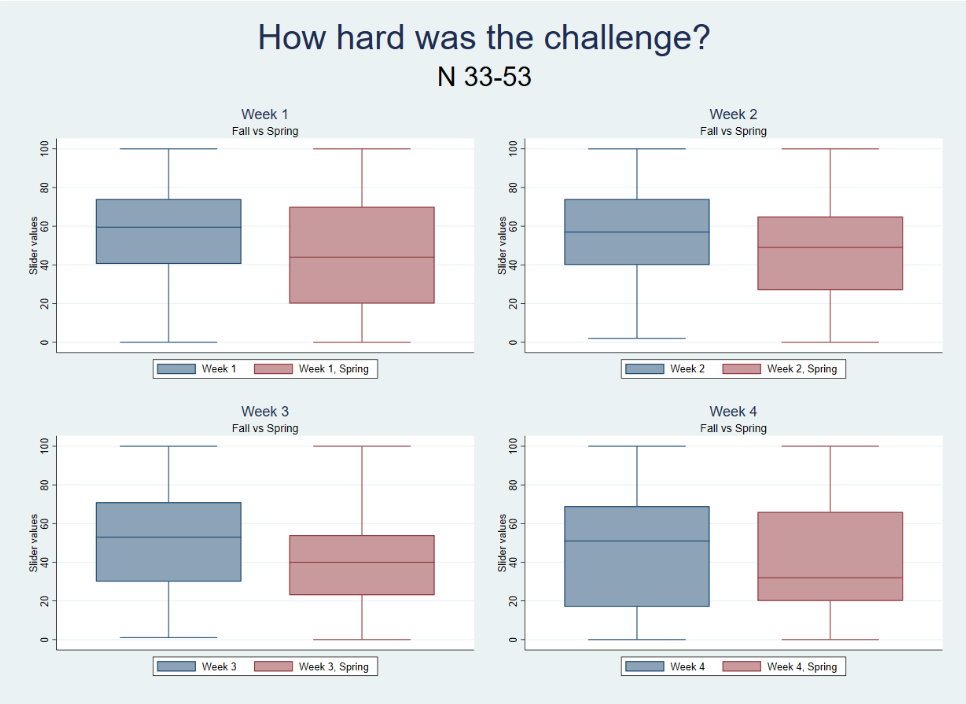


Figure A.13: Frequency of answers to the question "What strategies did you adopt to modify your smartphone behavior?" – Post-Midterms, Fall & Spring.

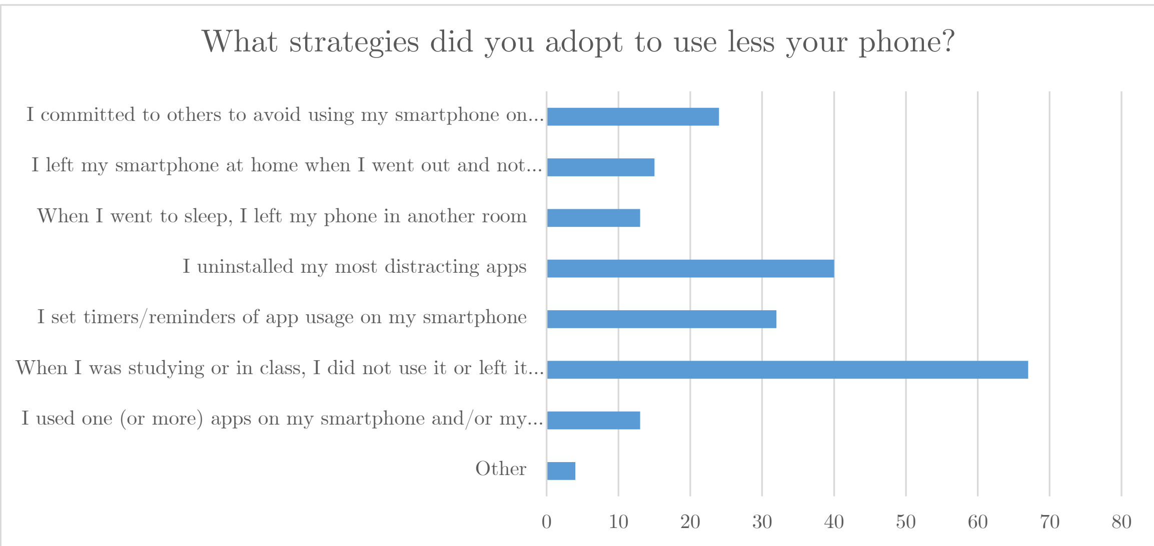
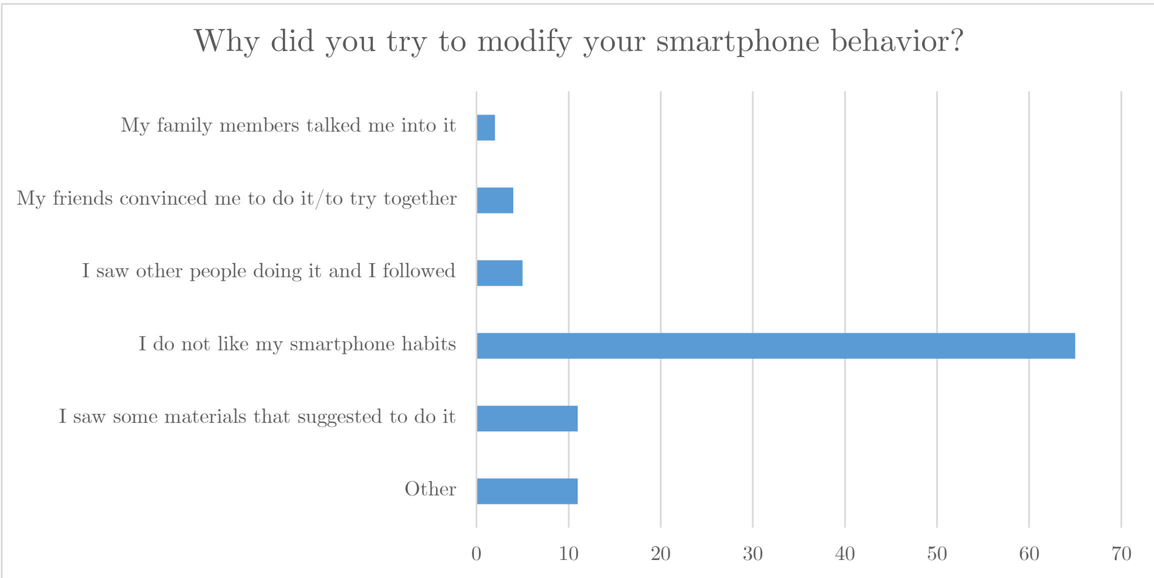


Figure A.14: Frequency of answers to the question "Why did you try to modify your smartphone behavior?" – Post-Midterms, Fall & Spring.



A.3.3 Students' Study Habits

For example, in Figure A.15 I display the frequency of reported listening to music while studying in Fall and Spring; during the cognitive interviews students reported using music as a neutral background when there is a distracting noise (e.g. in public spaces) but also as a concentration tool when doing exercises or other practical applications. In Figures A.16 and A.17 I detail respectively how often students report keeping their smartphones close while studying and the frequency of checking it, both in Fall and Spring. As for other possible sources of distractions, in Figures A.18 and A.19 I present whether students use messaging or social media apps on their laptops and, if so, whether they have these notifications turned on. Between 70% and 80% of the students use social apps or their browser versions, but only around 40-48% of them keep these notifications active.

As for the time use in general, students report spending their free time doing the most diverse activities, from watching movies and videos to listening to music and reading. For a more detailed representation of recreational occupations, see Figures A.20 (frequency of reported hobbies) and A.21 (distribution of time spent doing each of them, conditional on previous selection).

Figure A.15: Frequency of answers to the question "When you study, do you listen to music?" – Fall vs Spring.

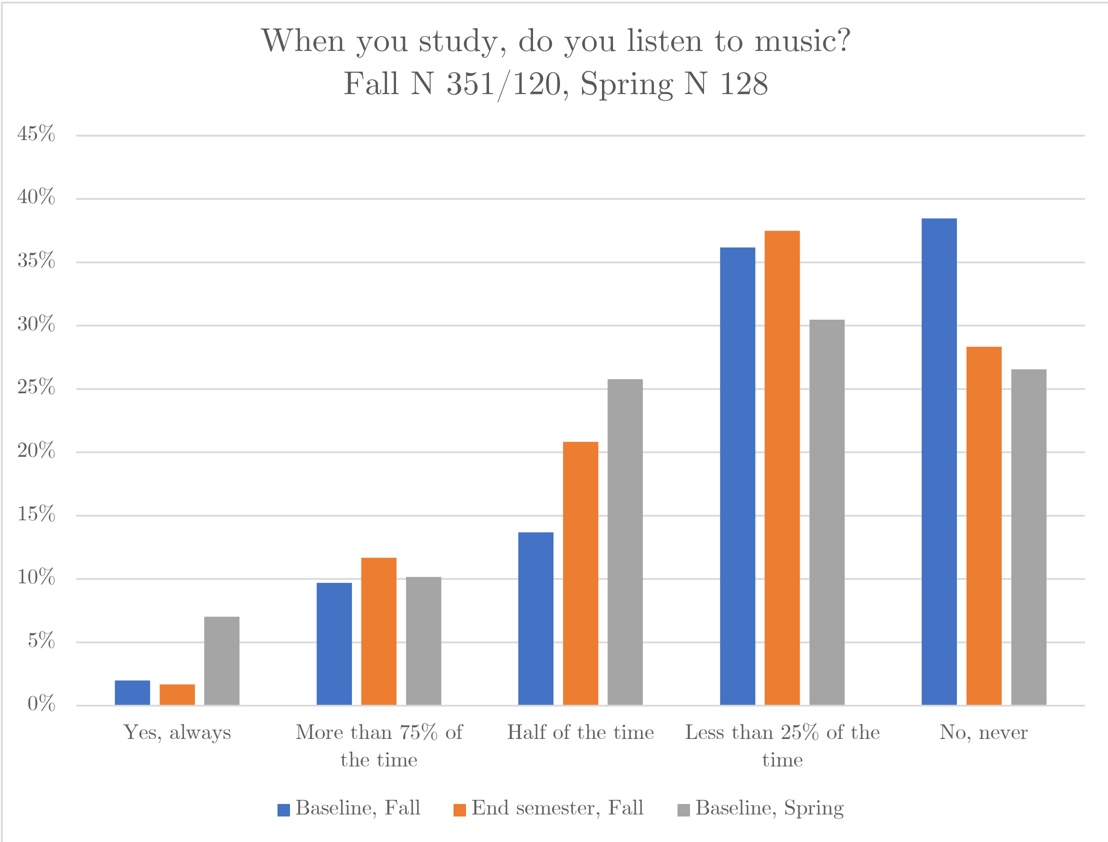


Figure A.16: Frequency of answers to the question "When you study, do you keep your smartphone handy?" – Fall vs Spring.

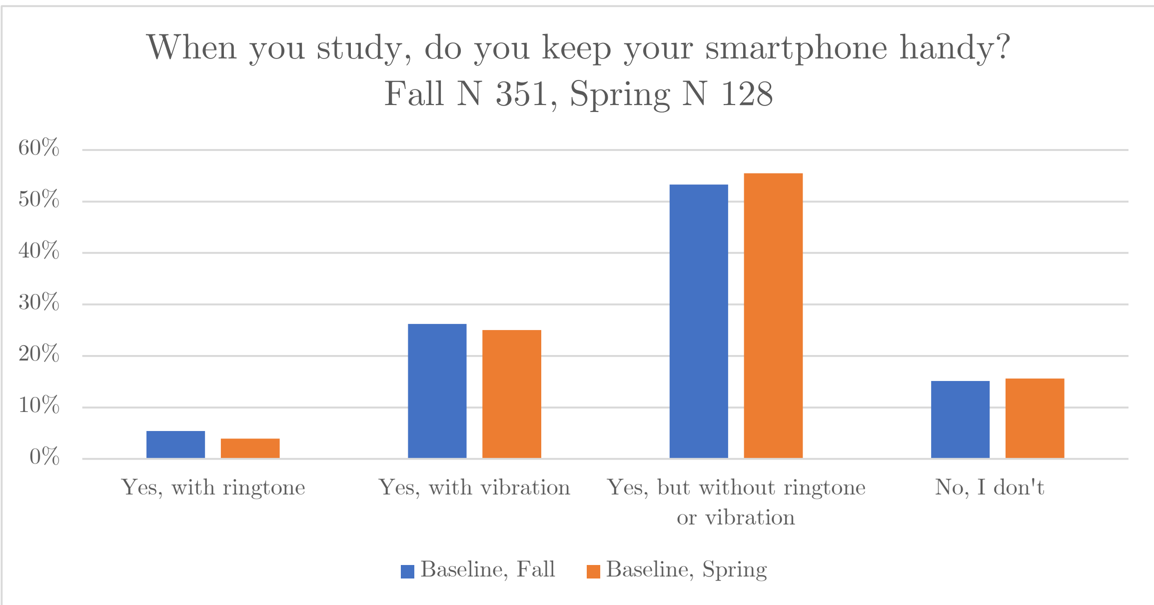


Figure A.17: Frequency of answers to the question "When you study, how often do you check your smartphone?" – Fall vs Spring.

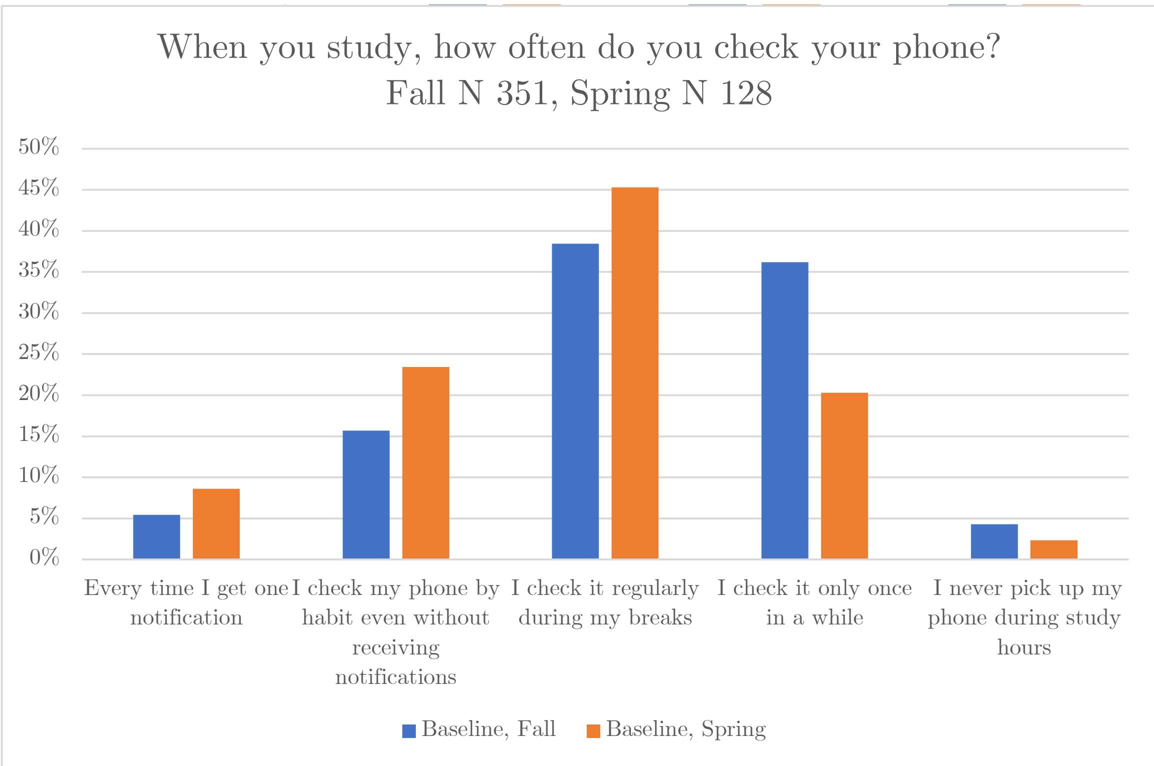


Figure A.18: Frequency of answers to the question "Do you use messaging apps or social media on your laptop?" – Fall vs Spring.

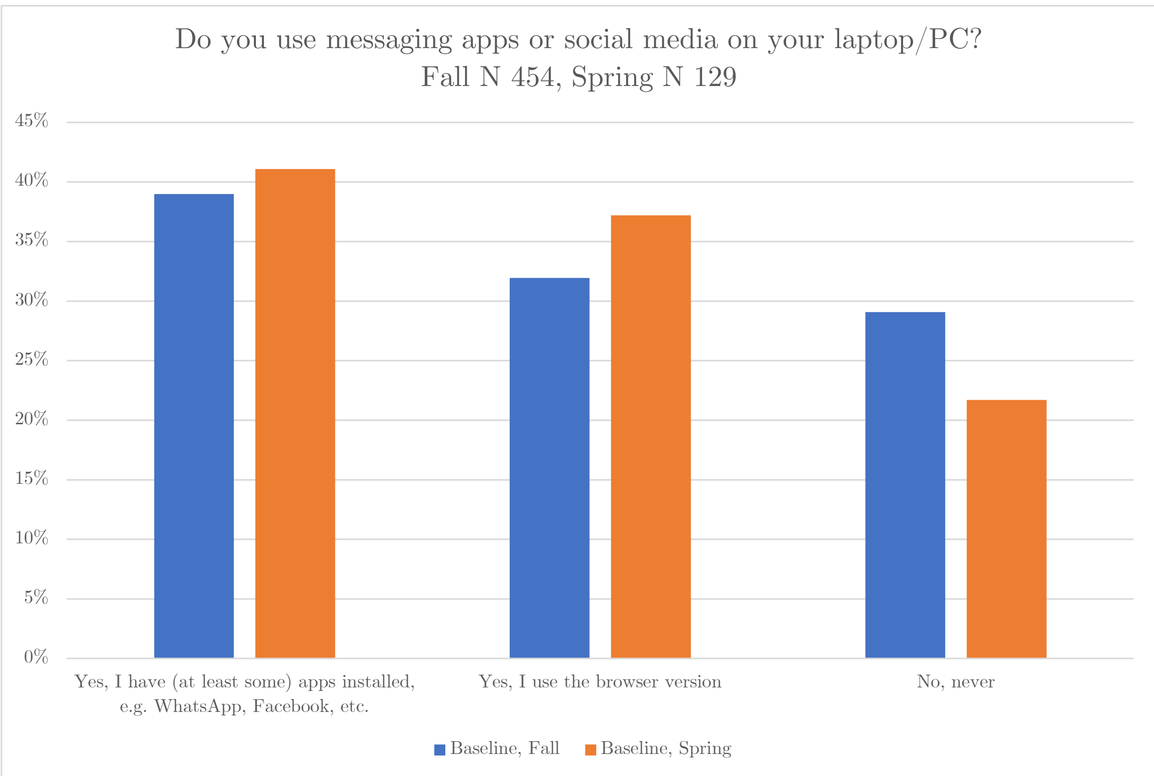


Figure A.19: Frequency of answers to the question "On your laptop do you have notifications turned on?" – Fall vs Spring.

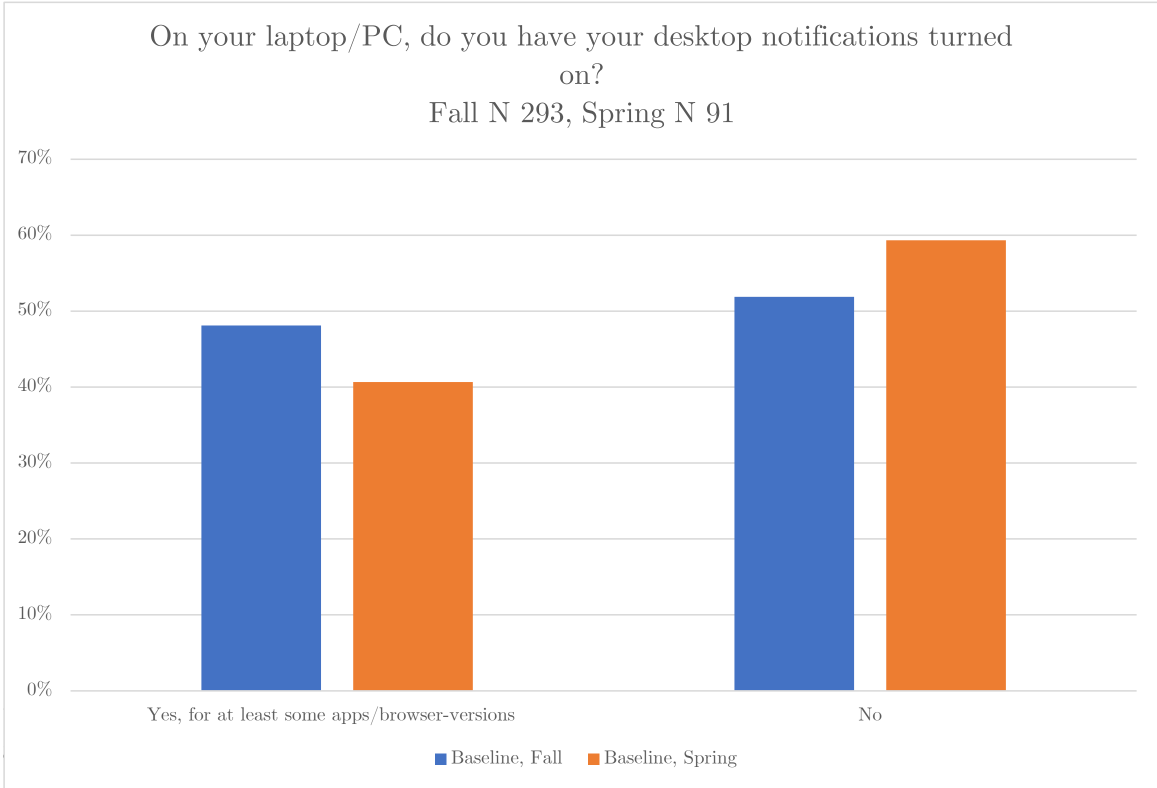


Figure A.20: Frequency of reported activities carried out regularly in the students' free time – Fall & Spring.

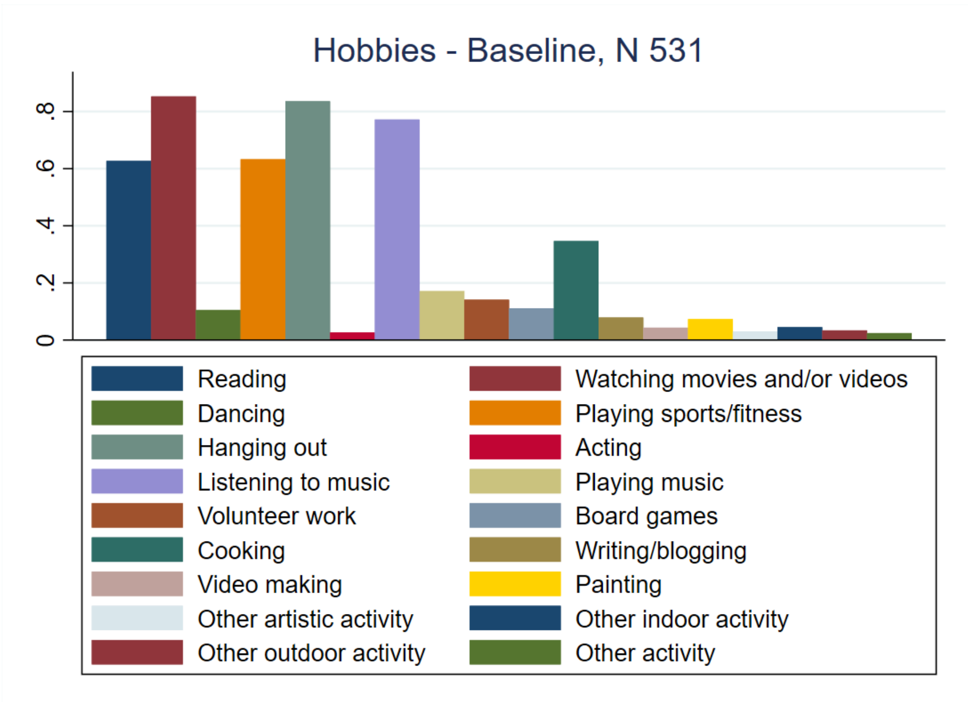
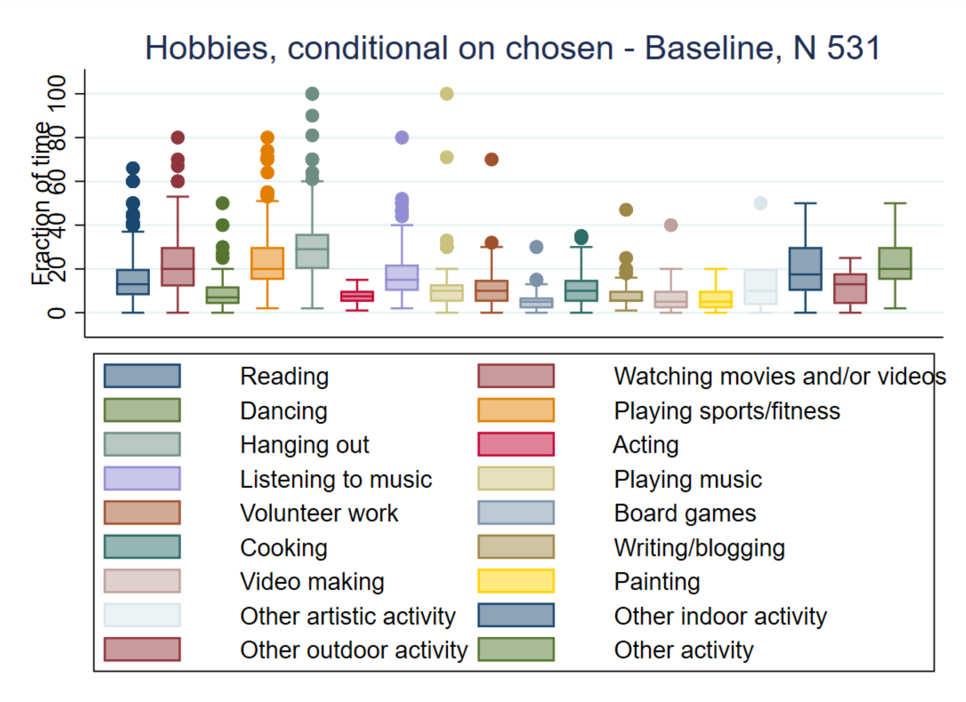


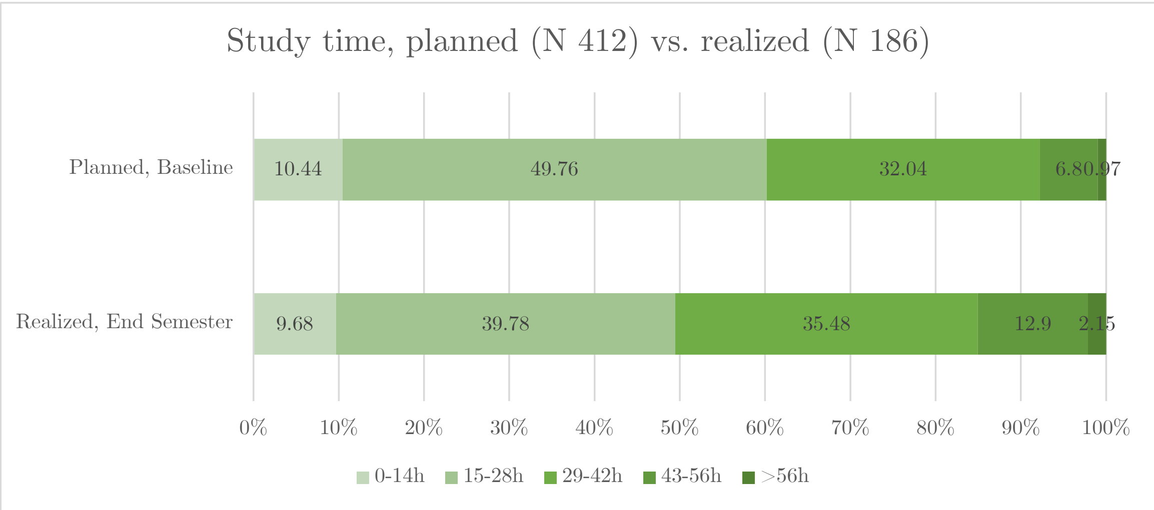
Figure A.21: Importance of free-time activities in terms of time dedicated to each of them, conditional on selecting them among relevant ones – Fall & Spring.



A.3.4 Students' Study Time

Figure A.22 reports aggregated answers about the planned weekly study time at the beginning of the semester (Baseline survey) and at the end (End-of-Semester survey). Fifty percent of the respondents plans to study on average between 15 and 28 hours in a week (from two to four hours per day) but only around 40% of them report doing so *ex post*; students on average report more study hours than planned.

Figure A.22: Reported planned study time at the beginning of the semester and reported realized study time at the end of the semester – Fall & Spring.



Let us now look at matched answers disaggregated by semester. Tables A.6 and A.7 present the discrepancy between *ex ante* planned and *ex post* reported study hours respectively in Fall and Spring. The rows present the answer to the question asked in the Baseline survey about the planned number of weekly study hours. The columns present the reported weekly study hours at the end of the semester. The tables account only for respondents who answered to this question in both waves. In Fall (Spring) 55% of respondents (48%) consistently reports having studied the planned amount, while 15% (26%) reports having studied less and 30% (26%) reports having studied more than expected.

This pattern may realize for many reasons. The share of students who sticks to their plans is quite big, and this may be the result of different factors; first of all, these students may be good planners and may have anticipated the workload and/or their desired effort level; second, they may be aware of the time they have available, if they are playing sports or commuting. Students who report having studied less than planned may have fallen into the trap of procrastination, or of exploring the university experience at the expenses of

Table A.6: Percentage of students that declared a number of planned weekly study hours in the Baseline survey (September) *versus* the reported weekly study hours in the End-of-Semester survey (December) – Fall.

Planned, September (%)	**Reported, December (%)**					
	0-14 hrs	**15-28 hrs**	**29-42 hrs**	**43-56 hrs**	**>56 hrs**	**Total row N**
0-14 hrs	5.88	5.88	0	0	0	10
15-28 hrs	5.88	18.82	23.53	3.53	1.18	45
29-42 hrs	1.18	7.06	14.12	7.06	0	25
43-56 hrs	0	0	2.35	2.35	1.18	5
Total column N	11	27	34	11	2	85

studying. The students who have studied more than planned may have not considered some aspects when organizing their semester; first, they may have underestimated the effort required or the difficulty of the subjects, in particular during the first semester; second, they may have experienced some external pressure (e.g. from motivated peers) to study more; third, they may have been driven to study more by the availability of more time, if the activities they used to carry out in their non-academic time have been affected by the COVID-19 pandemic, for example if a commuting student living with their family or a dorm-resident student was forced to stay at home by the fact that they had to enter into isolation[24].

[24] This may have happened for a number of reasons. In the period September-mid October 2020, most hard restrictions in Italy were not in place; therefore schools, bars, restaurants, sports clubs, gyms etc. were fully open provided that they could ensure social distancing. In the period February-mid March the situation was not very different, with bars and restaurants at least partially open, but sports clubs and gyms closed. Having been in touch with somebody that tested positive for Coronavirus infection meant having to undergo a voluntary isolation of 14 days; if in this period symptoms showed, then a nasopharyngeal swab was required. In this context, it is understandable that students living at home with their families may have been forced to stay at home if a parent or a sibling showed symptoms and tested positive, thus leading to more “free time” to study. The same is true for students living in dormitories that were exposed to even more peers. In the first week of October 2020, 9 students in a Bocconi residence tested positive for Coronavirus, thus leading to the isolation of all the 190 students living in the building; this strongly impacted the study time availability of students forced to stay in their small apartments. One article about this cluster episode can be found on www.fanpage.it (October 8, 2020).

Table A.7: Percentage of students that declared a number of planned weekly study hours in the Baseline survey (February) *versus* the reported weekly study hours in the End-of-Semester survey (May) – Spring.

Planned, February (%)	**Reported, May (%)**					
	0-14 hrs	**15-28 hrs**	**29-42 hrs**	**43-56 hrs**	**>56 hrs**	**Total row N**
0-14 hrs	2.9	2.9	0	0	0	4
15-28 hrs	4.35	18.84	15.94	0	0	27
29-42 hrs	0	17.39	20.29	7.25	0	31
43-56 hrs	0	1.45	2.90	4.35	0	6
>56 hrs	0	0	0	0	1.45	1
Total column N	5	28	27	8	1	69

A.3.5 Students' Expectations

Table A.8: Expected performance (percent chance of passing each exam, expected grade), own and with respect to the friends listed by name – Pre-Midterms, Fall (not asked in Spring).

	Own Mean	N	**Friends' Mean**	N	**Compared to expected friends' performance, own is...** lower, (%)	equal, (%)	higher, (%)	N
Percent chance of passing								
Fall semester								
Management	77.08	116	88.45	102	72	12	16	102
Mathematics	72.43	130	85.28	111	66	10	24	110
Microeconomics	75.76	104	87.7	91	73	15	12	91
Other subjects	72.32	117	86.12	39	79	5	16	38
(Derived) Expected grade								
Fall semester								
Management	25.02	116	27	95	85	1	14	95
Mathematics	24.47	131	26.09	103	72	2	26	103
Microeconomics	24.92	104	27	84	83	1	16	84
Other subjects	25.34	121	26.76	39	82	5	13	39

Figure A.23: Distribution of percent chances of passing the exams – Fall.

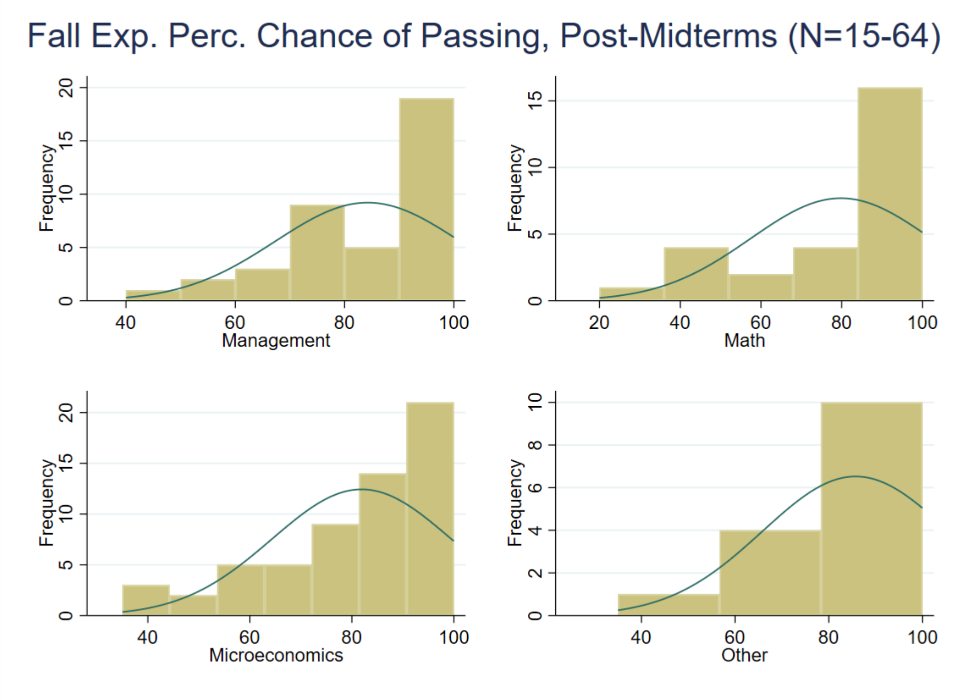


Figure A.24: Distribution of percent chances of passing the exams – Spring.

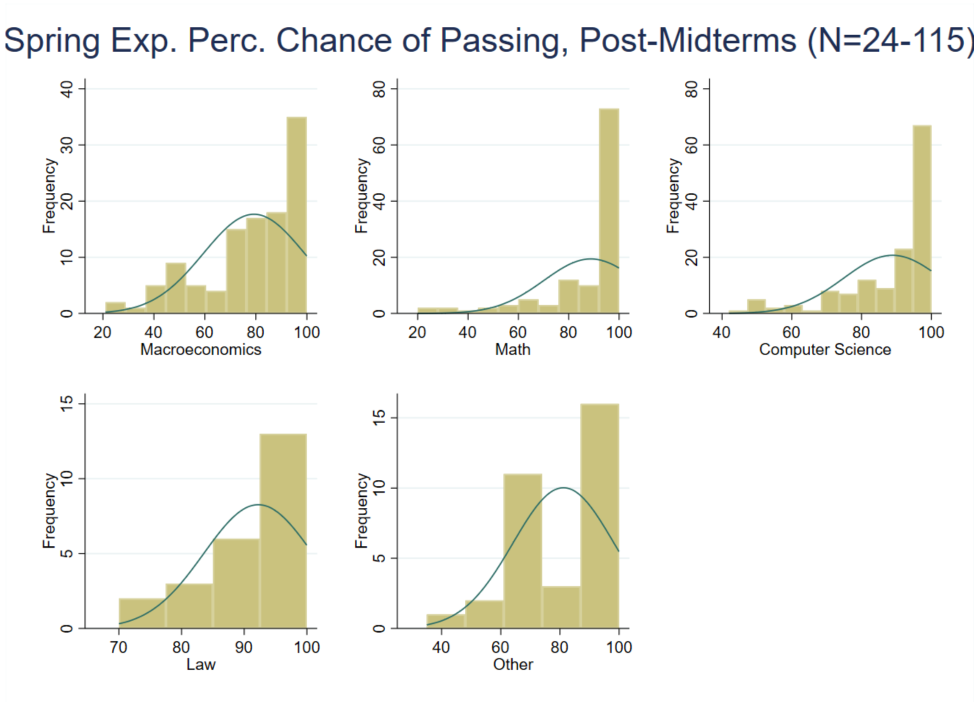


Figure A.25: Distribution of expected grades – Fall.

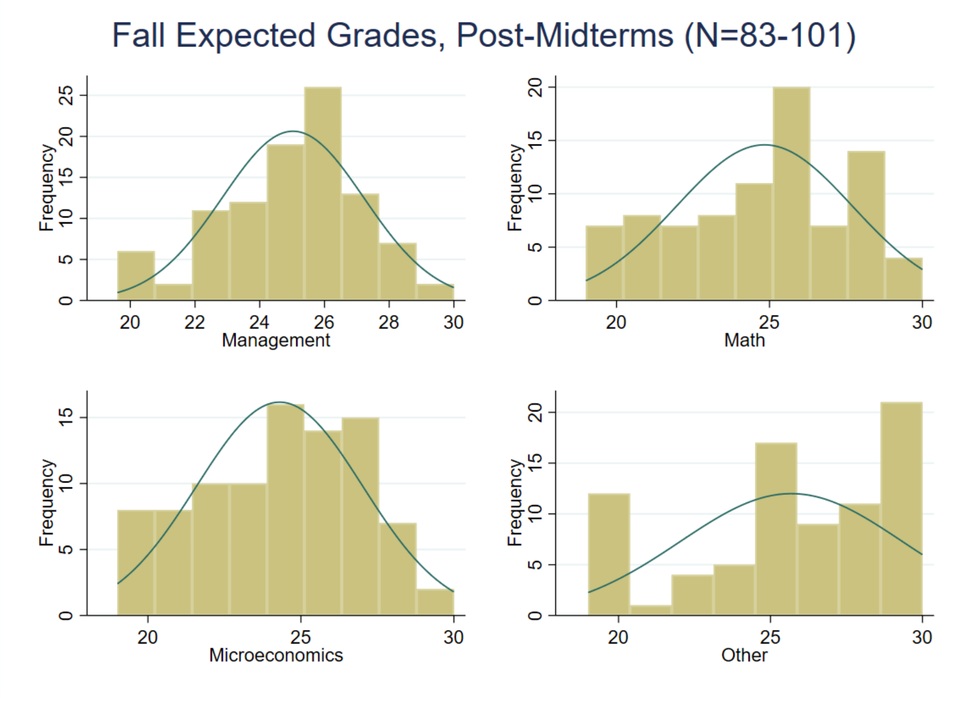
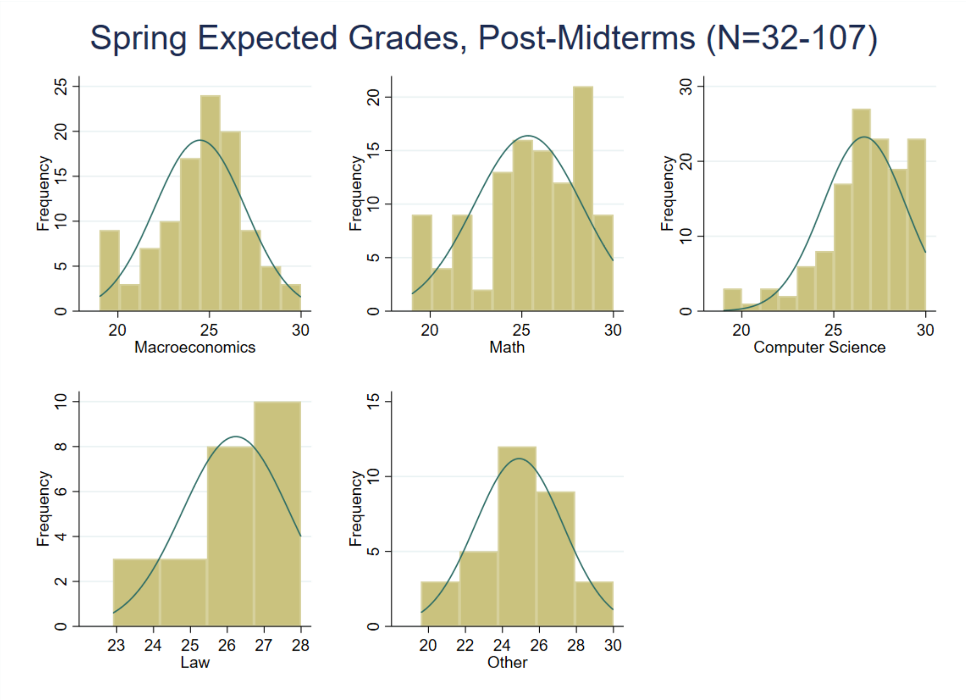


Figure A.26: Distribution of expected grades – Spring.



A.3.6 Students' Smartphone Habits

Table A.9: Differences over time of the Smartphone Addiction Scale items at Baseline, after the Midterms, and at the End of the Semester – Fall & Spring.

	Baseline	Post-Midterms	End of Semester	B-PM	B-EoS	PM-EoS
Part of my daily routine	82.29	84.31	86.73	-1.81*	-2.69**	1.35
	(20.77)	(18.18)	(15.30)	(1.35)	(1.36)	(1.33)
Checking has become a habit	79.78	80.19	84.23	-.16	-2.32*	.38
	(22.31)	(20.30)	(18.02)	(1.69)	(1.67)	(1.88)
Used to escape from real life	28.67	35.82	35.65	-2.60*	-2.23	-.21
	(27.62)	(29.07)	(30.47)	(1.96)	(2.16)	(2.64)
Used to relax	57.70	63.03	61.84	-4.13**	-1.99	1.30
	(25.14)	(24.41)	(25.77)	(1.91)	(1.90)	(2.03)
Used to interact	78.12	80.91	81.42	-1.92	-3.04*	-.30
	(21.50)	(16.98)	(17.28)	(1.77)	(1.84)	(1.62)
Used to maintain relationships	76.72	78.51	80.38	.41	-3.01**	-1
	(22.76)	(20.14)	(18.35)	(1.91)	(1.65)	(1.96)
Problems when using it instead of other things	49.31	51.48	58.10	2.85*	-6.06***	-5.01**
	(31.73)	(29.48)	(31.71)	(2.0)	(2.44)	(2.66)
Lose sleep due to time I spend on it	38.58	36.95	42.71	2.25	-3.57*	-4.15*
	(32.48)	(31.72)	(33.58)	(2.32)	(2.48)	(2.56)
Attempted to spend less time	29.71	34.84	38.16	-2.15	-6.03***	-3.77*
	(28.15)	(28.84)	(29.27)	(2.26)	(2.56)	(2.52)
N	480-497	178-180	173-177	138-144	135-142	103-105

B: Baseline, PM: Post-Midterms, EoS: End of Semester.
[a]: Full-sample averages.
[b]: Matched-answer averages.

Figure A.27: Frequency of reported reasons why using smartphone – Baseline, Fall & Spring.

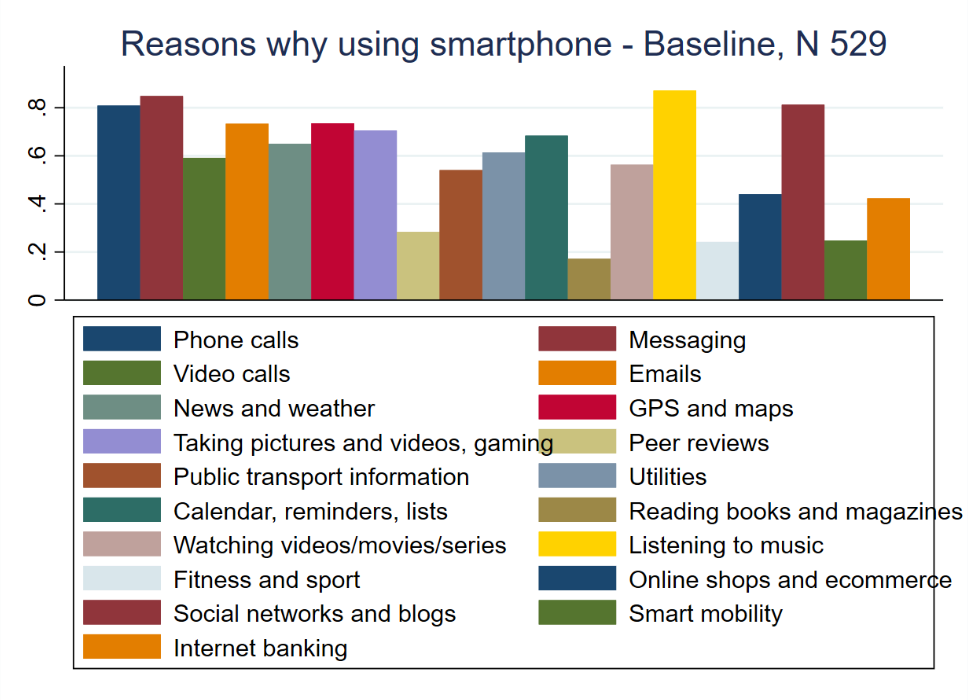


Figure A.28: Frequency of reported reasons why using smartphone – End of Semester, Fall & Spring.

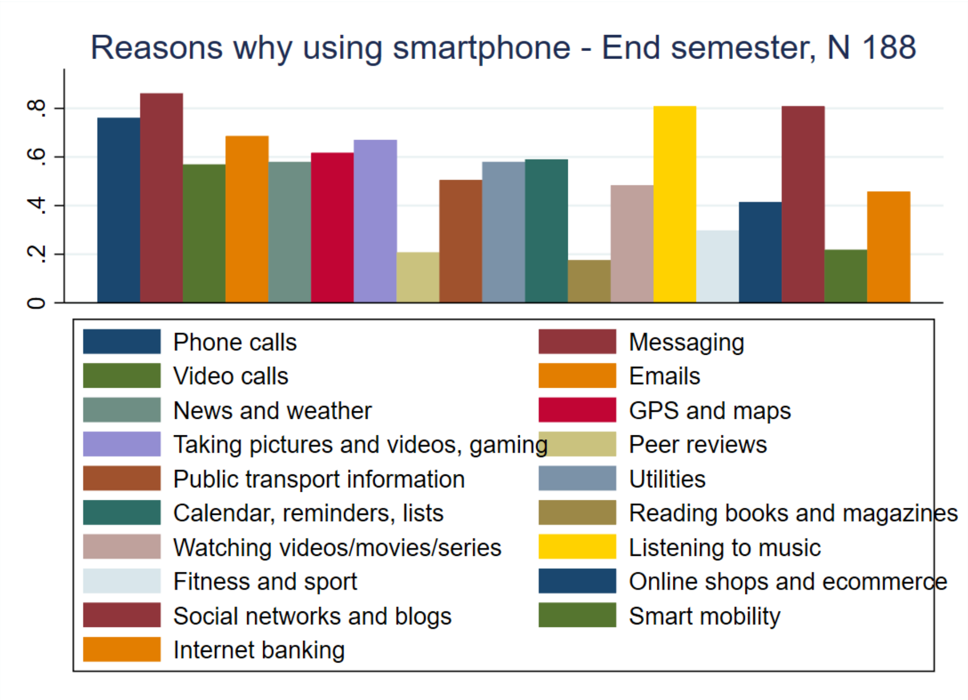


Figure A.29: Frequency of reported reasons why using smartphone – Baseline, Fall vs Spring.

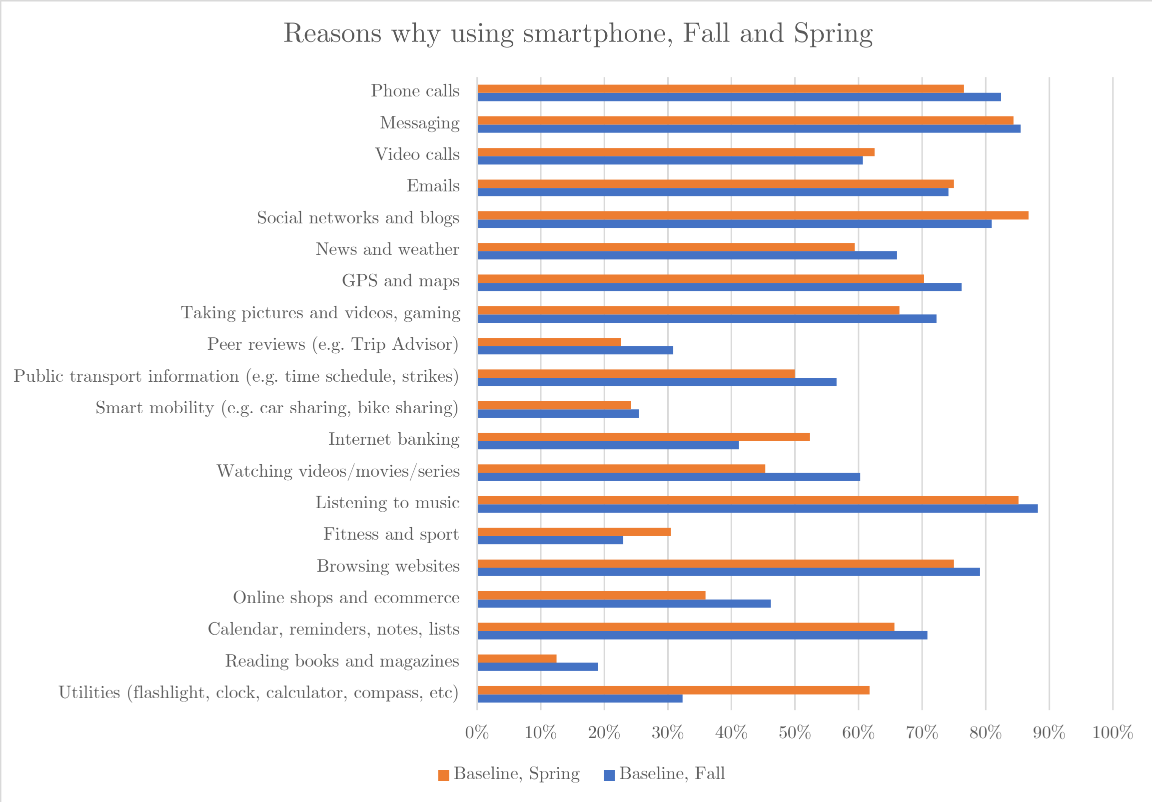


Figure A.30: Frequency of reported reasons why using smartphone during high school – Fall & Spring.

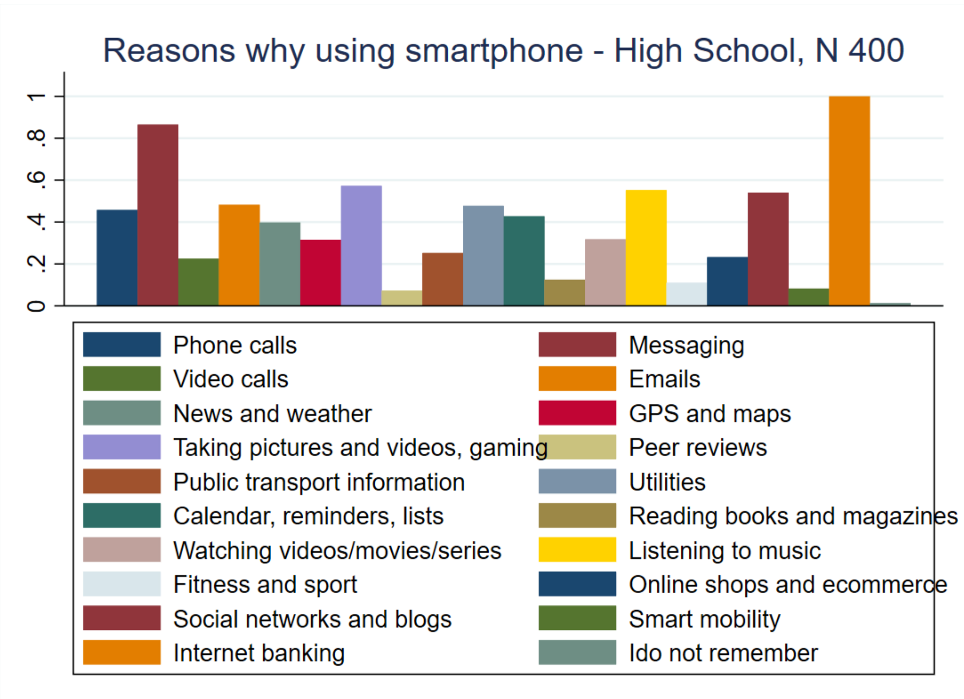


Figure A.31: Frequency of reported smartphone use on a daily basis – Baseline, Fall vs Spring.

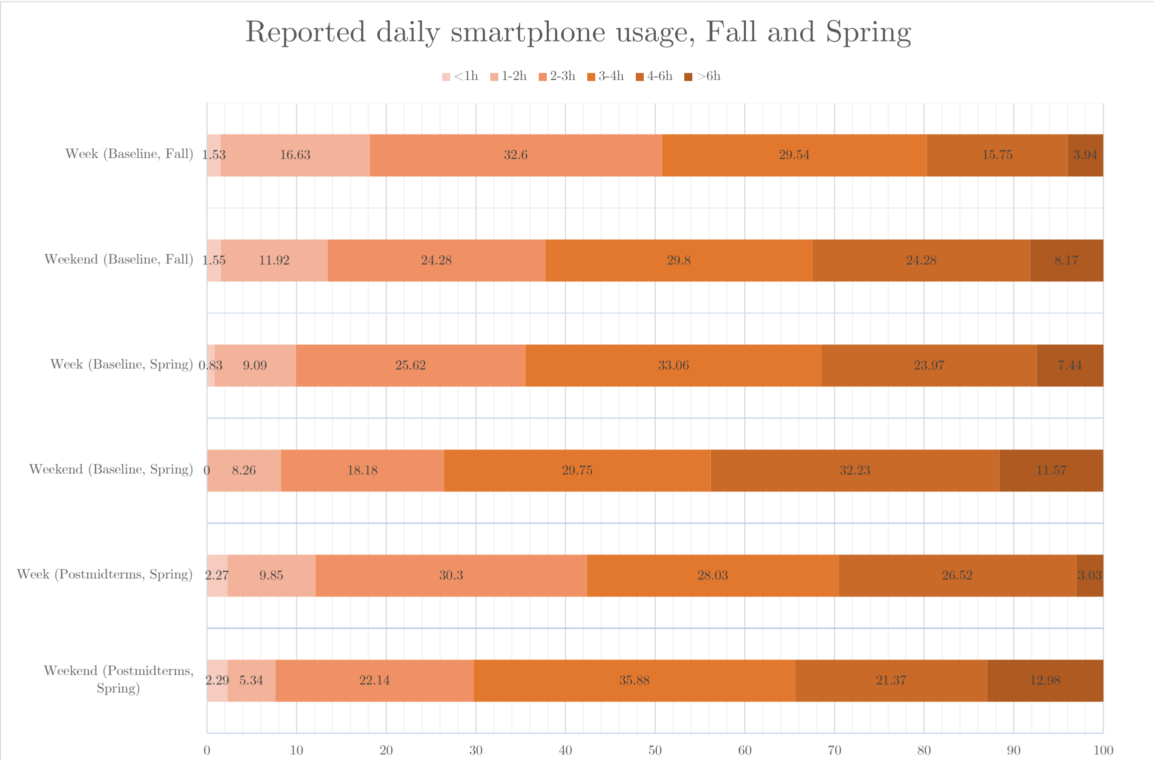


Table A.10: Reported smartphone usage – Fall & Spring.

	Own daily smartphone usage, reported					
	Baseline, Fall		Baseline, Spring		Postmidterms, Spring	
	Week	**Weekend**	**Week**	**Weekend**	**Week**	**Weekend**
Less than 1h	1.53	1.55	0.83	0	2.27	2.29
Between 1 and 2h	16.63	11.92	9.09	8.26	9.85	5.34
Between 2 and 3h	32.6	24.28	25.62	18.18	30.3	22.14
Between 3 and 4h	29.54	29.8	33.06	29.75	28.03	35.88
Between 4 and 6h	15.75	24.28	23.97	32.23	26.52	21.37
More than 6h	3.94	8.17	7.44	11.57	3.03	12.98
N	457	453	121	121	132	131

A.3.7 Personality and Anxiety

Figure A.32: Box-and-whiskers plot of personality traits as measured on a slider from 0 to 100 – Fall & Spring.

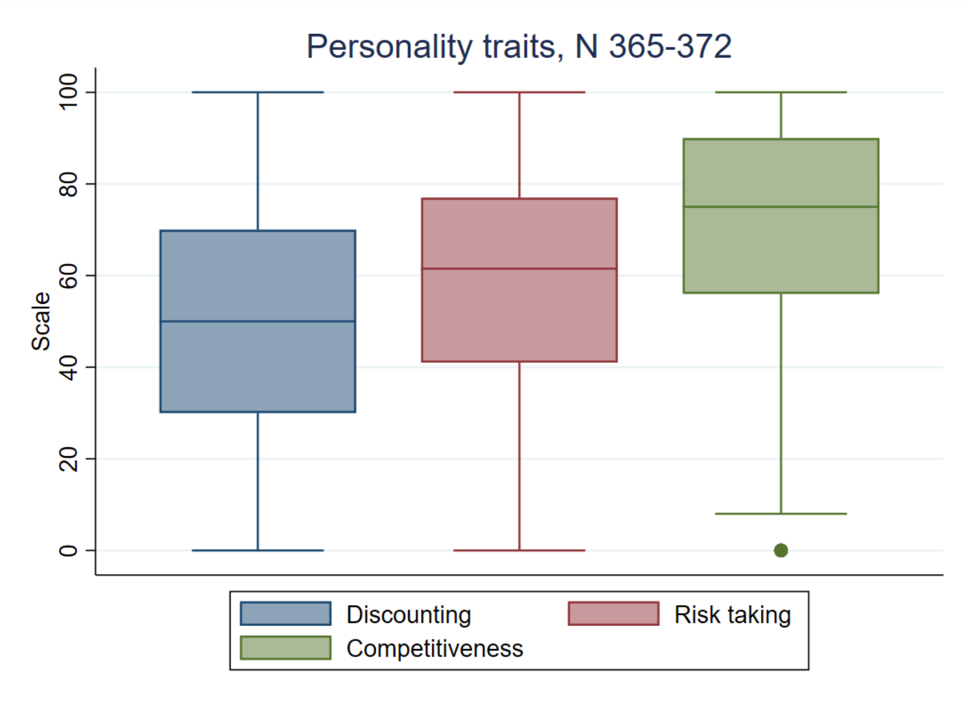


Table A.11: Summary statistics of Grit – Fall & Spring.

	Mean	Std. Dev.	Min	Median	Max	N
Grit value	3.46	.61	1.875	3.5	5	375
By gender						
Male students	3.42	.63	1.875	3.5	5	203
Female students	3.52	.60	2	3.5	4.625	172

A.3.8 Family and technology.

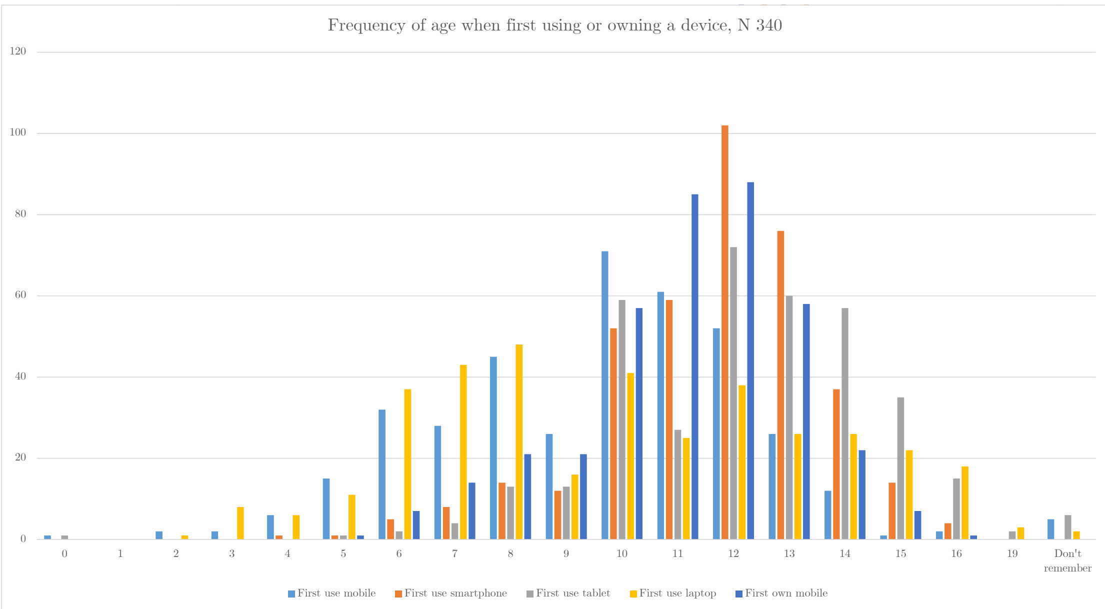
Role modeling is an important factor in a child's development, and mirroring behaviors of parents or older family members is relevant in one's growth.

While the surveys did not investigate quantitatively past use of mobile phones or smartphone by older family members, we can understand which is the relationship of the family with these technologies by looking at other current measures and some reported childhood experiences.

Figure A.33 presents the distribution of ages at which students used or owned for the first time some technological devices. We can see that the first use of a mobile happened as early as at two or three years old, and this trend steadily increases until it peaks at

11 years old, and then decreases until 16 or 17 years old. Owning a mobile for the first time is common among middle school students, as most of the students got this device for themselves between the ages of 10 to 13. Using a laptop for the first time seems to be popular among young children aged 6 to 8, probably because of early exposure in school. Tablets started being first used more by middle schoolers. First use of smartphone is also concentrated around this age group, but this might be due also to the availability of this technology 8 to 11 years ago (2010-2013).

Figure A.33: Age at which students first used or owned different devices – Fall & Spring.



Families in the past may have introduced restrictions on smartphone use. While many students report never having to follow rules (Figure A.34), others had to comply to impositions since elementary school, and 2% of them are restricted still now. Motivations attached to these impositions could be very diverse, as seen in Figure A.35. The least important motivations are related to a perceived negative effect on body image, and to the fact that parents disliked the technology altogether or because they thought it made them spend too much money. The highest rated reason is related to the critique that students were spending too much time on their mobile phones according to their parents.

Figure A.34: Frequency of reported imposition of parental smartphone rules – Fall & Spring.

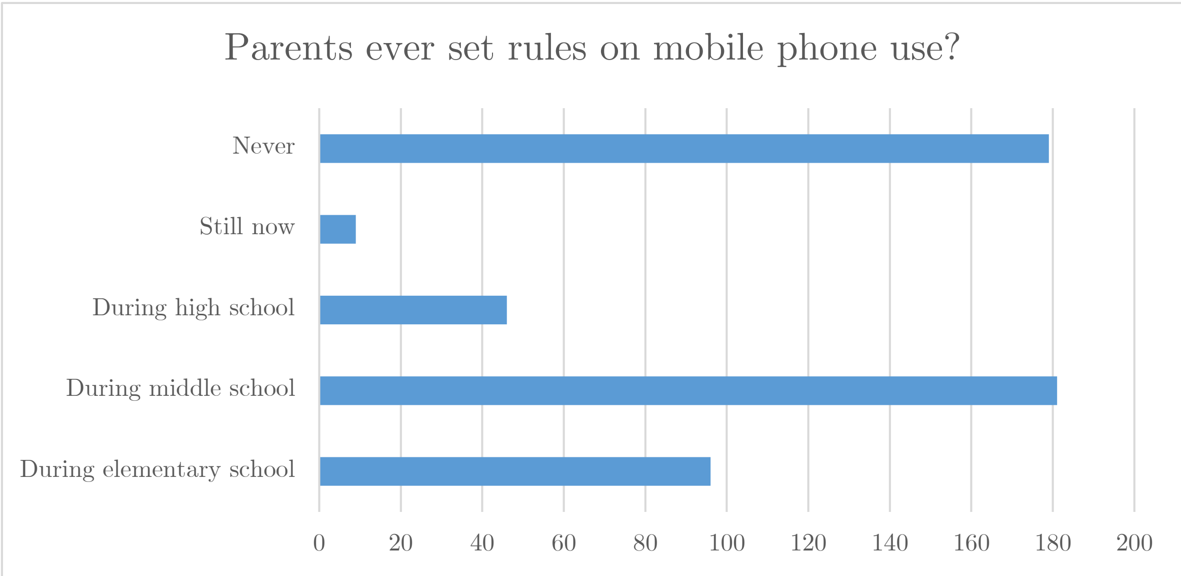
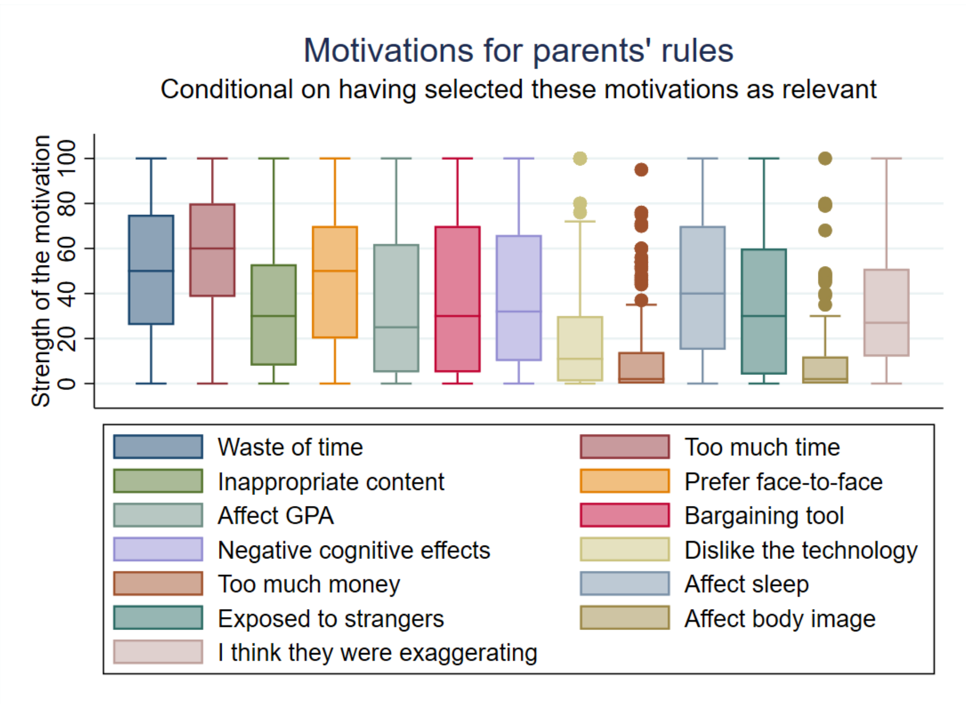


Figure A.35: Importance of factors in the imposition of smartphone rules by parents, conditional on having selected them as relevant – Fall & Spring.



A.3.9 The Network

The first weeks at Bocconi are the most important for establishing the network. Cognitive interviews in Spring 2020 have revealed that most friendships at the end of the third year of bachelor had started during the Math pre-courses and in the first days of lectures, by sitting next to people and chatting between classes.

In my surveys I tried to investigate the students' network by repeatedly asking them to name their closest friends. I first try to freeze the picture in the Fall Baseline during the very first week of regular courses, i.e. when the Math pre-courses are over, and in the Spring Baseline too. I also repeat the question in the Fall Pre-Midterms wave when discussing exam performance expectations (see section (1.4.4)).

In the Fall Baseline 284 students provided at least one valid name, mentioning on average 3.83 friends; in the Spring Baseline 128 students reported their friends' names, mentioning 4.32 of them on average (in both cases the maximum was 16 by survey design). Figure A.36 presents the outdegree frequency, i.e. the frequency of the number of peers nominated by each respondent.

Figure A.36: Frequency of the number of friends' names reported by respondents (outdegree) – Fall & Spring.

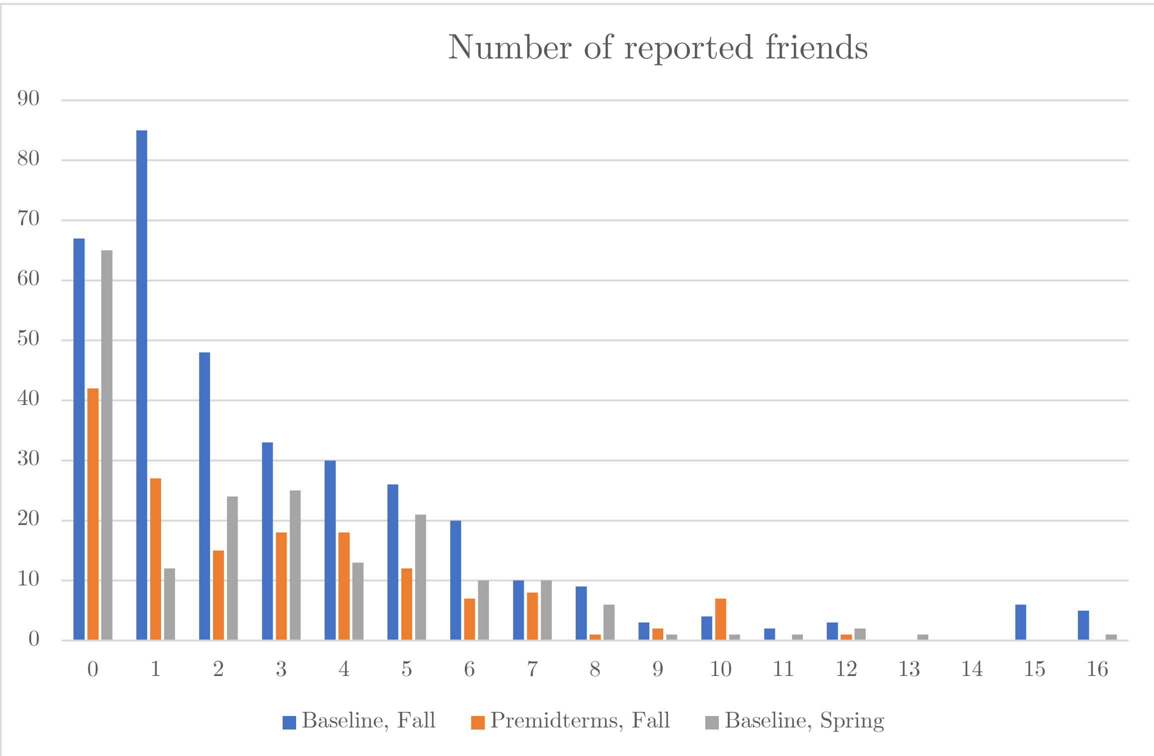


Figure A.37 presents a representation of the reconstructed network using the informa-

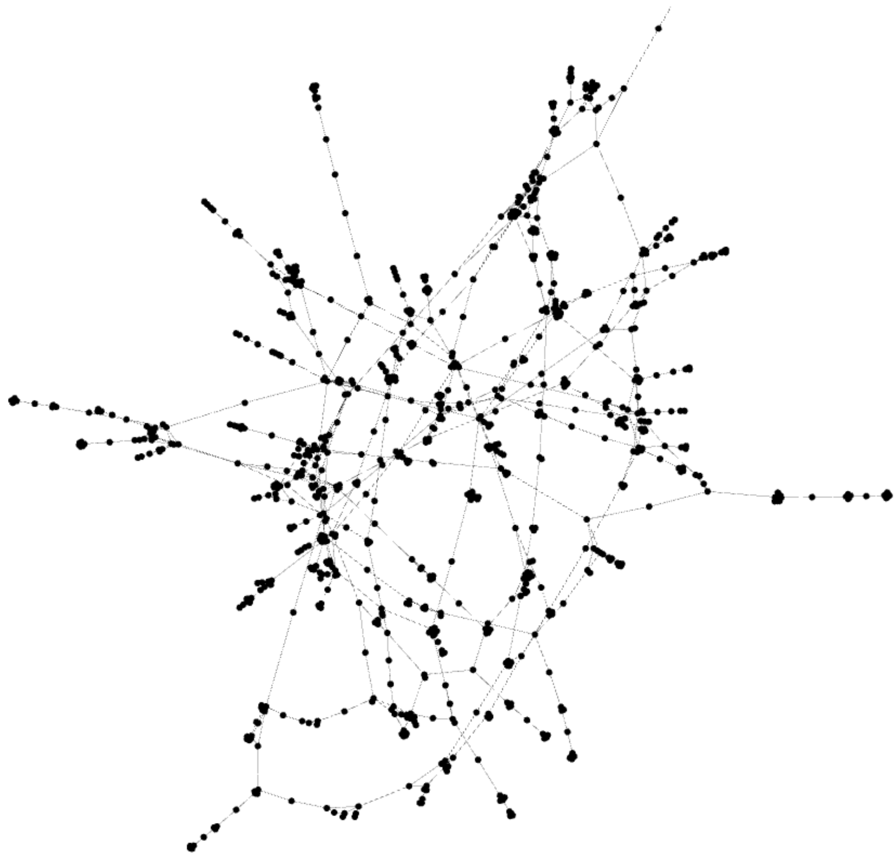
Table A.12: Summary statistics about the elicited network of friends – Fall & Spring.

Statistics	
N. Nodes	1230
N. Edges	1493
Avg. Degree	2.18
Avg. Clustering	0.082
Modularity	0.912
N. Communities	106
Avg. Path Length	10.786

Undirected graph

tion obtained from aggregating the three survey waves. Observations where friends could not be unambiguously identified have been discarded. In the graph the dots ("nodes") represent students, and the lines among them ("edges") represent friendship links; given the fact that the network is incomplete because I cannot observe the reports of each student, I consider these links as "undirected", in the sense that if A reports B as friend, then B will be considered to have A among his/her friends as well, despite the fact that B may have not answered the survey or have answered it without mentioning A. Table A.12 presents some summary statistics about the elicited network. It is easy to spot that compared to the 1230 people in the network (either nominated by others, or nominating friends, or both), the total number of edges (i.e. friendships links) is quite small, due to the fact that I miss them for the only-nominated students that never report their own network. The average degree (i.e. the average number of edges per node in a graph, i.e. average number of friendship connections per person) is quite small (2.18). The clustering coefficient can range from 0 to 1 and tells how much the nodes tend to be connected among themselves; a clustering coefficient of 1 means that, on average, if I take a node i and I look at its first degree neighbors (i.e. its direct connections), then all of them are connected among themselves, so 100% of the possible edges among them is in place. In this case it is relatively low (0.08) meaning that a student's reported friends have a low chance of being themselves connected possibly because of the non-reported friendship links.

Figure A.37: Representation of the elicited network – Fall & Spring.



I then provide some information about the potential network that could arise from connecting all the nodes for which I have information. Following Lee, Liu, et al. (2021) I use exogenous characteristics to predict a new adjacency matrix (i.e. a matrix that represents all the possible connections among these students). In Table A.13 I provide summary information about the administrative characteristics of the available nodes. I then expand my dataset in order to create all the possible friendship links[25] and I assess whether any two connected students share or not the same characteristics, using administrative information; Table A.14 summarises the fraction of potential edges that indeed have the same features. I then run a logistic regression to obtain the predicted adjacency matrix and the link formation probabilities, and I find evidence of homophily in the positive and significant coefficients for attending lectures in the same class, having the same citizenship[26], being of the same gender, and having a similar high school GPA, as presented in Table A.15. The McFadden's pseudo R^2 of the logistic regression is 0.19, suggesting that the dyadic characteristics considered may not be too informative in predicting alone the

[25] From 1230 nodes I obtain 1,492,062 potential edges.

[26] I divide citizenship into 9 macrocategories: Italian, Other European, Russian, Chinese, Other Asiatic, Middle Eastern, African, North American, South American.

Table A.13: Summary statistics of node characteristics – Fall & Spring.

	Mean	Std. Dev.	Min	Max
Female	.46	.50	0	1
Year of birth	2001	.583	1996	2003
Citizenship	*Italian*	83.36%		
	Other Europe	10.73 %		
	Middle East & Asia	3.45%		
	Rest of the World	2.46%		
Attendance Year	1	.161	1	3
Bachelor	*CLEAM*	39.02%		
	CLEF	8.92%		
	CLEACC	11.05%		
	BESS	6.87%		
	BIEF	7.2%		
	BIEM	16.37%		
	BIG	6.06%		
	BEMACS	3.68%		
	BAI	1.88%		
11^{th} grade GPA	8.45	.866	6	10
12^{th} grade GPA	8.59	.801	6	10
Tuition Category	*First*	3.68%		
	Second	4.42%		
	Third	5.89%		
	Fourth	86.01%		
N. obs.	1230			

Table A.14: Summary statistics of fraction of all potential edges sharing the same characteristics – Fall & Spring.

Same Gender	.
Both Born in Italy	.
Both Have Co-residing Parents	.
Both Have Older Siblings	.
Both Have Mothers with Education College+	.
Both Have Fathers with Education College+	.
Both Have Stay-at-Home Mothers	.
Both Have Blue-Collar Fathers	.
Same[a] 7^{th} grade GPA	.
N. obs.	585,990

[a]: within one standard deviation.

friendship formation.

Table A.15: Logistic regression of link formation – Fall & Spring.

Same Gender	.475***
	(.054)
Same Age	.018
	(.055)
Same Class	3.68***
	(.055)
Same^a 11th grade GPA	.246***
	(.060)
Same^a 12th grade GPA	.125**
	(.061)
Same Citizenship	.838***
	(.078)
Same Tuition Category	-.027
	(.059)
N. obs.	1,492,062
McFadden's pseudo R^2	0.1934

^{a}: within one standard deviation.
Standard errors in parentheses.
Statistical significance: *** p<0.01; ** p<0.05; * p<0.1.

A.3.10 The COVID-19 Pandemic

The pandemic crisis of 2020 had a deep impact on students' behaviors and expectations. In particular it affected the feasibility of and the willingness to be on campus. In July 2020 students were asked by the administration whether they had issues that prevented their physical presence in Milan and were then "opting out" of in-presence attendance, or whether they would be capable of attending classes on campus ("opting in"). Bocconi reported at the end of August 2020 that 90% of the students opted in[27].

In the baseline survey in the Fall semester I try to investigate some relevant features related to the COVID-19 perception and expectations. The following results are discussed splitting the sample into students who have opted out and those who have opted in, according to their self-reported status in my surveys.

Among respondents, in mid September 3% reports having tested positive for Coronavirus in the previous months, and an additional 5% suspects having been infected even without the confirmation of a test. Those who had not been infected in the past have been asked to report their own subjective probability of contracting the virus under different circumstances. Figures A.38 and A.39 show the distribution of infection probabilities if students were either fully on campus, or attending half of their classes in presence and half online, or fully online, conditional on their opt-in or opt-out status respectively. The subjective probabilities are decreasing across the three scenarios, and by comparing distributions for students who opted in *versus* those who opted out, conditional on choosing not to be on campus the median subjective probability of being infected is higher for both

[27]Refer to the article published by La Repubblica on August 31, 2020: milano.repubblica.it/bocconi.

Figure A.38: Own probability of being infected with Coronavirus under different attendance scenarios, conditional on having opted in for on-campus lectures – Baseline, Fall.

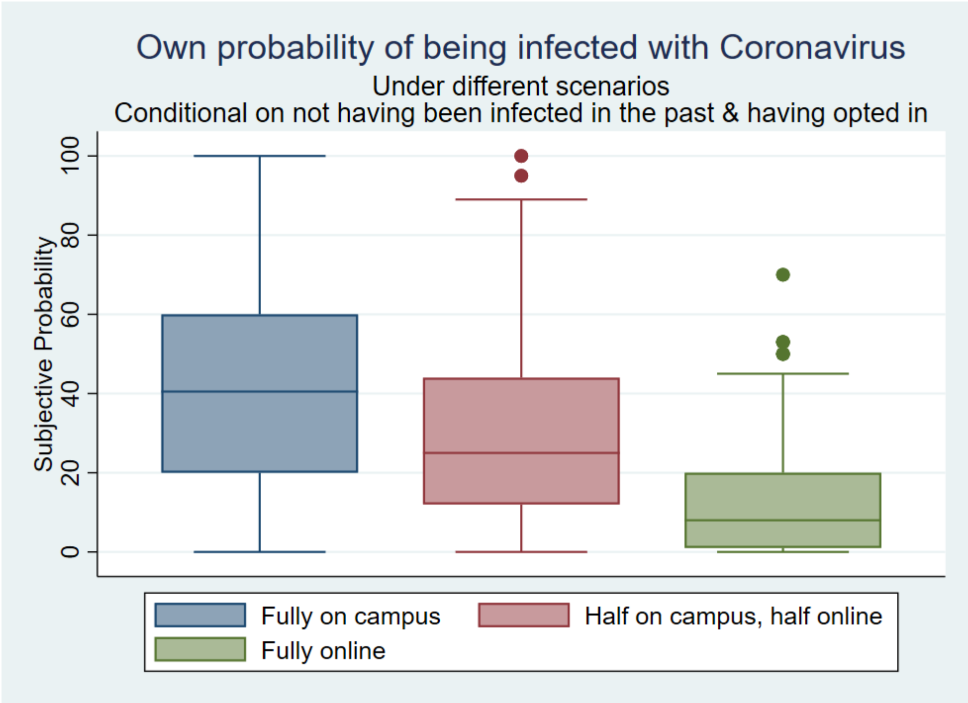


Figure A.39: Own probability of being infected with Coronavirus under different attendance scenarios, conditional on having opted out of on-campus lectures – Baseline, Fall.

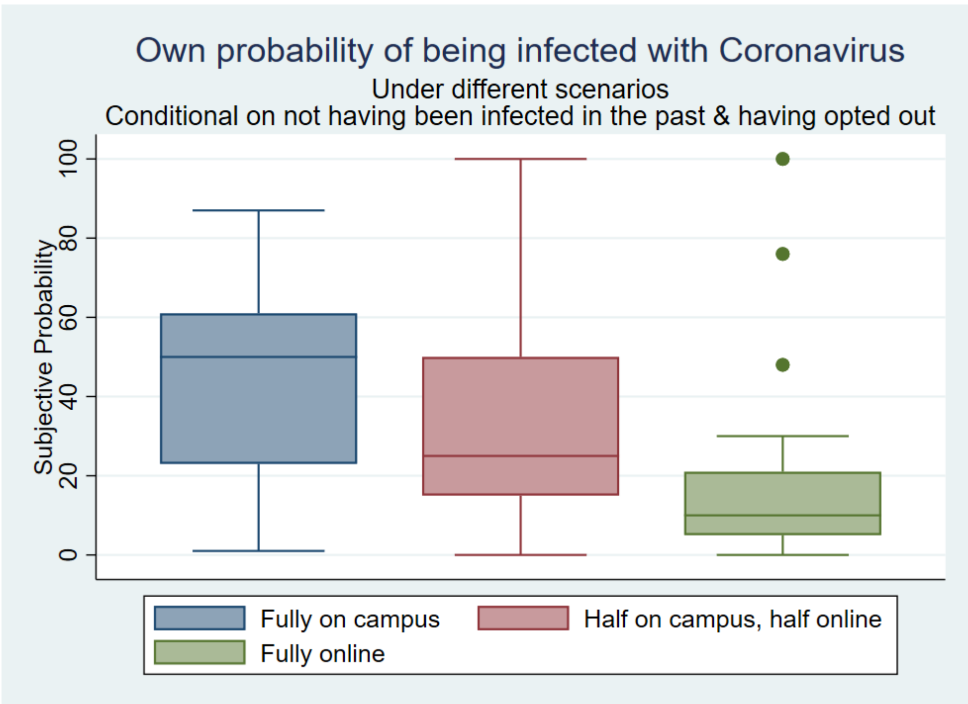
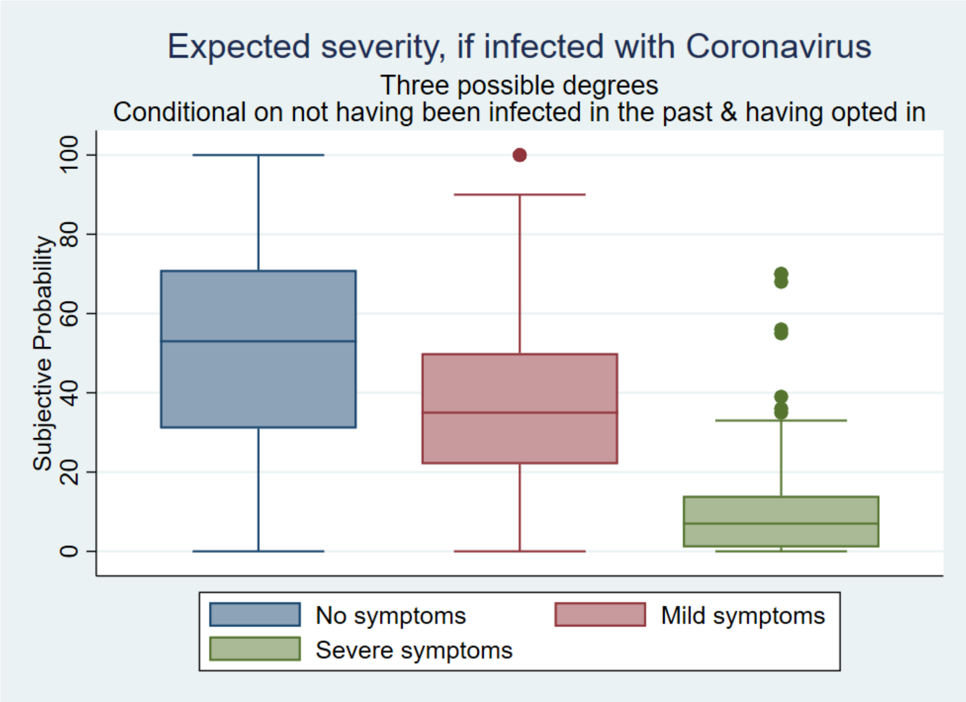


Figure A.40: Expected severity of symptoms if infected with Coronavirus, conditional on having opted in for on-campus lectures and not having been infected in the past – Baseline, Fall.



fully on campus and fully online, and the same for a blended situation.

An important concern is related to the severity of symptoms once infected with the virus. In fact, people aged 20 to 25 have lower risks of developing severe symptoms if not affected by other pre-existing conditions, and this may lead to the misconception that Coronavirus infection is not dangerous for this age group. Figures A.40 and A.41 report the distributions of subjective probabilities of developing either no symptoms, or mild or severe forms (probabilities across the three options had to sum to 100). The median subjective probability of developing no symptoms is actually higher for people that have opted out of on-campus presence, but in both subsamples the distribution ranges until 100. The median subjective probability of developing mild symptoms is higher for students who opted in, and of severe symptoms it is higher for people who opted out, as might be expected, even if the distribution for people who have opted in is less concentrated (probably due also to the smaller sample size of the opted-out sub-sample).

On top of health conditions we can expect students to care also about educational achievements. What are their expectations about GPAs under these different scenarios of attendance? In Figures A.42 and A.43 we see that students who have opted in expect a higher GPA under all scenarios.

In the survey students were asked which are the most important factors that led to

Figure A.41: Expected severity of symptoms if infected with Coronavirus, conditional on having opted out of on-campus lectures and not having been infected in the past – Baseline, Fall.

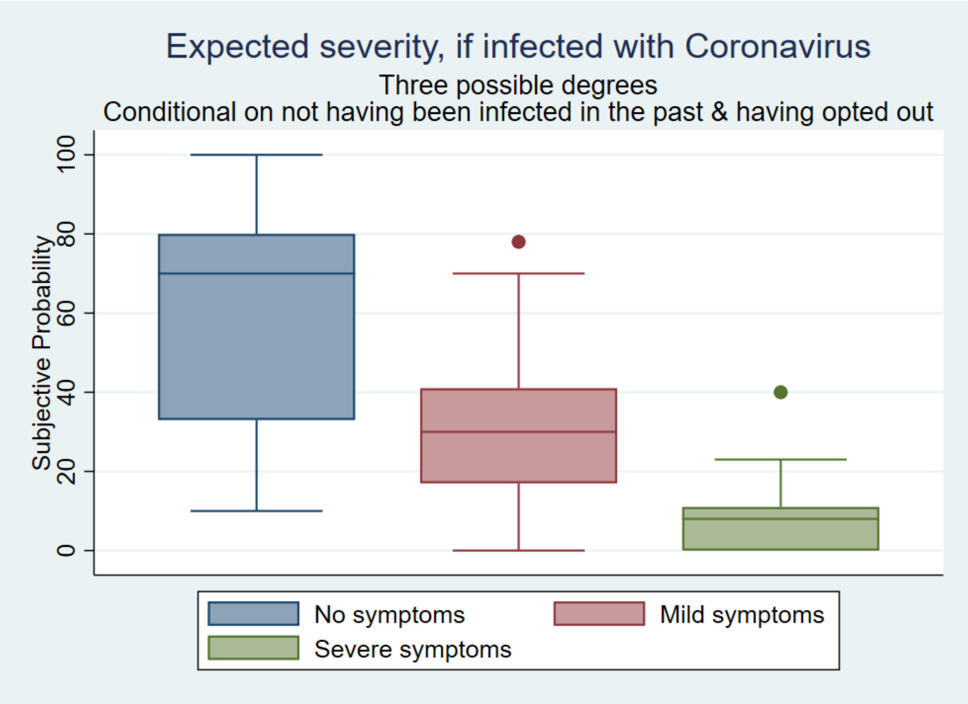


Figure A.42: Expected GPA under different attendance scenarios, conditional on having opted in for on-campus lectures – Baseline, Fall.

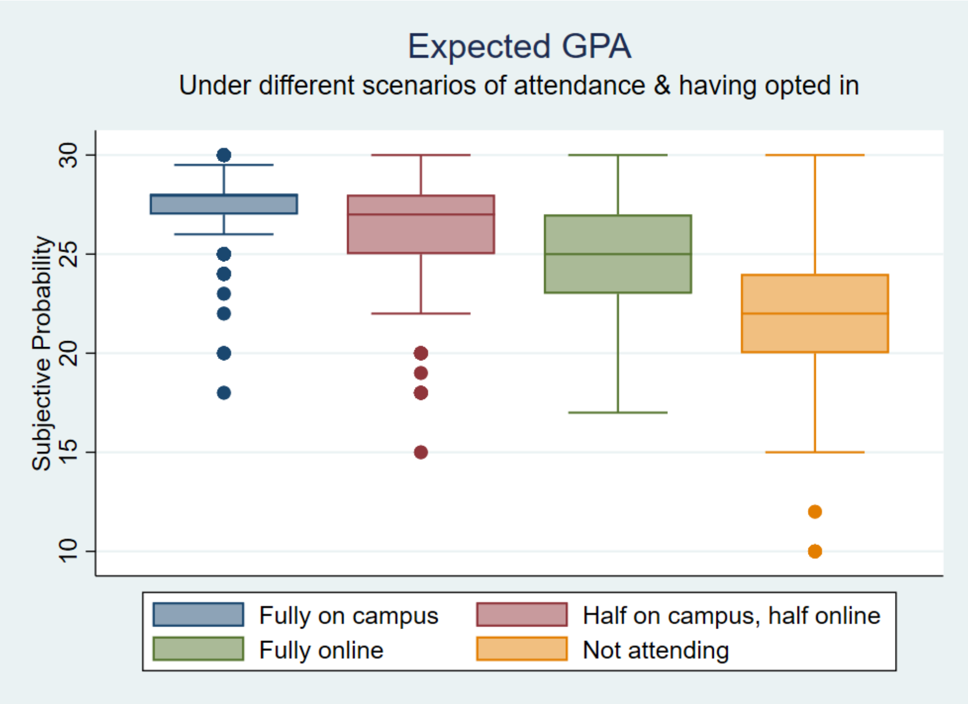
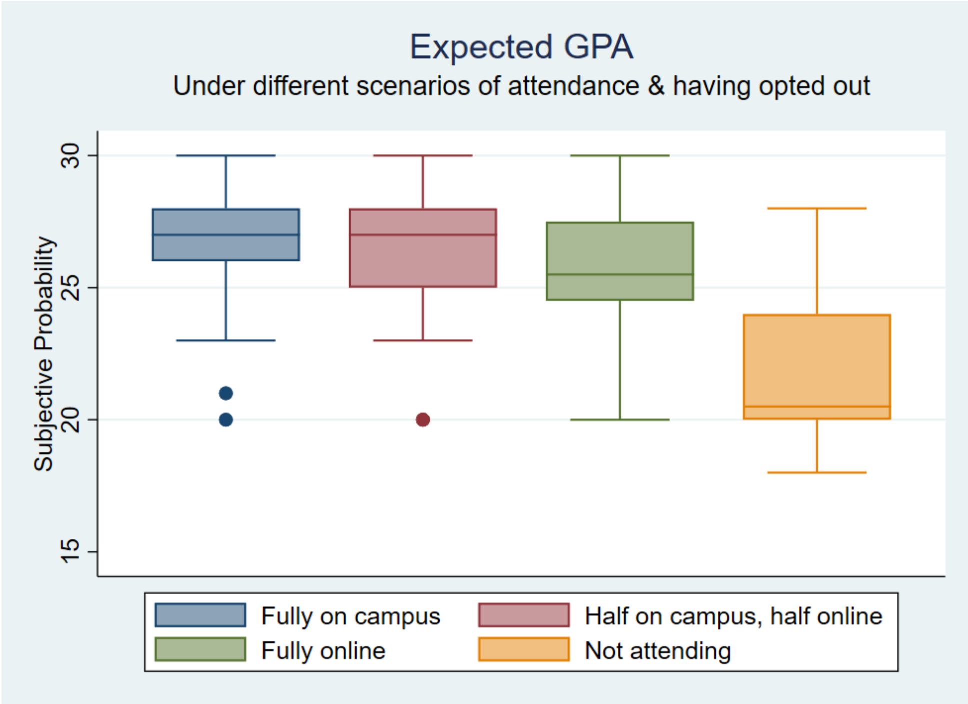


Figure A.43: Expected GPA under different attendance scenarios, conditional on having opted out of on-campus lectures – Baseline, Fall.



their choice, in both cases. Figure A.44 summarizes the most frequently chosen options, and conditional on choosing them Figure A.45 displays the distribution of the strength of the importance attributed to each motivation. Most of the selected choices refer to the preference for the on-campus experience and networking, together with a desire for independence and the expectation of better grades. For students who opted out, the most important factor seems to be the hard constraint of travel restrictions, visa and other bureaucratic issues, while health issues and the risk of Coronavirus infection seem to have a more moderate impact.

Figure A.44: Importance of different factors in the choice of attending classes on campus, by frequency of selection – Wave 1.

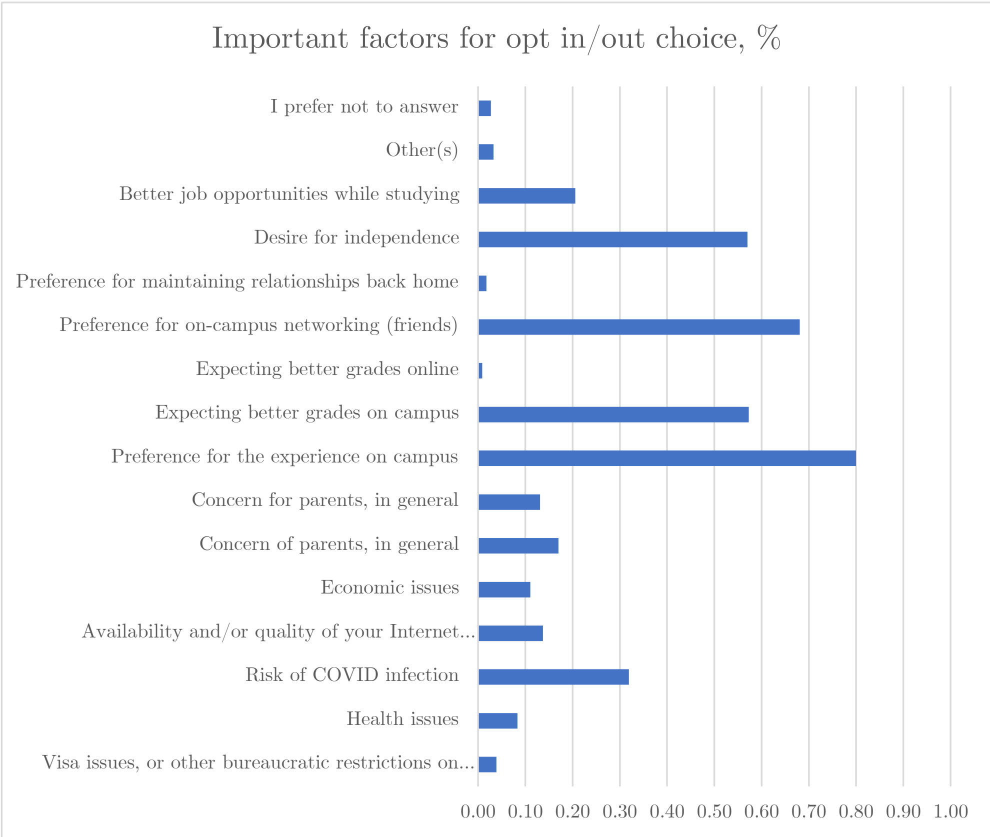
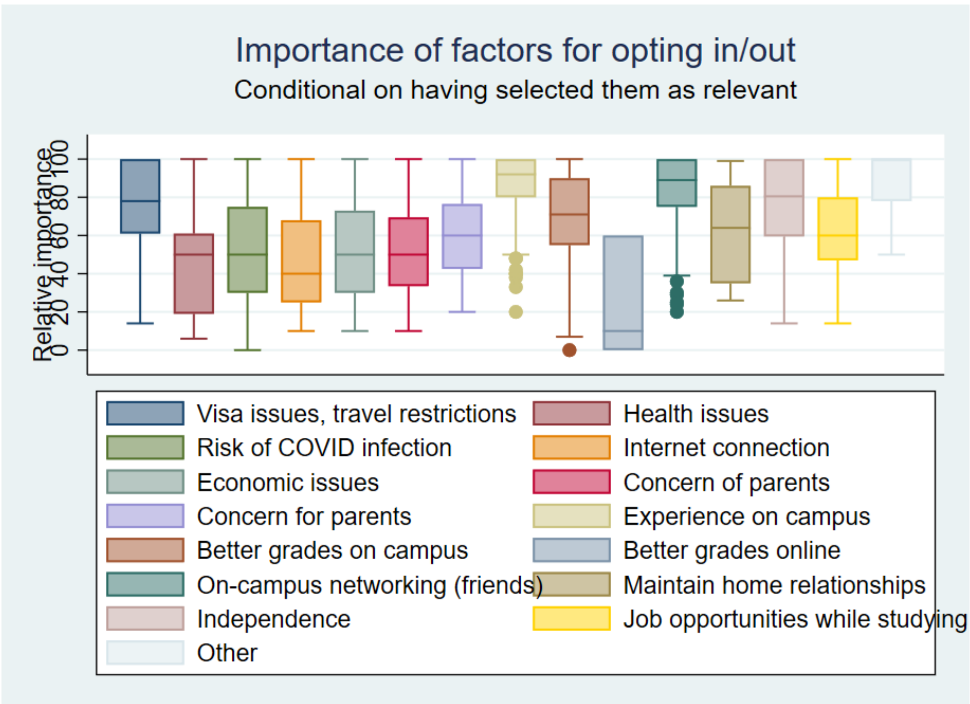


Figure A.45: Importance of different factors in the choice of attending classes on campus, conditional on having selected them as relevant – Wave 1.



A.4 Potential Selection Layers

A.4.1 Layer 2: Assigned to the Treatment *versus* Not Assigned

Table A.16: Administrative Variables, Assigned Never Participating vs Assigned Participating.

	Never Treated		Treated		Difference	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Year of birth	2001.164	0.589	2001.267	0.545	-0.103*	0.049
Female *(dummy)*	0.444	0.497	0.478	0.501	-0.035	0.042
Non-Italian citizen	0.179	0.384	0.180	0.385	-0.001	0.032
Bachelor programme	3.254	2.336	3.950	2.321	-0.696***	0.196
High School GPA	8.515	0.800	8.565	0.759	-0.050	0.067
Multiple Hypotheses Testing						F(5,1346)= 3.69 Prob> F = 0.0025
Observations	1218		161		1379	

A.4.2 Layer 3: Assigned to the Treatment *versus* Participating Users

Table A.17: Smartphone Addiction Scale Items at Baseline, Assigned Never Participating vs Assigned Participating.

	Assigned, Never		Assigned, Participating		Difference	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Part of my daily routine	84.821	13.887	87.718	18.525	-2.897	3.360
Checking has become a habit	82.513	16.097	83.077	21.610	-0.564	3.914
Used to escape from real life	27.974	26.742	39.842	30.984	-11.868*	5.835
Used to relax	51.947	28.037	63.513	24.884	-11.565*	5.134
Used to interact	74.051	23.237	83.590	18.990	-9.538*	4.019
Used to maintain relationships	81.308	18.088	81.090	20.703	0.218	3.898
Have problems when using it instead of doing other things	56.692	31.068	60.000	31.992	-3.308	6.215
Lose sleep due to time I spend on it	42.474	31.889	46.000	34.250	-3.526	6.640
Attempted to spend less time, but unable to	32.763	30.022	41.077	31.093	-8.314	6.083
Number of social media *(registered user)*	8.897	3.177	9.732	4.483	-0.834	0.800
Posting stories? *(dummy)*	0.641	0.486	0.831	0.377	-0.190*	0.082
Pressure to answer quickly *(slider: 0-100)*	43.923	29.924	47.885	28.281	-3.962	5.655
Multiple Hypotheses Testing						F(12,97)= 1.76 Prob> F = 0.0652
Observations	39		82		121	

Table A.18: Distractions Factors at Baseline, Assigned Never Participating vs Assigned Participating.

	Assigned, Never		Assigned, Participating		Difference	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Physical lecture						
Smartphone	29.884	25.067	34.269	26.651	-4.386	4.958
Laptop/tablet	8.767	11.246	8.936	11.402	-0.168	2.155
Other technological devices	1.744	5.067	1.359	6.077	0.385	1.090
Environment	22.326	18.723	23.487	17.729	-1.162	3.435
I don't get/seek distractions	34.535	32.849	31.692	33.393	2.843	6.306
Other	2.744	12.189	0.256	2.265	2.488	1.418
Online lecture						
Smartphone	45.442	25.090	51.584	26.011	-6.143	4.890
Laptop/tablet	12.000	15.376	16.909	18.274	-4.909	3.293
Other technological devices	1.326	5.567	1.130	6.195	0.196	1.138
Environment	13.698	17.867	9.545	14.718	4.152	3.029
I don't get/seek distractions	25.977	25.762	19.896	26.231	6.081	4.962
Other	0.930	6.100	0.844	5.584	0.086	1.099
Studying in a public space						
Smartphone	32.070	22.806	27.234	19.683	4.836	3.969
Laptop/tablet	4.698	9.130	6.987	11.140	-2.289	1.993
Other technological devices	1.581	6.021	0.545	3.817	1.036	0.899
Environment	28.581	19.745	38.935	27.278	-10.354*	4.733
I don't get/seek distractions	28.744	26.353	26.104	29.411	2.640	5.399
Other	4.163	17.166	0.195	1.405	3.968*	1.961
Studying at home						
Smartphone	39.233	21.434	43.104	27.361	-3.871	4.838
Laptop/tablet	11.186	15.881	12.208	15.471	-1.022	2.973
Other technological devices	2.395	7.932	1.377	6.479	1.019	1.338
Environment	10.558	16.317	13.455	19.507	-2.896	3.510
I don't get/seek distractions	33.256	29.463	28.506	30.946	4.749	5.792
Other	1.907	12.505	0.740	3.918	1.167	1.541
Multiple Hypotheses Testing						F(23,96)= 1.42 Prob> F = 0.1206
Observations	43		78		121	

Table A.19: Expected GPA at Baseline under Different Scenarios, Assigned Never Participating vs Assigned Participating.

	Assigned, Never		Assigned, Participating		Difference	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Fully on campus	26.393	4.745	26.712	4.095	-0.319	0.841
Half on campus, half online	26.012	2.607	26.630	1.983	-0.618	0.432
Fully online	24.000	4.631	25.158	3.852	-1.158	0.815
Not attending	21.051	4.953	22.222	4.622	-1.171	0.942
Multiple Hypotheses Testing						F(4,106)=1.48 Prob> F = 0.2137
Observations	42		73		115	

Table A.20: Personality Measures at Baseline, Assigned Never Participating vs Assigned Participating.

	Assigned, Never		Assigned, Participating		Difference	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Discounting *(slider: 0-100)*	47.923	25.473	50.058	28.552	-2.135	5.507
Risk taking *(slider: 0-100)*	57.300	21.456	57.271	25.523	0.029	4.783
Competitiveness *(slider: 0-100)*	66.675	23.097	71.286	24.100	-4.611	4.706
Grit *(scale: 0-8)*	3.337	0.648	3.500	0.640	-0.163	0.128
Multiple Hypotheses Testing						F(4,102)=0.68 Prob> F = 0.6098
Observations	40		70		110	

Table A.21: Administrative Variables, Assigned Never Participating vs Assigned Participating.

	Assigned, Never		Assigned, Participating		Difference	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Year of birth	2001.236	0.576	2001.283	0.530	-0.047	0.091
Female *(dummy)*	0.400	0.494	0.519	0.502	-0.119	0.083
Non-Italian citizen	0.182	0.389	0.179	0.385	0.003	0.064
Bachelor programme	3.509	2.410	4.179	2.250	-0.670	0.383
High School GPA	8.565	0.792	8.565	0.745	0.000	0.126
Multiple Hypotheses Testing						F(5,155)=1.27 Prob> F = 0.2815
Observations	55		106		161	

A.4.3 Layer 4: Participating *versus* Compliers

Table A.22: Smartphone Addiction Scale Items at Baseline, Participating vs Complying.

	Participating		Compliers		Difference	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Part of my daily routine	84.600	14.082	87.932	18.849	-3.332	8.612
Checking has become a habit	78.400	43.964	83.397	19.759	-4.997	10.039
Used to escape from real life	37.000	30.846	40.042	31.202	-3.042	14.428
Used to relax	61.200	25.626	63.671	25.007	-2.471	11.575
Used to interact	70.000	38.581	84.521	17.007	-14.521	8.678
Used to maintain relationships	67.200	32.958	82.041	19.589	-14.841	9.482
Have problems when using it instead of doing other things	40.000	48.249	61.370	30.587	-21.370	14.683
Lose sleep due to time I spend on it	31.250	42.074	46.808	33.937	-15.558	17.613
Attempted to spend less time, but unable to	31.200	36.355	41.753	30.874	-10.553	14.417
Number of social media *(registered user)*	11.000	4.301	9.649	4.510	1.351	2.076
Posting stories? *(dummy)*	0.800	0.447	0.833	0.375	-0.033	0.175
Pressure to answer quickly *(slider: 0-100)*	44.800	25.163	48.096	28.627	-3.296	13.154
Multiple Hypotheses Testing						F(12,61)=0.65 Prob> F = 0.7882
Observations	5		77		82	

Table A.23: Distractions Factors at Baseline, Participating vs Complying.

	Participating		Compliers		Difference	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Physical lecture						
Smartphone	26.000	18.193	34.836	27.131	-8.836	12.359
Laptop/tablet	7.800	11.628	9.014	11.464	-1.214	5.304
Other technological devices	0.000	0.000	1.452	6.274	-1.452	2.823
Environment	41.600	21.420	22.247	16.920	19.353*	7.945
I don't get/seek distractions	24.600	33.776	32.178	33.547	-7.578	15.514
Other	0.000	0.000	0.274	2.341	-0.274	1.053
Online lecture						
Smartphone	51.000	9.566	51.625	26.815	-0.625	12.109
Laptop/tablet	12.000	17.889	17.250	18.375	-5.250	8.486
Other technological devices	0.000	0.000	1.208	6.402	-1.208	2.881
Environment	28.200	25.193	8.250	13.035	19.950**	6.453
I don't get/seek distractions	8.800	17.021	20.667	26.663	-11.867	12.135
Other	0.000	0.000	0.903	5.773	-0.903	2.598
Studying in a public space						
Smartphone	24.800	7.463	27.403	20.276	-2.603	9.159
Laptop/tablet	9.200	12.775	6.833	11.103	2.367	5.179
Other technological devices	0.000	0.000	0.583	3.946	-0.583	1.776
Environment	60.000	25.426	37.472	26.956	22.528	12.430
I don't get/seek distractions	6.000	13.416	27.500	29.754	-21.500	13.465
Other	0.000	0.000	0.208	1.453	-0.208	0.654
Studying at home						
Smartphone	36.200	22.421	43.583	27.739	-7.383	12.709
Laptop/tablet	18.400	12.482	11.778	15.638	6.622	7.162
Other technological devices	0.000	0.000	1.472	6.692	-1.472	3.011
Environment	29.000	36.346	12.375	17.739	16.625	8.876
I don't get/seek distractions	16.400	25.146	29.347	31.280	-12.947	14.329
Other	0.000	0.000	0.792	4.049	-0.792	1.822
Multiple Hypotheses Testing						F(22,54)= 0.78 Prob> F = 0.7781
Observations	5		73		78	

Table A.24: Expected GPA at Baseline under Different Scenarios, Participating vs Complying.

	Participating		Compliers		Difference	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Fully on campus	24.000	7.906	26.912	3.701	-2.912	1.879
Half on campus, half online	26.000	1.225	26.676	2.026	-0.676	0.922
Fully online	26.600	2.191	25.051	3.936	1.549	1.788
Not attending	18.000	10.464	22.537	3.860	-4.537*	2.089
Multiple Hypotheses Testing						F(4,67)= 3.58 Prob> F = 0.0105
Observations	5		68		73	

Table A.25: Personality Measures at Baseline, Participating vs Complying.

	Participating		Compliers		Difference	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Discounting *(slider: 0-100)*	64.600	12.954	48.922	29.175	15.678	13.219
Risk taking *(slider: 0-100)*	51.000	29.741	57.754	25.372	-6.754	11.904
Competitiveness *(slider: 0-100)*	61.600	23.352	72.031	24.171	-10.431	11.195
Grit *(scale: 0-8)*	3.375	0.540	3.508	0.648	-0.133	0.332
Multiple Hypotheses Testing						F(4,63)=0.72 Prob> F = 0.5838
Observations	5		65		70	

Table A.26: Administrative Variables, Participating vs Complying.

	Participating		Compliers		Difference	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Year of birth	2001.400	0.548	2001.277	0.531	0.123	0.244
Female *(dummy)*	0.600	0.548	0.515	0.502	0.085	0.231
Non-Italian citizen	0.000	0.000	0.188	0.393	-0.188	0.176
Bachelor programme	6.600	2.074	4.059	2.199	2.541*	1.005
High School GPA	8.167	1.016	8.584	0.730	-0.418	0.340
Multiple Hypotheses Testing						F(5,100)=2.74 Prob> F = 0.0230
Observations	5		101		106	

A.4.4 Across Semesters: Assigned to the Treatment, Fall *versus* Spring

Table A.27: Expected GPA at Baseline under Different Scenarios, Fall vs Spring.

	Fall		Spring		Difference	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Fully on campus	27.313	1.731	26.108	5.534	0.836	0.922
Half on campus, half online	26.143	2.238	26.777	2.107	-0.478	0.502
Fully online	24.769	2.416	24.750	5.125	0.380	0.939
Not attending	21.875	2.952	21.977	5.628	0.070	0.976
Multiple Hypotheses Testing						F(4,248)=6.85 Prob> F = 0.000
Observations	56		65		96	

Table A.28: Personality Measures at Baseline, Fall vs Spring.

	Fall		Spring		Difference	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Discounting	46.860	26.744	50.911	29.394	-5.135	5.977
Rsik taking	57.707	23.692	59.397	25.190	0.976	5.091
Competitiveness	68.069	25.397	71.914	21.568	-2.462	5.146
Grit	3.575	0.714	3.485	0.573	0.149	0.137
Multiple Hypotheses Testing						F(4,291)=0.95 Prob> F = 0.4352
Observations	58		58		89	

Table A.29: ADMINISTRATIVE VARIABLES, FALL VS SPRING.

	Fall		**Spring**		**Difference**	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Year of birth	2001.153	0.634	2001.211	0.695	-0.157	0.104
Female *(dummy)*	0.458	0.499	0.508	0.502	-0.052	0.086
Non-Italian citizen	0.166	0.373	0.188	0.392	-0.109	0.066
Bachelor programme	3.414	2.444	3.781	2.401	-0.585	0.418
High School GPA	8.531	0.789	8.608	0.783	-0.172	0.134
Multiple Hypotheses Testing						F(5,509)=1.07 Prob> F = 0.3769
Observations	596		128		540	

A.5 Propensity Score Balance Checks

Table A.30: FALL & SPRING MIDTERM GRADES – BALANCING CHECK FROM **pstest**.

	Fall				**Spring**				
Variable	**Managem.**	**Math**	**Micro**	**Other**	**Macro**	**Math**	**Computer Sc.**	**Law**	**Other**
Year of birth	0.687	0.674	0.863	0.943	0.825	0.82	0.971	0.838	0.891
Female *(dummy)*	0.985	0.988	0.916	0.695	0.829	0.973	0.985	0.772	0.872
Non-Italian citizen	0.696	0.692	0.833	0.944	0.998	0.757	0.959	0.987	0.832
Bachelor programme	0.842	0.748	0.869	0.963	0.794	0.798	0.748	0.796	.
High School GPA	0.975	0.808	0.822	0.931	0.892	0.935	0.958	0.977	0.624
SAS: Part of my daily routine	0.905	0.868			0.775	0.811	0.73	0.986	0.996
SAS: Used to escape from reality	0.722	0.918			0.64	0.68	0.668	0.669	0.793
SAS: Used to maintain relationships	0.724	0.879			0.869	0.802	0.754	0.91	0.916
SAS: Problems when use it instead of doing other things	0.972	0.603			0.585	0.701	0.523	0.941	0.951
SAS: Lose sleep due to time spent on smartphone	0.971	0.68			0.656	0.903	0.56	0.83	0.775
SAS: Attempted to spend less time, but unable to	0.74	0.594			0.452	0.652	0.389	0.652	0.813
Num. Social Media	0.371	0.671			0.598	0.633	0.648	0.858	0.93
Pressure to answer	0.81	0.885			0.819	0.896	0.662	0.872	0.705

SAS: Smartphone Addiction Scale item.

Table A.31: Fall & Spring Midterm Aggregated Grades and GPA – Balancing check from **pstest**.

	Aggregated Grades				Midterms GPA
Variable	**Quantitative**	**Qualitative**	**Economic Principles**	**Other**	
Year of birth	0.966	0.671	0.923	0.676	0.821
Female *(dummy)*	0.874	0.855	0.878	0.787	0.925
Non-Italian citizen	0.817	0.988	0.935	0.852	0.61
Bachelor programme	0.718	0.749	0.871	.	0.952
High School GPA	0.926	0.883	0.99	0.949	0.905
SAS: Part of my daily routine	0.775	0.834	0.755	0.984	0.894
SAS: Used to escape from reality	0.559	0.709	0.542	0.937	0.756
SAS: Used to maintain relationships	0.872	0.88	0.91	0.952	0.986
SAS: Problems when use it instead of doing other things	0.64	0.748	0.573	0.826	0.797
SAS: Lose sleep due to time spent on smartphone	0.64	0.768	0.724	0.871	0.852
SAS: Attempted to spend less time, but unable to	0.668	0.623	0.708	0.605	0.902
Num. Social Media	0.55	0.744	0.477	0.834	0.536
Num Midterms	0.763	0.641	0.734	0.661	0.927
Pressure to answer					0.863

SAS: Smartphone Addiction Scale item.

Table A.32: Fall & Spring Midterm Expected Grades – Balancing check from **pstest**.

	Fall				Spring				
Variable	**Managem.**	**Math**	**Micro**	**Other**	**Macro**	**Math**	**Computer Sc.**	**Law**	**Other**
Year of birth	0.975	0.83	0.539	0.561	0.978	0.629	0.746	0.878	0.798
Female *(dummy)*	0.955	0.687	0.684	0.777	0.948	0.628	0.439	0.753	0.997
Non-Italian citizen	0.97	0.728	0.819	0.949	0.946	0.491	0.711	0.875	0.813
Bachelor programme	0.678	0.964	0.524	0.799	0.756	0.99	0.367	0.709	0.774
High School GPA	0.854	0.9	0.698	0.596	0.864	0.927	0.492	0.536	0.902
SAS: Part of my daily routine	0.892	0.569	0.665	0.938			0.699		
SAS: Used to escape from reality	0.971	0.799	0.509	0.907			0.22		
SAS: Used to maintain relationships	0.859	0.688	0.495	0.98			0.864		
SAS: Problems when use it instead of doing other things	0.874	0.932	0.442	0.691			0.324		
SAS: Lose sleep due to time spent on smartphone	0.967	0.828	0.603	0.972			0.583		
SAS: Attempted to spend less time, but unable to	0.979	0.74	0.457	0.87			0.658		
Num. Social Media	0.908	0.954	0.897	0.93			0.463		
Pressure to answer	0.743	0.908	0.774	0.942			0.833		

SAS: Smartphone Addiction Scale item.

Table A.33: Fall & Spring Midterm Percent Chance of Passing – Balancing check from **pstest**.

Variable	Fall				Spring				
	Managem.	**Math**	**Micro**	**Other**	**Macro**	**Math**	**Computer Sc.**	**Law**	**Other**
Year of birth	0.622	0.929	0.759	0.297	0.414	0.836	0.786	0.878	0.828
Female *(dummy)*	0.978	0.808	0.754	0.373	0.881	0.94	0.973	0.753	0.724
Non-Italian citizen	0.761	0.855	0.588	0.253	0.802	0.95	0.972	0.875	0.709
Bachelor programme	0.726	0.581	0.745	0.505	0.62	0.952	0.699	0.709	0.859
High School GPA	0.883	0.744	0.733	0.643	0.639	0.795	0.876	0.536	0.993
SAS: Part of my daily routine				0.556	0.406	0.713	0.917		
SAS: Used to escape from reality				0.306	0.881	0.718	0.996		
SAS: Used to maintain relationships				0.543	0.645	0.804	0.743		
SAS: Problems when use it instead of doing other things				0.247	0.894	0.818	0.847		
SAS: Lose sleep due to time spent on smartphone				0.565	0.652	0.526	0.637		
SAS: Attempted to spend less time, but unable to				0.379	0.632	0.589	0.722		
Num. Social Media				0.458	0.502	0.727	0.959		
Pressure to answer				0.806	0.733	0.999	0.931		

SAS: Smartphone Addiction Scale item.

Table A.34: Fall & Spring Midterm Course Evaluations (Lecturer stimulates interest) – Balancing check from **pstest**.

Variable	Fall				Spring				
	Managem.	**Math**	**Micro**	**Other**	**Macro**	**Math**	**Computer Sc.**	**Law**	**Other**
Year of birth	0.648	0.785	0.947	0.717	0.768	0.886	0.778	0.631	0.922
Female *(dummy)*	0.855	0.993	0.959	0.98	0.824	0.933	0.973	1	0.913
Non-Italian citizen	0.94	0.937	0.911	0.952	0.543	0.817	0.811	0.804	0.715
Bachelor programme	0.866	0.837	0.944	0.878	0.927	0.959	0.704	0.649	0.988
High School GPA	0.994	0.845	0.582	0.846	0.866	0.881	0.798	0.24	0.972
SAS: Part of my daily routine	0.61	0.732	0.902	0.689	0.632	0.633	0.947		
SAS: Used to escape from reality	0.686	0.904	0.77	0.918	0.794	0.82	0.961		
SAS: Used to maintain relationships	0.697	0.686	0.831	0.623	0.531	0.598	0.724		
SAS: Problems when use it instead of doing other things	0.728	0.764	0.852	0.829	0.964	0.779	0.793		
SAS: Lose sleep due to time spent on smartphone	0.726	0.712	0.999	0.841	0.637	0.774	0.669		
SAS: Attempted to spend less time, but unable to	0.629	0.835	0.876	0.912	0.562	0.668	0.793		
Num. Social Media	0.826	0.874	0.948	0.959	0.227	0.431	0.996		
Pressure to answer	0.948	0.939	0.987	0.916	0.596	0.952	0.98		

SAS: Smartphone Addiction Scale item.

Table A.35: Fall & Spring Midterm Course Evaluations (Topics are hard) – Balancing check from **pstest**.

	Fall				Spring				
Variable	**Managem.**	**Math**	**Micro**	**Other**	**Macro**	**Math**	**Computer Sc.**	**Law**	**Other**
Year of birth	0.648	0.784	0.953	0.794	0.768	0.886	0.778	0.631	0.922
Female *(dummy)*	0.855	0.991	0.957	0.851	0.824	0.933	0.973	1	0.913
Non-Italian citizen	0.94	0.933	0.929	0.957	0.543	0.817	0.811	0.804	0.715
Bachelor programme	0.866	0.838	0.942	0.959	0.927	0.959	0.704	0.649	0.988
High School GPA	0.994	0.842	0.576	0.923	0.866	0.881	0.798	0.24	0.972
SAS: Part of my daily routine	0.61	0.728	0.902	0.973	0.632	0.633	0.947		
SAS: Used to escape from reality	0.686	0.906	0.769	0.914	0.794	0.82	0.961		
SAS: Used to maintain relationships	0.697	0.685	0.836	0.737	0.531	0.598	0.724		
SAS: Problems when use it instead of doing other things	0.728	0.764	0.852	0.821	0.964	0.779	0.793		
SAS: Lose sleep due to time spent on smartphone	0.726	0.712	0.998	0.728	0.637	0.774	0.669		
SAS: Attempted to spend less time, but unable to	0.629	0.834	0.878	0.684	0.562	0.668	0.793		
Num. Social Media	0.826	0.872	0.947	0.878	0.227	0.431	0.996		
Pressure to answer	0.948	0.939	0.986	0.886	0.596	0.952	0.98		

SAS: Smartphone Addiction Scale item.

Table A.36: Fall & Spring Midterm Course Evaluations (Personal interest) – Balancing check from **pstest**.

	Fall				Spring				
Variable	**Managem.**	**Math**	**Micro**	**Other**	**Macro**	**Math**	**Computer Sc.**	**Law**	**Other**
Year of birth	0.648	0.784	0.953	0.769	0.768	0.886	0.778	0.458	0.922
Female *(dummy)*	0.855	0.991	0.957	0.998	0.824	0.933	0.973	0.808	0.913
Non-Italian citizen	0.94	0.933	0.929	0.906	0.543	0.817	0.811	0.877	0.715
Bachelor programme	0.866	0.838	0.942	0.988	0.927	0.959	0.704	0.815	0.988
High School GPA	0.994	0.842	0.576	0.87	0.866	0.881	0.798	0.449	0.972
SAS: Part of my daily routine	0.61	0.728	0.902	0.817	0.632	0.633	0.947		
SAS: Used to escape from reality	0.686	0.906	0.769	0.949	0.794	0.82	0.961		
SAS: Used to maintain relationships	0.697	0.685	0.836	0.599	0.531	0.598	0.724		
SAS: Problems when use it instead of doing other things	0.728	0.764	0.852	0.74	0.964	0.779	0.793		
SAS: Lose sleep due to time spent on smartphone	0.726	0.712	0.998	0.786	0.637	0.774	0.669		
SAS: Attempted to spend less time, but unable to	0.629	0.834	0.878	0.917	0.562	0.668	0.793		
Num. Social Media	0.826	0.872	0.947	0.991	0.227	0.431	0.996		
Pressure to answer	0.948	0.939	0.986	0.993	0.596	0.952	0.98		

SAS: Smartphone Addiction Scale item.

Table A.37: Fall & Spring Midterm Course Evaluations (Helpful online activities) – Balancing check from **pstest**.

	Fall				Spring				
Variable	**Managem.**	**Math**	**Micro**	**Other**	**Macro**	**Math**	**Computer Sc.**	**Law**	**Other**
Year of birth	0.703	0.899	0.999	0.851	0.731	0.885	0.817	0.458	0.717
Female *(dummy)*	0.979	0.924	0.815	0.982	0.763	0.927	0.987	0.808	0.788
Non-Italian citizen	0.973	0.888	0.935	0.831	0.798	0.808	0.955	0.877	0.776
Bachelor programme	0.996	0.796	0.958	0.897	0.8	0.961	0.996	0.815	0.979
High School GPA	0.994	0.949	0.717	0.565	0.729	0.871	0.957	0.449	0.987
SAS: Part of my daily routine	0.856	0.775	0.757	0.937	0.678	0.611	0.729		
SAS: Used to escape from reality	0.866	0.778	0.703	0.85	0.773	0.848	0.832		
SAS: Used to maintain relationships	0.677	0.831	0.984	0.864	0.605	0.609	0.603		
SAS: Problems when use it instead of doing other things	0.862	0.78	0.877	0.862	0.884	0.769	0.714		
SAS: Lose sleep due to time spent on smartphone	0.818	0.689	0.907	0.813	0.652	0.803	0.519		
SAS: Attempted to spend less time, but unable to	0.872	0.642	0.779	0.853	0.564	0.688	0.719		
Num. Social Media	0.811	0.866	0.883	0.933	0.326	0.434	0.976		
Pressure to answer	0.84	0.826	0.938	0.889	0.574	0.949	0.978		

SAS: Smartphone Addiction Scale item.

Table A.38: Fall & Spring Anxiety Levels – Balancing check from **pstest**.

	Fall		Spring	
Variable	**Pre-Midterms**	**End of Semester**	**Post-Midterms**	**End of Semester**
Year of birth	0.771	0.917	0.523	0.825
Female *(dummy)*	0.777	0.992	0.88	0.465
Non-Italian citizen	0.856	0.777	0.562	0.641
Bachelor programme	0.923	0.807	0.512	0.587
High School GPA	0.866	0.928	0.838	0.629
SAS: Part of my daily routine	0.978	0.998	0.978	0.976
SAS: Used to escape from reality	0.721	0.744	0.854	0.575
SAS: Used to maintain relationships	0.911	0.772	0.916	0.968
SAS: Problems when use it instead of doing other things	0.595	0.944	0.907	0.436
SAS: Lose sleep due to time spent on smartphone	0.996	0.742	0.506	0.917
SAS: Attempted to spend less time, but unable to	0.78	0.819	0.743	0.854
Num. Social Media	0.673	0.838	0.597	0.991
Pressure to answer	0.913	0.966	0.871	0.796

SAS: Smartphone Addiction Scale item.

Table A.39: Fall & Spring Study Time – Balancing check from **pstest**.

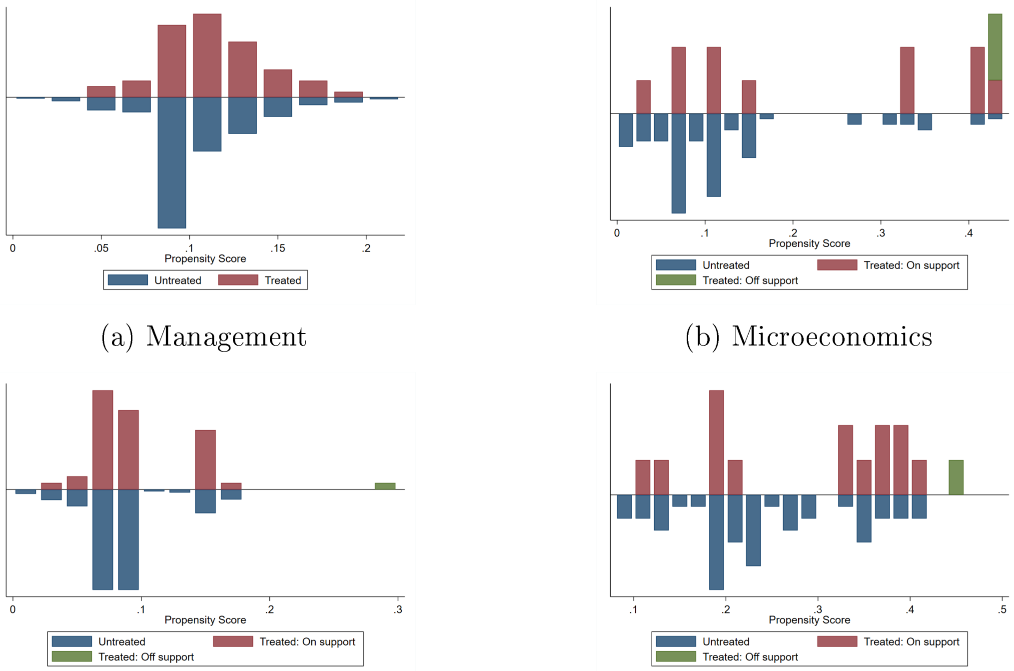
Variable	**Fall**	**Spring**
Year of birth	0.849	0.725
Female *(dummy)*	0.913	0.886
Non-Italian citizen	0.654	0.744
Bachelor programme	0.887	0.555
High School GPA	0.466	0.562
Planned study time (Baseline)	0.169	0.653
SAS: Part of my daily routine	0.403	0.954
SAS: Used to escape from reality	0.542	0.823
SAS: Used to maintain relationships	0.932	0.81
SAS: Problems when use it instead of doing other things	0.486	0.961
SAS: Lose sleep due to time spent on smartphone	0.354	0.561
SAS: Attempted to spend less time, but unable to	0.422	0.819
Num. Social Media	0.316	0.762
Pressure to answer	0.771	0.8

SAS: Smartphone Addiction Scale item.

A.5.1 Graphical Checks of Overlap

The propensity scores were constructed using both the administrative information and the survey measures that proved to be unbalanced at baseline. Where the sub-caption reports “Admin only” then survey measures were excluded for the purposes of this representation.

Figure A.46: Overlap of treatment and control groups – Fall Midterm Grades



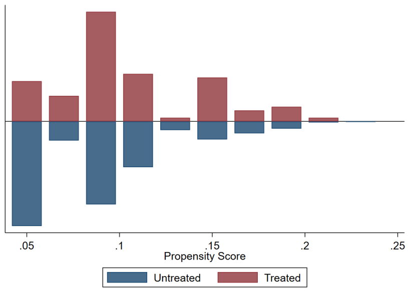
(a) Management

(b) Microeconomics

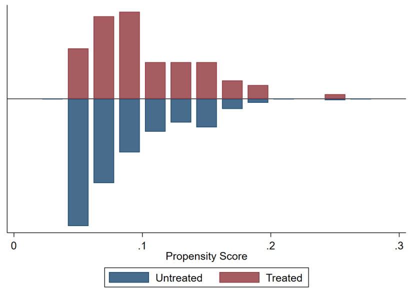
(c) Mathematics

(d) Other

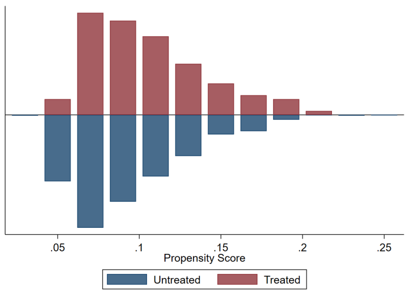
Figure A.47: Overlap of treatment and control groups – Spring Midterm Grades



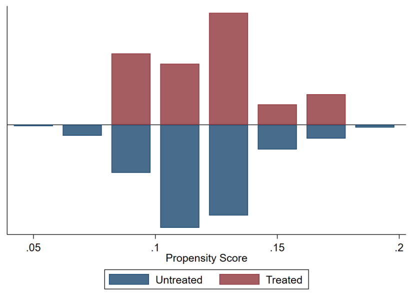
(a) Macroeconomics



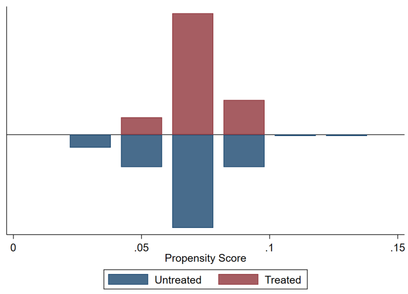
(b) Mathematics



(c) Computer Science

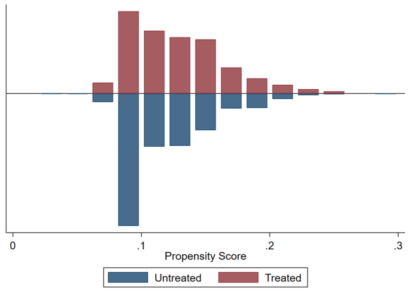


(d) Law

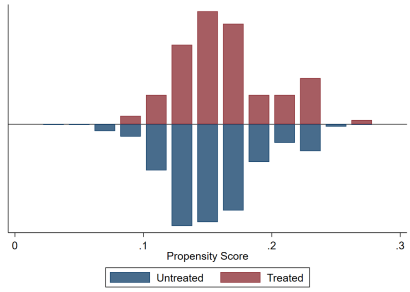


(e) Other

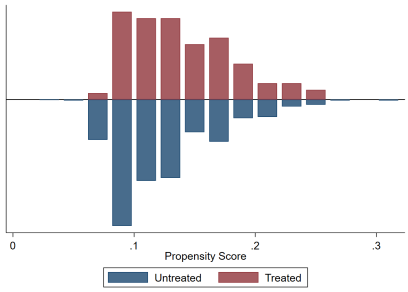
Figure A.48: Overlap of treatment and control groups – Fall & Spring Aggregated Midterm Grades



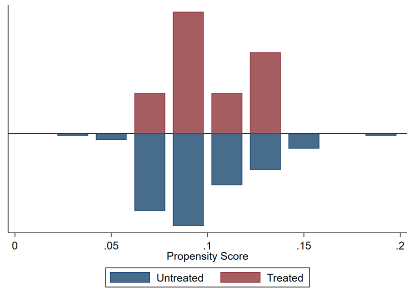
(a) Quantitative



(b) Qualitative

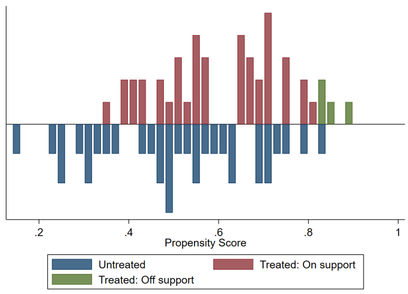


(c) Economic Principles

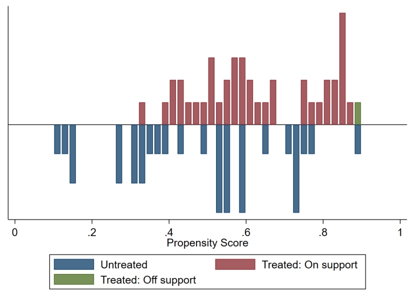


(d) Other

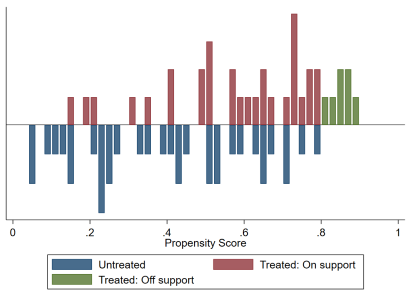
Figure A.49: Overlap of treatment and control groups – Fall Expected Grades



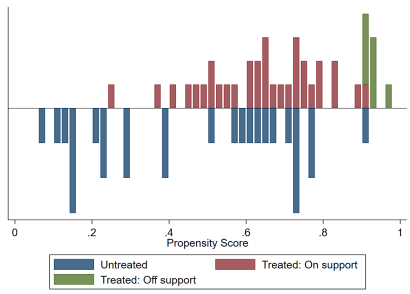
(a) Management



(b) Microeconomics

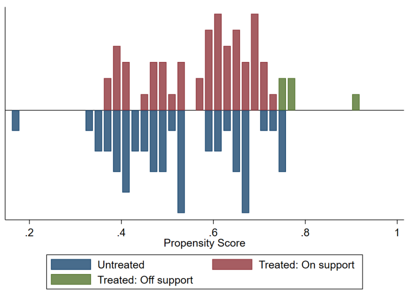


(c) Mathematics

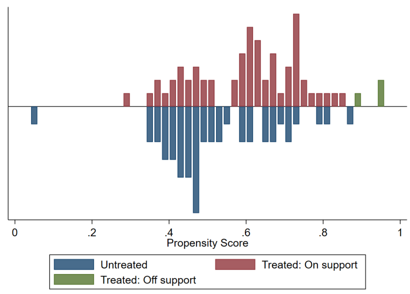


(d) Other

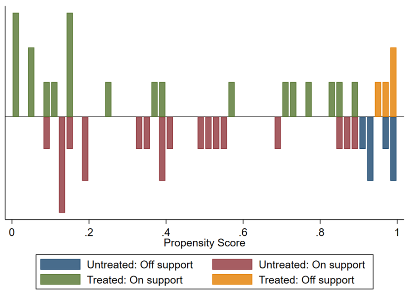
Figure A.50: Overlap of treatment and control groups – Spring Expected Grades



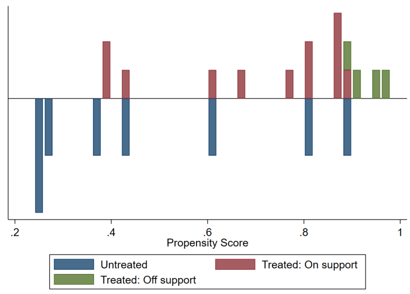
(a) Macroeconomics (Admin Only)



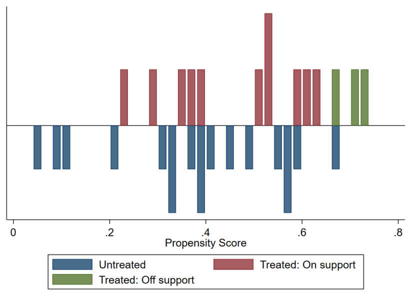
(b) Mathematics (Admin Only)



(c) Computer Science

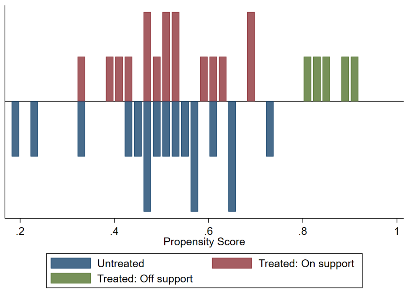


(d) Law (Admin Only)

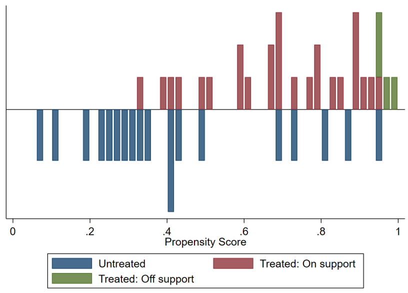


(e) Other (Admin Only)

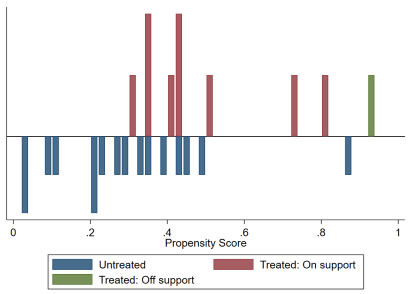
Figure A.51: Overlap of treatment and control groups – Fall Expected Percent Chance of Passing the Exam



(a) Management (Admin Only)

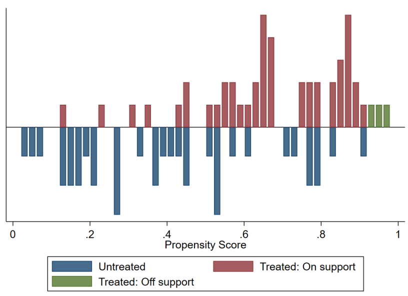


(b) Microeconomics

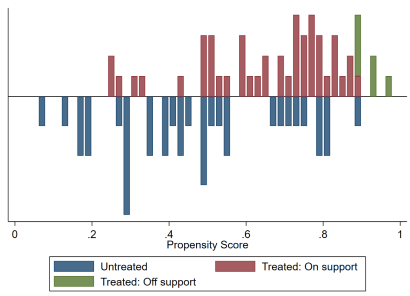


(c) Mathematics (Admin Only)

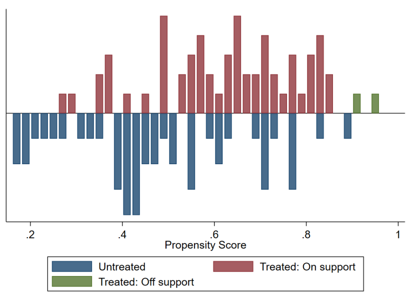
Figure A.52: Overlap of treatment and control groups – Spring Expected Percent Chance of Passing the Exam



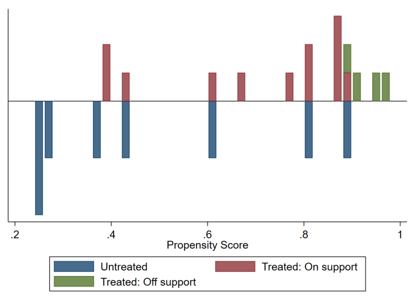
(a) Macroeconomics



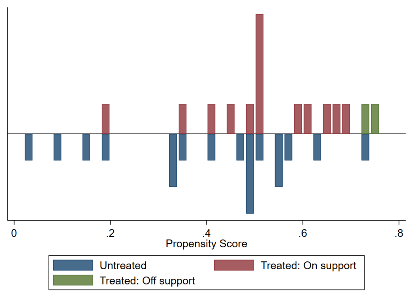
(b) Mathematics



(c) Computer Science

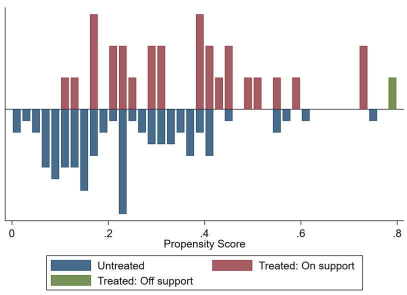


(d) Law (Admin Only)

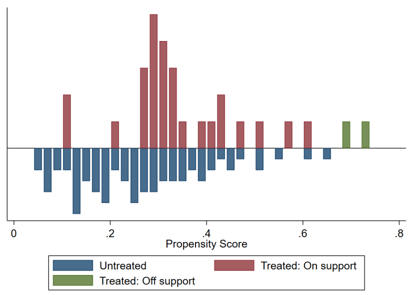


(e) Other (Admin Only)

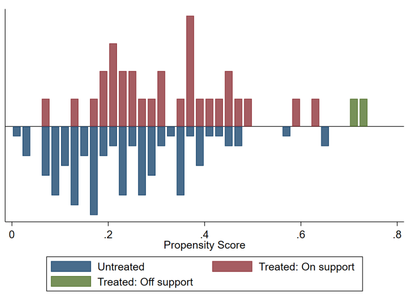
Figure A.53: Overlap of treatment and control groups – Fall Course Evaluations (Lecturer stimulates interest)



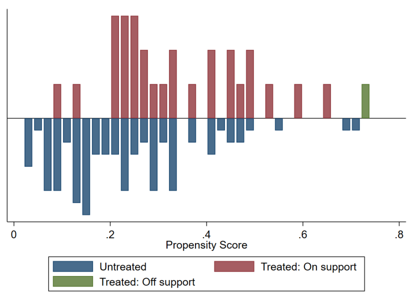
(a) Management



(b) Microeconomics

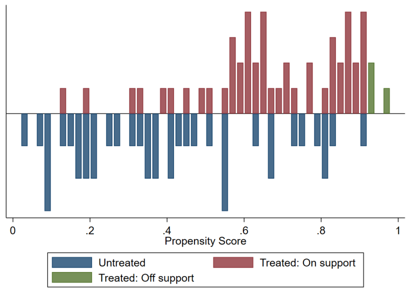


(c) Mathematics

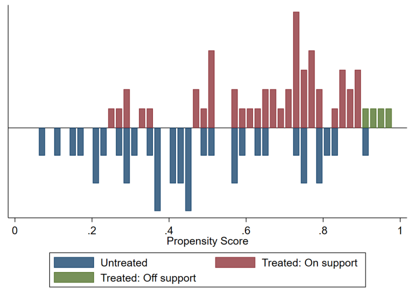


(d) Other

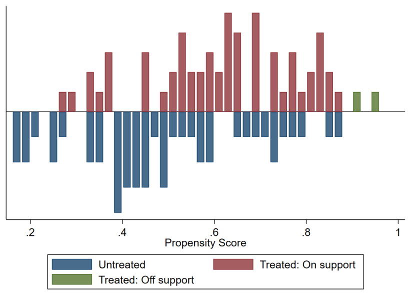
Figure A.54: Overlap of treatment and control groups – Spring Course Evaluations (Lecturer stimulates interest)



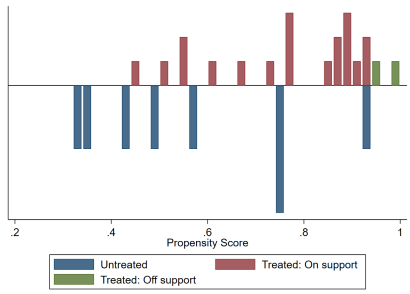
(a) Macroeconomics



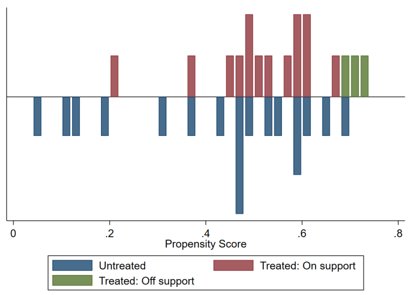
(b) Mathematics



(c) Computer Science

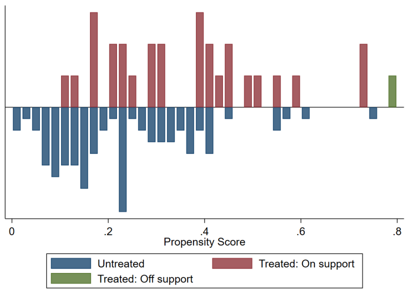


(d) Law (Admin Only)

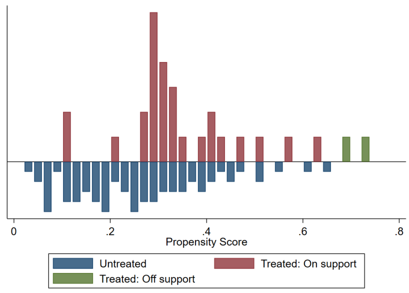


(e) Other (Admin Only)

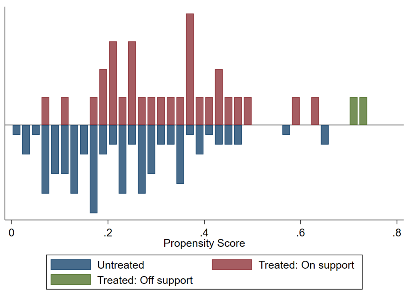
Figure A.55: Overlap of treatment and control groups – Fall Course Evaluations (Topics are hard)



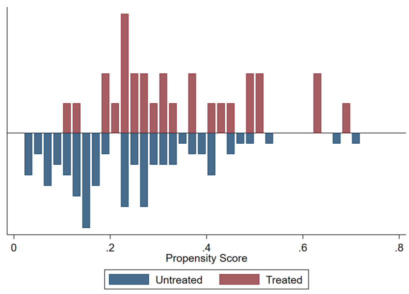
(a) Management



(b) Microeconomics

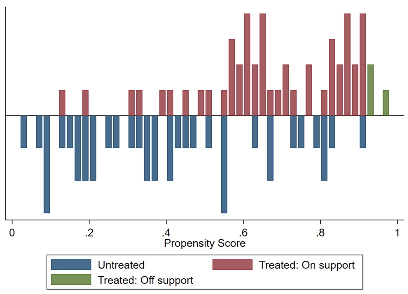


(c) Mathematics

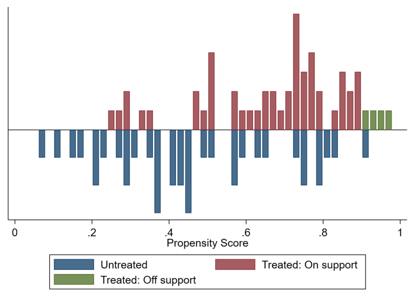


(d) Other

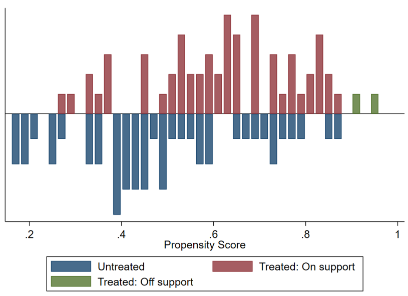
Figure A.56: Overlap of treatment and control groups – Spring Course Evaluations (Topics are hard)



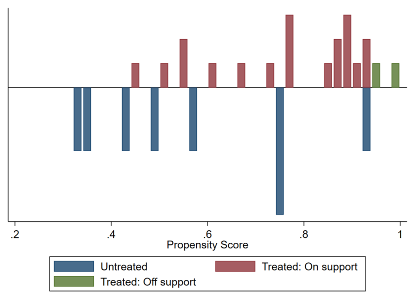
(a) Macroeconomics



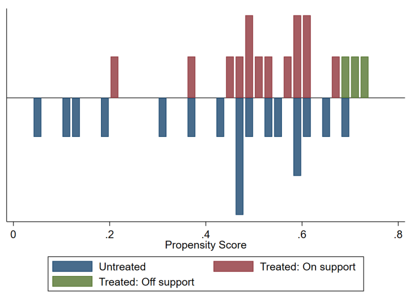
(b) Mathematics



(c) Computer Science

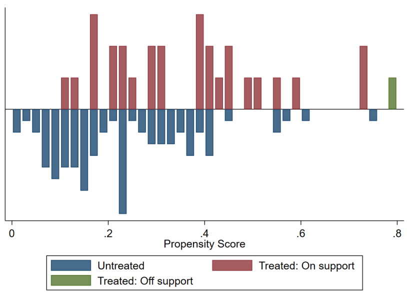


(d) Law (Admin Only)

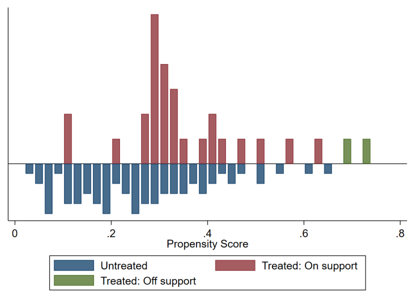


(e) Other (Admin Only)

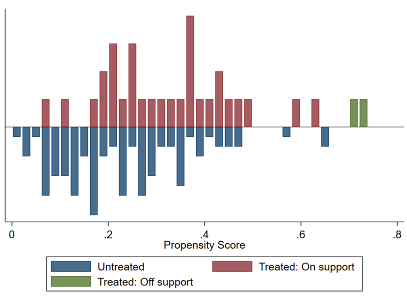
Figure A.57: Overlap of treatment and control groups – Fall Course Evaluations (Personal interest)



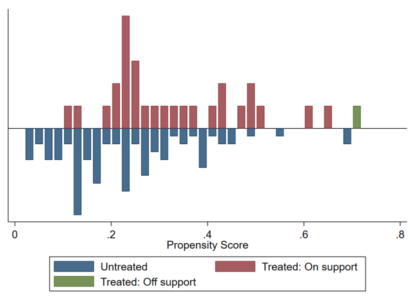
(a) Management



(b) Microeconomics

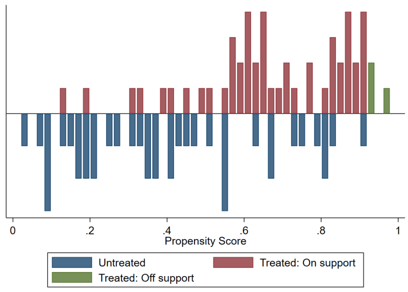


(c) Mathematics

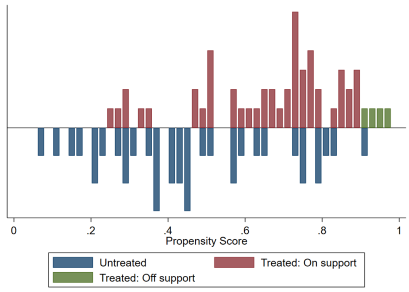


(d) Other

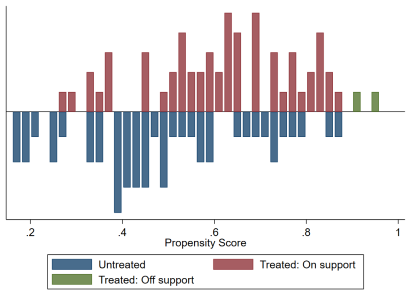
Figure A.58: Overlap of treatment and control groups – Spring Course Evaluations (Personal interest)



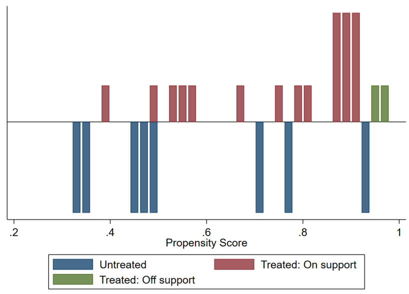
(a) Macroeconomics



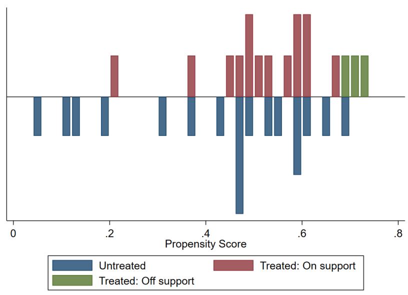
(b) Mathematics



(c) Computer Science

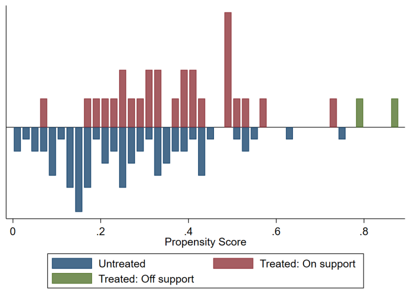


(d) Law (Admin Only)

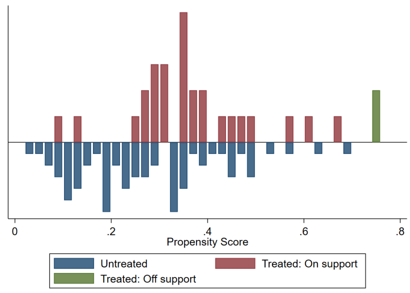


(e) Other (Admin Only)

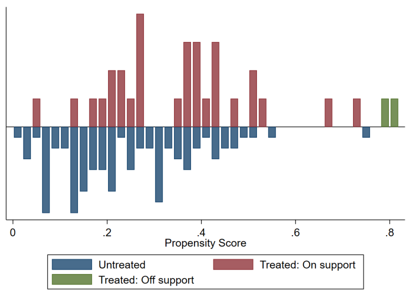
Figure A.59: Overlap of treatment and control groups – Fall Course Evaluations (Online activities helpful)



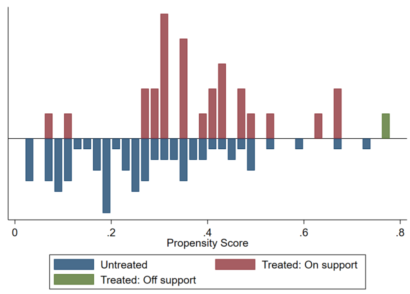
(a) Management



(b) Microeconomics

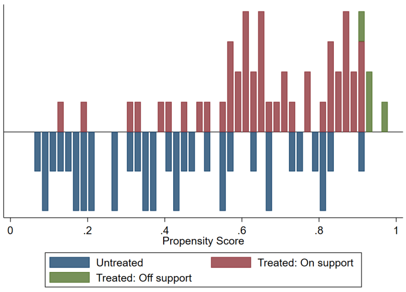


(c) Mathematics

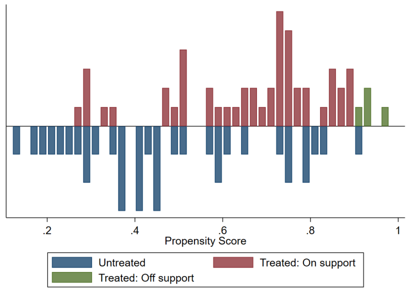


(d) Other

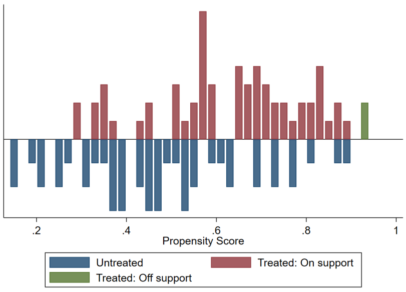
Figure A.60: Overlap of treatment and control groups – Spring Course Evaluations (Online activities helpful)



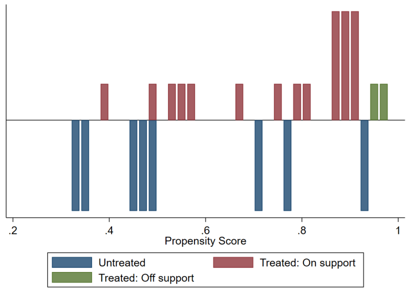
(a) Macroeconomics



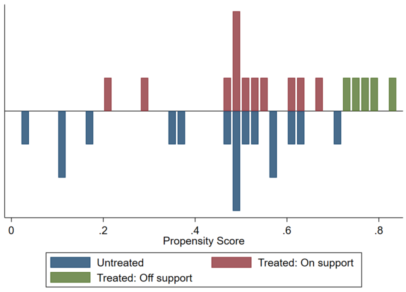
(b) Mathematics



(c) Computer Science

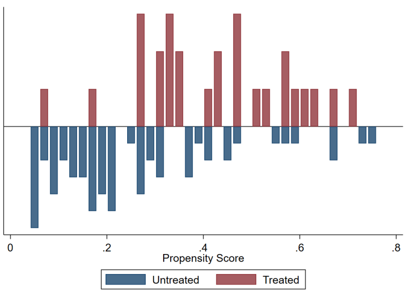


(d) Law (Admin Only)

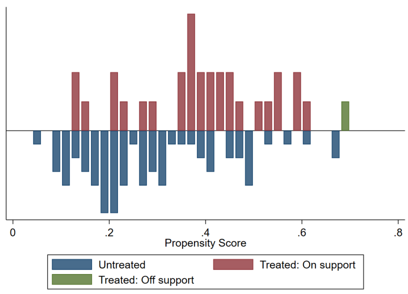


(e) Other (Admin Only)

Figure A.61: Overlap of treatment and control groups – Fall Anxiety

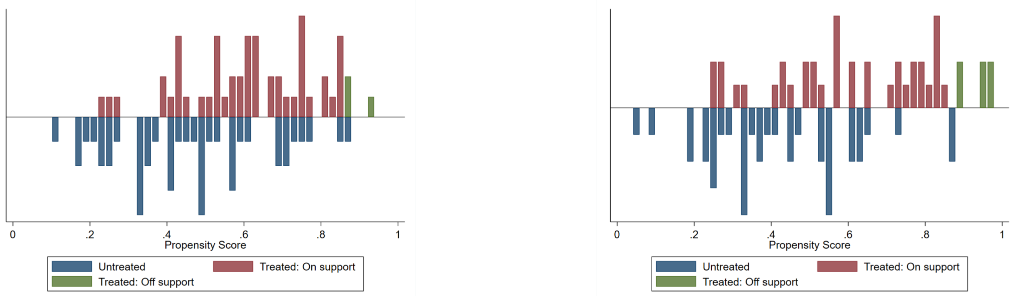


(a) Pre-midterms



(b) End of Semester

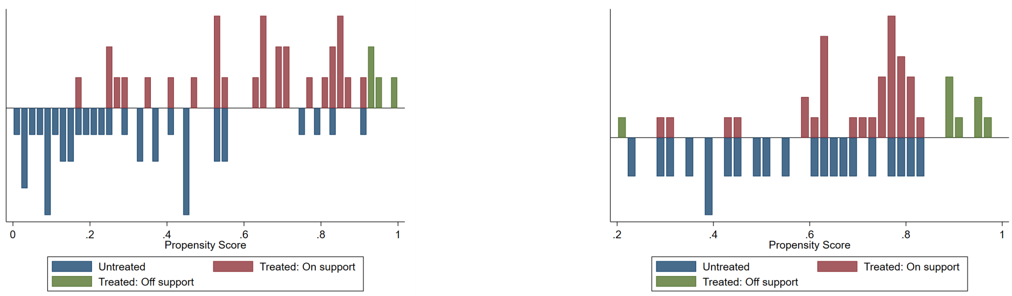
Figure A.62: Overlap of treatment and control groups – Spring Anxiety



(a) Post-midterms

(b) End of Semester

Figure A.63: Overlap of treatment and control groups – Study Time



(a) Fall

(b) Spring

A.6 Results

Table A.40: Aggregated Midterms Grades, Fall & Spring – Treatment Effects with Propensity Score using Administrative Data Only, Conditional on Ever Engaging

	Quantitative	Qualitative	Economic Principles	Other
ATT	0.655	0.910*	0.602	0.958
	(0.451)	(0.408)	(0.576)	(0.723)
Treated	26.745	25.495	24.565	28.214
Control	26.089	24.585	23.963	27.257
N	593	528	557	85

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Propensity score includes only administrative variables. Sample: all students who ever engaged with the intervention and/or surveys.

Table A.41: Aggregated Midterms Grades, Fall & Spring – Treatment Effects with Propensity Score using Administrative Data Only

	Quantitative	Qualitative	Economic Principles	Other
ATT	0.408	1.237**	0.501	1.179
	(0.411)	(0.397)	(0.538)	(0.662)
Treated	26.745	25.495	24.565	28.214
Control	26.337	24.258	24.064	27.036
N	1264	675	1108	146

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Propensity score includes only administrative variables. Sample: all students for which administrative data was available.

Table A.42: Fall & Spring Midterms, Expected Grades – Treatment Effects with Propensity Score using Administrative Data Only

	Management	**Math**	**Micro**	**Other**	**Macro**	**Math**	**Computer Sc.**	**Law**	**Other**
ATT	0.409	0.572	0.755	-0.795	0.443	-0.745	-0.046	-0.253	-0.020
	(0.934)	(1.222)	(0.887)	(1.267)	(0.505)	(0.621)	(0.422)	(0.803)	(0.910)
Treated	24.703	24.054	24.210	24.548	24.570	24.978	26.561	25.978	25.146
Control	24.294	23.482	23.455	25.343	24.127	25.723	26.607	26.232	25.166
N	98	87	90	81	107	110	132	24	32

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes only administrative variables.
Sample: all students who ever engaged with the intervention and/or surveys.

Table A.43: Fall & Spring Midterms, Percent Chance of Passing – Treatment Effects with Propensity Score using Administrative Data Only

	Management	**Math**	**Micro**	**Other**	**Macro**	**Math**	**Computer Sc.**	**Law**	**Other**
ATT	8.674	1.107	-7.344	.	6.289	-0.910	2.752	1.687	-1.375
	(6.047)	(11.280)	(6.504)	.	(4.365)	(4.327)	(3.084)	(4.085)	(7.797)
Treated	89.429	83.200	70.600	.	79.746	86.629	88.500	92.250	80.469
Control	80.755	82.093	77.944	.	73.457	87.538	85.748	90.563	81.844
N	38	26	63	.	112	115	140	24	34

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes only administrative variables.
Sample: all students who ever engaged with the intervention and/or surveys.

Table A.44: Fall & Spring Course Evaluations (Lecturer stimulates interest) – Treatment Effects with Propensity Score using Administrative Data Only

	Management	Math	Micro	Other	Macro	Math	Computer Sc.	Law	Other
ATT	-1.750	3.237	2.557	1.480	7.140	11.104*	3.887	0.481	-2.026
	(4.539)	(4.175)	(4.027)	(5.283)	(4.334)	(4.902)	(4.368)	(15.797)	(8.268)
Treated	80.812	73.528	80.258	55.561	77.700	74.880	73.807	74.762	66.941
Control	82.563	70.290	77.701	54.081	70.560	63.776	69.921	74.281	68.967
N	134	150	120	138	122	121	146	29	35

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes only administrative variables.
Sample: all students who ever engaged with the intervention and/or surveys.

Table A.45: Fall & Spring Course Evaluations (Topics are hard)) – Treatment Effects with Propensity Score using Administrative Data Only

	Management	Math	Micro	Other	Macro	Math	Computer Sc.	Law	Other
ATT	0.461	-0.353	-4.978	2.240	-3.440	0.617	-3.437	12.985	-9.063
	(3.551)	(4.382)	(4.235)	(5.827)	(3.781)	(3.995)	(4.195)	(10.286)	(9.481)
Treated	52.031	67.111	62.806	45.424	65.471	63.944	43.940	42.095	51.853
Control	51.570	67.464	67.784	43.184	68.912	63.326	47.377	29.111	60.916
N	133	152	121	138	122	121	146	29	35

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes only administrative variables.
Sample: all students who ever engaged with the intervention and/or surveys.

Table A.46: Fall & Spring Course Evaluations (Personal interest) – Treatment Effects with Propensity Score using Administrative Data Only

	Management	Math	Micro	Other	Macro	Math	Computer Sc.	Law	Other
ATT	-1.375	-2.814	-0.800	-1.653	-0.377	-3.146	5.449	3.453	-13.625
	(3.840)	(6.027)	(3.976)	(5.256)	(3.802)	(5.131)	(4.469)	(17.090)	(8.145)
Treated	83.906	61.222	79.742	58.106	80.957	64.843	74.963	73.050	71.647
Control	85.282	64.036	80.542	59.759	81.334	67.989	69.514	69.597	85.272
N	134	152	121	139	121	120	145	28	35

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes only administrative variables.
Sample: all students who ever engaged with the intervention and/or surveys.

Table A.47: Fall & Spring Course Evaluations (Online activities helpful) – Treatment Effects with Propensity Score using Administrative Data Only

	Management	Math	Micro	Other	Macro	Math	Computer Sc.	Law	Other
ATT	3.886	6.213	5.205	4.202	6.620	5.283	3.734	7.959	0.997
	(5.272)	(5.022)	(5.603)	(6.289)	(5.198)	(5.331)	(4.504)	(17.310)	(9.797)
Treated	71.906	73.306	75.000	55.955	61.838	66.986	72.790	60.750	65.059
Control	68.021	67.092	69.795	51.752	55.218	61.703	69.056	52.791	64.061
N	122	145	114	123	119	119	143	28	34

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes only administrative variables.
Sample: all students who ever engaged with the intervention and/or surveys.

Table A.48: Fall & Spring Anxiety Levels – Treatment Effects with Propensity Score using Administrative Data Only

	Fall		Spring	
	Pre Midterms	**End Semester**	**Post Midterms**	**End Semester**
ATT	-1.130	2.873	-0.483	0.595
	(2.348)	(2.569)	(2.338)	(2.505)
Treated	53.438	55.833	53.470	51.278
Control	54.568	52.960	53.952	50.682
N	107	116	123	107

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Propensity score includes only administrative variables. Sample: all students who ever engaged with the intervention and/or surveys.

Table A.49: Fall & Spring Semester Study Time, Controlling for Planned Time – Treatment Effects with Propensity Score using Administrative Data Only

	Fall				Spring			
	15-28h	**29-42h**	**43-56h**	**> 56h**	**15-28h**	**29-42h**	**43-56h**	**> 56h**
ATT	-0.103	-0.042	0.167*	0.013	-0.019	-0.110	0.031	0.028
	(0.107)	(0.114)	(0.081)	(0.036)	(0.139)	(0.138)	(0.080)	(0.028)
Treated	0.257	0.4	0.228	0.028	0.389	0.389	0.111	0.028
Control	0.360	0.441	0.061	0.015	0.408	0.498	0.080	0
N	85	85	85	85	69	69	69	69

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes only administrative variables.
Sample: all students who ever engaged with the intervention and/or surveys.

A.7 Heterogeneity Analysis

The Hypotheses. Heterogeneity analysis can be carried out exploiting both administrative and survey measures. As for the first source of data, I explore differences in terms of gender or location of high school completion. Survey questions provide me with a lot of information about family background, childhood habits and history in terms of technological exposure, and network dimension at the start of each semester.

Heterogeneity in results may stem from very diverse mechanisms. I here outline some of the aspects I am going to tackle in the next paragraphs.

- Gender. Female students tend to be more psychologically affected by technology and screen time (Khan et al. (2021)), but there is no clear prior on what could be the impact of this intervention on performance.

- Location of high school completion. In Italy high school achievements are rather different in particular between North and South (Martini (2020), Argentin and Triventi (2015)). I want to check whether these differences persist and whether the intervention has differential effects on different groups of students.

- Family background. Higher socio-economic status or living with the parents may be proxies for parental supervision and literacy (PISA 2015, Doepke and Zilibotti (2019)).

- The network. As Jain and Langer (2019) study, in knowledge-intensive networks having more friends may be beneficial because well-connected peers aggregate information more efficiently, but at the same time having more connections is associated with too many distractions that impede collaborative engagements; there is a trade off between the information flow and the number of relationships to establish and maintain.

- The previous-semester GPA, for Spring midterm grades only. High school GPA might not be the best proxy for ability, considering the different standards applied by schools and the different curricular paths of the students; in this case I control for the GPA of the Fall semester to see whether students previously performing below or above the sample average are differently impacted by the intervention.

- Personality traits. Competitiveness may be linked to the likelihood of participating in such interventions, while studies in the psychological literature have linked grit, discounting and risk taking to academic success and less addictive behaviors.

All estimates are obtained by using the "full" propensity score, i.e. the one including both administrative variables and unbalanced survey measures.

Gender. Tables A.50 and A.51 show that there are no statistically significant gender differences in the Fall exam performances.

Table A.50: Fall Midterms Grades – Treatment Effects, by Gender

	Management		Math		Microeconomics		Other	
	Male	Female	Male	Female	Male	Female	Male	Female
ATT	1.176	0.477	0.017	-0.031	-0.157	.	.	.
	(0.777)	(0.656)	(0.010)	(0.055)	(2.834)	.	.	.
Treated	26.391	25.391	1.000	0.950	26.400	24.667	0.889	1.000
Control	25.215	24.914	0.983	0.981	26.557	.	.	.
N	190	180	193	169	31	22	26	23

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes administrative variables and survey measures that were unbalanced at baseline.

Table A.51: Spring Midterms Grades – Treatment Effects, by Gender

	Macroeconomics		Math		Computer Science		Law	
	Male	Female	Male	Female	Male	Female	Male	Female
ATT	0.764	0.969	-0.230	0.430	0.639	1.041	-1.860	.
	(1.015)	(0.819)	(0.976)	(0.621)	(0.756)	(0.612)	(1.656)	.
Treated	26.909	25.848	26.708	26.692	13.459	13.950	23.500	.
Control	26.145	24.879	26.938	26.262	12.820	12.909	25.360	.
N	163	138	175	114	223	196	51	.

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes administrative variables and survey measures that were unbalanced at baseline.

Location of High School Completion. Tables A.52 and A.53 divide the analytic sample on the basis of where the student obtained the high school diploma, regardless of citizenship. High schools located in any municipality in Emilia Romagna, Friuli Venezia Giulia, Liguria, Lombardia, Piemonte, Trentino Alto-Adige, Valle d'Aosta, and Veneto are classified as "North", in Lazio, Marche, Toscana, and Umbria as "Center", in Abruzzo, Basilicata, Calabria, Campania, Molise, Puglia, Sardegna, and Sicilia as "South". All other municipalities fall in the "Foreign" category. Columns may be missing because of an insufficient number of observations.

The only statistically significant improvement can be seen in Computer Science for students holding a foreign high school diploma.

Table A.52: Fall Midterms Grades – Treatment Effects, by Geographical Location of High School Completion

The categories refer to the geographic location of the high school in which the student obtained the diploma in Italy. 'North', 'Center', and 'South' refer to the standard classification of the Regions, and 'South' includes also the islands. 'Foreign' captures the fact the the student obtained a high school diploma in a foreign country, regardless of citizenship.

	Management				**Math**				**Microeconomics**		**Other**	
	North	**Center**	**South**	**Foreign**	**North**	**Center**	**South**	**Foreign**	**North**	**Foreign**	**North**	**Foreign**
ATT	0.594	.	.	0.465	0.025	.	.	-0.113	.	.	.	.
	(0.617)	.	.	(1.725)	(0.014)	.	.	(0.145)	.	.	.	.
Treated	26.207	24.750	25.667	25.500	1.000	25.880	1.000	0.900	25.900	28.000	0.923	-8.242
Control	25.613	.	.	25.035	0.975	.	.	1.013	.	.	.	.
N	183	32	72	83	175	34	70	83	30	19	23	23

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes administrative variables and survey measures that were unbalanced at baseline.

Table A.53: Spring Midterms Grades – Treatment Effects, by Geographical Location of High School Completion

The categories refer to the geographic location of the high school in which the student obtained the diploma in Italy. 'North', 'Center', and 'South' refer to the standard classification of the Regions, and 'South' includes also the islands. 'Foreign' captures the fact the the student obtained a high school diploma in a foreign country, regardless of citizenship.

	Macroeconomics				Math				Computer Science				Law		Other	
	North	**Center**	**South**	**Foreign**	**North**	**Center**	**South**	**Foreign**	**North**	**Center**	**South**	**Foreign**	**North**	**Foreign**	**North**	**Center**
ATT	0.718	.	.	0.067	0.616	.	1.678	-0.099	0.847	.	-1.721	1.759*	1.305	.	.	.
	(0.731)	.	.	(1.487)	(0.712)	.	(1.054)	(1.442)	(0.593)	.	(2.314)	(0.848)	(1.884)	.	.	.
Treated	26.345	29.000	25.857	25.077	26.567	26.667	28.429	25.900	14.268	13.250	11.900	13.667	27.625	28.768	23.163	29.500
Control	25.627	.	.	25.010	25.951	.	26.750	25.999	13.421	.	13.621	11.907	26.320	.	.	.
N	149	29	58	63	137	27	57	64	208	39	78	89	36	39	35	7

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes administrative variables and survey measures that were unbalanced at baseline.

Family Background. Tables A.54 and A.55 present the results dividing the sample into two groups: students who live with their families *versus* those who don't[28].

The improvement in performance is statistically significant for the Computer Science students living with their families. Students living at home might have more environment distractions if their family members were also living and working from home because of the pandemic, but might also receive more social media and messaging notifications if they used these tools to keep in touch with distant fellow students.

Table A.54: Fall Midterms Grades – Treatment Effects, by whether the student lives with the family.

The relevant variable is a dummy. Results are presented distinguishing the groups where the dummy is equal to zero (*d=0*) or one (*d=1*).

	Management		**Math**		**Microeconomics**		**Other**	
	d=0	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**
ATT	1.068	0.059	-0.039	0.030	1.342	.	.	.
	(0.641)	(0.844)	(0.053)	(0.016)	(0.757)	.	.	.
Treated	25.958	25.762	0.947	1.000	27.375	81.972	1.000	0.857
Control	24.891	25.703	0.986	0.970	26.033	.	.	.
N	217	145	205	149	36	22	26	17

Standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Looking at parental education, again I find positive statistically significant results mostly for the Spring courses. Having a father with at least a college degree increases the performance in Macroeconomics, Computer Science and the Other Spring exams (Table A.57); similarly, an educated mother is associated with an increased performance in Computer Science (Table A.59) but also in Math (Table A.58).

[28] While in normal academic years there is a share of students who live with their families both in Milan or in Lombardy and commute daily, in the a.y. 2020/21 due to COVID-19 some students chose not to move to Milan and kept living with their families even if far away from the campus. Therefore the share of students living with their families in this academic year was higher because of the students who chose not to move for health/precautionary reasons and/or to save the rent money. Students who were initially living with their families in Fall may have moved back home by Spring during the worsening of the pandemic situation and fear of new lockdowns.

Table A.55: SPRING MIDTERMS GRADES – TREATMENT EFFECTS, BY WHETHER THE STUDENT LIVES WITH THE FAMILY.

The relevant variable is a dummy. Results are presented distinguishing the groups where the dummy is equal to zero (*d=0*) or one (*d=1*).

	Macroeconomics		**Math**		**Computer Science**		**Law**		**Other**	
	d=0	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**
ATT	1.252	1.218	0.362	1.082	1.238	1.531*	-0.633	.	.	.
	(1.036)	(0.650)	(0.854)	(0.685)	(0.700)	(0.519)	(1.610)	.	.	.
Treated	25.613	26.905	26.214	27.200	12.809	15.074	24.200	27.000	43.552	30.000
Control	24.361	25.686	25.852	26.118	11.571	13.543	24.833	.	.	.
N	167	125	160	121	245	165	51	36	45	21

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes administrative variables and survey measures that were unbalanced at baseline.

Table A.56: FALL MIDTERMS GRADES – TREATMENT EFFECTS, BY WHETHER THE STUDENT'S FATHER HAD UNIVERSITY EDUCATION OR MORE.

The relevant variable is a dummy. Results are presented distinguishing the groups where the dummy is equal to zero (*d=0*) or one (*d=1*).

	Management		**Math**		**Microeconomics**		**Other**	
	d=0	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**
ATT	0.732	0.451	0.013	-0.031	.	-1.604	.	0.004
	(0.854)	(0.624)	(0.015)	(0.057)	.	(2.198)	.	(0.198)
Treated	26.130	25.591	1.000	0.944	26.833	25.333	0.833	1.000
Control	25.399	25.140	0.987	0.976	.	26.937	.	0.996
N	139	218	140	208	17	43	13	34

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A.57: Spring Midterms Grades – Treatment Effects, by whether the student's father had university education or more.

The relevant variable is a dummy. Results are presented distinguishing the groups where the dummy is equal to zero (*d=0*) or one (*d=1*).

	Macroeconomics		**Math**		**Computer Science**		**Law**		**Other**	
	d=0	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**
ATT	0.419	1.479*	1.383	0.761	1.027	1.170*	.	0.527	.	3.326*
	(1.185)	(0.671)	(0.893)	(0.728)	(0.683)	(0.556)	.	(1.550)	.	(1.397)
Treated	25.706	26.455	26.800	26.406	14.375	13.292	27.000	23.778	.	29.000
Control	25.287	24.976	25.417	25.645	13.348	12.122	.	23.251	.	25.674
N	110	180	108	169	154	251	18	60	.	41

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes administrative variables and survey measures that were unbalanced at baseline.

Table A.58: Fall Midterms Grades – Treatment Effects, by whether the student's mother had university education or more.

The relevant variable is a dummy. Results are presented distinguishing the groups where the dummy is equal to zero (*d=0*) or one (*d=1*).

	Management		**Math**		**Microeconomics**		**Other**	
	d=0	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**
ATT	0.705	0.808	-0.039	0.023*	.	-0.105	.	.
	(1.068)	(0.561)	(0.062)	(0.011)	.	(1.505)	.	.
Treated	25.778	25.926	0.947	1.000	24.000	26.231	.	.
Control	25.073	25.117	0.987	0.977	.	26.335	.	.
N	105	250	112	234	8	51	.	.

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A.59: Spring Midterms Grades – Treatment Effects, by whether the student's mother had university education or more.

The relevant variable is a dummy. Results are presented distinguishing the groups where the dummy is equal to zero (*d=0*) or one (*d=1*).

	Macroeconomics		**Math**		**Computer Science**		**Law**		**Other**	
	d=0	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**
ATT	0.191	1.187	2.210	0.151	-0.528	1.451*	.	1.181	.	0.727
	(1.312)	(0.661)	(1.205)	(0.661)	(0.958)	(0.525)	.	(1.726)	.	(1.000)
Treated	26.105	26.000	27.471	26.161	13.520	13.646	26.000	24.667	29.000	28.750
Control	25.914	24.813	25.260	26.011	14.048	12.195	.	23.485	.	28.023
N	96	194	83	193	123	280	15	70	23	43

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes administrative variables and survey measures that were unbalanced at baseline.

Starting Network Dimension. In the Baseline survey at the start of each semester I asked students how many friends they already had at Bocconi. I then asked to write down their names. In Fall I received 284 answers and an average number of nominated friends of 3.83; in Spring 128 students reported at least one friend name and 4.32 on average. Most of the students report having met their friends in the Math pre-courses in the last week of August and during the first weeks of classes in September, so given the timing of my survey in Fall it is not strange to see that the starting number of friends in Fall is not too far from the starting number of friends in Spring, given that in both cases it is likely that some groups had already formed.

Tables A.60 and A.61 distinguish between students who report 4 or less friends' names *versus* students who report at least 5 names in the Baseline survey. In both cases there is no detectable heterogeneity in the results that can be attributed to the starting network size.

Table A.60: Fall Midterms Grades – Treatment Effects, by whether the student reported more than 5 friends' names at the beginning of Fall.

The relevant variable is a dummy. Results are presented distinguishing the groups where the dummy is equal to zero (*d=0*) or one (*d=1*).

	Management		**Math**		**Microeconomics**		**Other**	
	d=0	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**
ATT	0.578	-0.712	-0.032	0.000	-2.882	.	.	.
	(0.768)	(1.233)	(0.043)	(0.000)	(2.222)	.	.	.
Treated	25.741	26.105	0.960	1.000	25.500	26.500	0.929	1.000
Control	25.162	26.818	0.992	1.000	28.382	.	.	.
N	142	61	129	60	29	9	23	7

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes administrative variables and survey measures that were unbalanced at baseline.

Table A.61: Spring Midterms Grades – Treatment Effects, by whether the student reported more than 5 friends' names at the beginning of Spring.

The relevant variable is a dummy. Results are presented distinguishing the groups where the dummy is equal to zero (*d=0*) or one (*d=1*).

	Macroeconomics		**Math**		**Computer Science**		**Law**		**Other**	
	d=0	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**
ATT	0.240	-0.240	-1.026	-2.229	1.024	0.097	.	.	.	.
	(1.132)	(1.867)	(1.051)	(1.575)	(1.431)	(1.510)	.	.	.	.
Treated	26.231	26.579	26.692	27.056	14.057	14.500	25.250	27.143	.	.
Control	25.991	26.819	27.718	29.285	13.033	14.403	.	.	.	.
N	43	34	42	33	63	46	7	12	.	.

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes administrative variables and survey measures that were unbalanced at baseline.

Previous-semester Ability. In my analysis I control for ability by including high school GPA, computed as the mean of the 11th and 12th grade GPA from administrative data.

In the following table I consider only the results from the Spring semester controlling for the GPA of the students in my sample from the Fall semester. I compute each students' Fall GPA by using the administrative data regarding the final performance (i.e. the grade that the administration registered as final in each student's career). Then I create a dummy that captures whether the student's GPA is above or below the average Fall GPA in my dataset. Table A.62 shows no statistically significant result.

I repeat the analysis also controlling for the number of exams completed in the Fall semester (that can vary across bachelor programs) and results do not change.

Table A.62: Spring Midterms Grades – Treatment Effects, by whether the student in Fall had a GPA above the sample average.

The relevant variable is a dummy. Results are presented distinguishing the groups where the dummy is equal to zero (*d=0*) or one (*d=1*).

	Macroeconomics		**Math**		**Computer Science**		**Law**		**Other**	
	d=0	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**
ATT	0.395	1.044	-1.850	0.331	2.942	0.265	4.480	-0.067	.	.
Treated	23.071	27.893	23.400	27.909	13.000	14.306	24.857	26.833	28.500	29.500
Control	22.677	26.849	25.250	27.578	10.058	14.041	20.377	26.900	.	.
N	110	173	104	155	162	219	33	52	38	22

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes administrative variables and survey measures that were unbalanced at baseline.

Personality. Some specific personality traits may help a student success in the academic career, or may help in staying away from temporary distractions and rewards.

Using my survey measures I create dummy variables by using the average value of that personality trait in my sample. I therefore distinguish people who report a value below or above the average. Tables from A.63 to A.70 report the results, presenting respectively results for above average discounting, risk taking, competitiveness and grit, for both the Fall and Spring semesters.

Students with a discounting score above the mean perform better in Computer Science;

those with higher competitiveness perform worse in the Other Fall exams; those with a competitiveness score below the mean perform better in Computer Science.

Table A.63: Fall Midterms Grades – Treatment Effects, by whether the student had a discounting score above the mean.

The relevant variable is a dummy. Results are presented distinguishing the groups where the dummy is equal to zero (*d=0*) or one (*d=1*).

	Management		**Math**		**Microeconomics**		**Other**	
	d=0	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**
ATT	0.480	0.600	-0.046	0.000	.	.	-10.180	-0.976
	(0.949)	(0.802)	(0.059)	(0.000)	.	.	(8.031)	(6.347)
Treated	25.720	26.050	0.950	1.000	25.800	27.000	7.333	11.400
Control	25.240	25.450	0.996	1.000	.	.	17.514	12.376
N	106	93	96	89	15	11	37	40

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes administrative variables and survey measures that were unbalanced at baseline.

Table A.64: Spring Midterms Grades – Treatment Effects, by whether the student had a discounting score above the mean.

The relevant variable is a dummy. Results are presented distinguishing the groups where the dummy is equal to zero (*d=0*) or one (*d=1*).

	Macroeconomics		**Math**		**Computer Science**		**Law**		**Other**	
	d=0	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**
ATT	1.493	0.438	0.241	-0.508	1.000	1.885*	.	.	.	.
	(0.951)	(0.946)	(0.859)	(1.066)	(0.721)	(0.964)	.	.	.	.
Treated	26.522	27.050	26.571	27.000	13.813	13.655	26.833	-1.278	.	.
Control	25.029	26.612	26.330	27.508	12.812	11.770	.	.	.	.
N	87	83	84	87	124	115	28	28	.	.

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes administrative variables and survey measures that were unbalanced at baseline.

Table A.65: Fall Midterms Grades – Treatment Effects, by whether the student had a risk taking score above the mean.

The relevant variable is a dummy. Results are presented distinguishing the groups where the dummy is equal to zero (*d=0*) or one (*d=1*).

	Management		**Math**		**Microeconomics**		**Other**	
	d=0	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**
ATT	1.035	0.917	-0.077	0.002	.	.	.	-0.976
	(1.010)	(0.807)	(0.077)	(0.015)	.	.	.	(7.420)
Treated	26.053	25.778	0.929	1.000	28.750	24.600	5.286	11.917
Control	25.018	24.861	1.005	0.998	.	.	.	12.893
N	93	107	81	105	15	15	38	36

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes administrative variables and survey measures that were unbalanced at baseline.

Table A.66: Spring Midterms Grades – Treatment Effects, by whether the student had a risk taking score above the mean.

The relevant variable is a dummy. Results are presented distinguishing the groups where the dummy is equal to zero (*d=0*) or one (*d=1*).

	Macroeconomics		**Math**		**Computer Science**		**Law**		**Other**	
	d=0	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**
ATT	1.373	0.345	0.903	0.489	1.272	0.614	0.836	.	.	.
	(1.055)	(0.927)	(0.991)	(0.875)	(1.119)	(0.637)	(2.444)	.	.	.
Treated	28.235	26.000	27.588	26.292	13.040	14.270	24.556	-25.738	.	.
Control	26.862	25.655	26.685	25.803	11.768	13.656	23.720	.	.	.
N	76	96	72	100	105	136	27	30	.	.

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes administrative variables and survey measures that were unbalanced at baseline.

Table A.67: Fall Midterms Grades – Treatment Effects, by whether the student had a competitiveness score above the mean.

The relevant variable is a dummy. Results are presented distinguishing the groups where the dummy is equal to zero (*d=0*) or one (*d=1*).

	Management		**Math**		**Microeconomics**		**Other**	
	d=0	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**
ATT	1.643	0.111	-0.067	0.005	.	.	.	-9.192*
	(0.935)	(0.769)	(0.067)	(0.013)	.	.	.	(4.771)
Treated	26.833	25.286	0.944	1.000	26.667	26.333	10.500	9.000
Control	25.190	25.175	1.011	0.995	.	.	.	18.192
N	85	116	79	108	14	15	33	45

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes administrative variables and survey measures that were unbalanced at baseline.

Table A.68: Spring Midterms Grades – Treatment Effects, by whether the student had a competitiveness score above the mean.

The relevant variable is a dummy. Results are presented distinguishing the groups where the dummy is equal to zero (*d=0*) or one (*d=1*).

	Macroeconomics		**Math**		**Computer Science**		**Law**		**Other**	
	d=0	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**
ATT	1.486	0.861	-0.786	-0.230	1.965*	-0.833	.	.	.	.
	(1.027)	(0.931)	(0.948)	(0.773)	(0.759)	(0.886)	.	.	.	.
Treated	27.143	26.609	26.722	26.913	14.036	13.559	46.817	24.000	.	.
Control	25.657	25.748	27.509	27.143	12.071	14.392	.	.	.	.
N	73	100	67	106	106	136	23	35	.	.

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes administrative variables and survey measures that were unbalanced at baseline.

Table A.69: FALL MIDTERMS GRADES – TREATMENT EFFECTS, BY WHETHER THE STUDENT HAD A GRIT SCORE ABOVE THE MEAN.

The relevant variable is a dummy. Results are presented distinguishing the groups where the dummy is equal to zero (*d=0*) or one (*d=1*).

	Management		**Math**		**Microeconomics**		**Other**	
	d=0	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**
ATT	0.680	0.910	0.006	-0.043	.	.	-7.647	-11.431
	(1.182)	(0.698)	(0.016)	(0.043)	.	.	(4.580)	(12.737)
Treated	25.071	26.226	1.000	0.963	27.250	25.800	3.667	11.125
Control	24.392	25.316	0.994	1.006	.	.	11.314	22.556
N	87	114	79	108	22	11	54	24

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes administrative variables and survey measures that were unbalanced at baseline.

Table A.70: SPRING MIDTERMS GRADES – TREATMENT EFFECTS, BY WHETHER THE STUDENT HAD A GRIT SCORE ABOVE THE MEAN.

The relevant variable is a dummy. Results are presented distinguishing the groups where the dummy is equal to zero (*d=0*) or one (*d=1*).

	Macroeconomics		**Math**		**Computer Science**		**Law**		**Other**	
	d=0	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**	**d=0**	**d=1**
ATT	1.628	0.343	-0.343	-0.410	1.045	0.945	.	.	.	.
	(0.865)	(1.147)	(0.954)	(0.863)	(0.856)	(0.690)	.	.	.	.
Treated	25.950	27.478	26.105	27.455	12.576	15.107	22.571	27.571	.	.
Control	24.322	27.135	26.448	27.865	11.531	14.162	.	.	.	.
N	72	100	69	105	113	129	26	31	.	.

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Propensity score includes administrative variables and survey measures that were unbalanced at baseline.

Preliminary Qualitative Investigations

A.8 Focus group, December 2019

In December 2019 I sent out an online survey to small groups of university students that I could reach through friends, without any official involvement of Bocconi.

This survey, a sort of online focus group, was administered to 15 students coming from three distinct groups: some Bocconi master students in Economics, some Engineering master students from the University of Padova, some Economics bachelor students from Montpellier Business School.

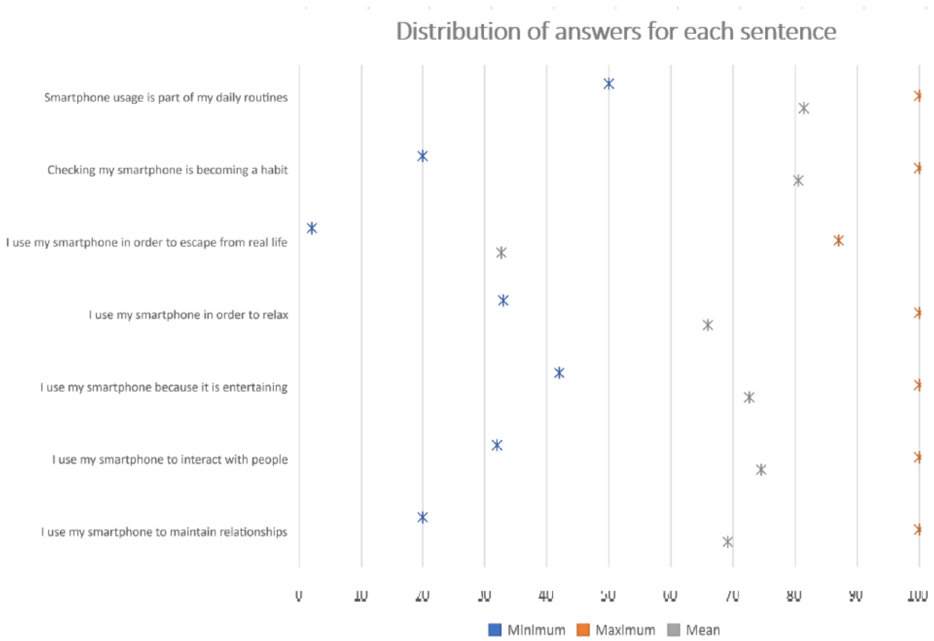
60% of respondents declared that in the past they had tried to modify their smartphone behavior, and 78% of these reported having been unable to reach their goals, but still being trying. In order to effectively change habits, among this sample the most popular choice was not to use the smartphone or to leave it in another room while studying or while in class; 3 people reported using distraction-blocking apps (such as YourHour and AppDetox), 2 students declared to leave it at home when going out knowing they don't need it, and 1 person committed to family or friends not to use the smartphone on certain occasions. Other strategies involve uninstalling social media apps, setting time counters, or directly switching off the phone or activate the airplane mode. The 40% of the sample that declared to have never tried to modify their behavior was instead presented with a question concerning whether they would be interested in trying to do so; out of these 6 people, one declared to be so, while the other 5 declared indifference.

Of the 15 interviewed students, only one declared to know or have heard of the app that I use in the intervention. 14 students declared they would not be willing to pay for the premium version ($7.99 USD per semester), but when presented with the option of obtaining the premium version without having to pay for it, 8 students declared that they would then use it.

In order to assess the "willingness-to-accept" (WTA) I have asked them first "If you got access to the premium version without paying it AND somebody paid you 0 euros, would you use the app for one week? (Only Mon-Fri, four hours in the afternoon).", then to those who answered "No" I asked the same question but progressively increasing the amount of money, namely to 2.5, 5, 7.5, 10, 15 euros; last, those who still refused the 15 euros could write down their own request. 9 people (60%) declared to be willing to accept a payment of 0 euros (no payment) to use the app for one week, if provided with the premium version for free; 1 person would have accepted 7.5 euros, another one 10, another 15. Of the four people left, one wrote that he/she needed to be paid 40 euros for such an intervention, and another one 80'000, signaling a very high perceived value attached to using the phone freely.

It is also interesting to have an idea of these students' habits with respect to their smartphone usage. Right at the beginning of this survey, respondents where presented with 7 sentences and for each of them were asked to declare the extent to which they agreed or not, on a scale from 0 ("it does not describe you at all") to 100 ("fully fits your behavior"), with 50 as a neutral position.

Figure A.64: Minimum, maximum and average answers for each sentence from the 15 observations – Focus Group.



As we can see from Table A.64, the highest minimum values are those attached to the sentences "Smartphone usage is part of my daily routines" and to "I use my smartphone because it is entertaining". The distribution of reactions to the sentence "I use my smartphone in order to escape from real life" is the one more shifted towards the left, having the minimum values of declared minimum, average, and maximum (it is, in fact, the only sentence for which the maximum answer is different from 100).

A.9 Cognitive interviews, Spring 2020

Qualitative interviews have been conducted with Bocconi bachelor students in order to investigate habits and opinions related to technology and distractions.

The students have been invited directly via email by some teachers and the interviews have been scheduled over the course of two weeks. Of the 16 invitations sent out, 15 have been accepted and one has never been answered. All students are Italian and attending the third year of a bachelor at the time of the interview (April 2020). The involved bachelor programs are BIEF (Bachelor in Economics and Finance), BESS (Bachelor in Economics and Social Sciences), and BEMACS (Bachelor in Economics, Managements and Computer Science).

The duration of interviews ranged from a minimum of 18 minutes, to a maximum of 36, with average duration 26 minutes. Most of the interviews have been conducted via Skype, one over the phone, one using Zoom.

The interview protocol had been previously spelled out, following the suggestions of Castillo-Montoya (2016) and Jacob and Furgerson (2012).

The topics were seven, as illustrated below. The main question (in bold) was usually formulated in a straight way by the interviewer, while the secondary information was sought through colloquial prompts during the conversation.

1. **Warm-up question: Tell me about yourself and why you are at Bocconi**

2. **How would you describe your relationship with your smartphone?** *Topics discussed:* reasons for and amount of usage, desired changes (if any)

3. **How would you describe your attitude towards your family's and your friends' smartphone usage?** *Topics discussed:* friends' usage, family usage, social pressure

4. **Tell me about your friends at Bocconi and how you met them. Do you think that your relationship with them has influenced you approach to university or your study habits?** *Topics discussed:* network formation, impact on habits and/or attitude

5. **Tell me about your study habits.** *Topics discussed:* where and with whom, whether listening to music, whether taking notes and how, if studying on digital formats or on paper

6. **In your opinion, why do students get distracted? Both in class and when they study.** *Topics discussed:* general reasons for being/getting distracted

7. **How is your experience with the current e-learning environment going?** *Topics discussed:* preference for live or recorded lectures, study strategies, how distractions have changed, peer interactions.

For all the respondents the primary reason for which they use their smartphone is communication, mostly WhatsApp; social media are also very important (Instagram has been mentioned the most) even if some students reported not having accounts on most platforms, followed by news and web-search purposes. Some report having games or learning apps, others use their smartphone for listening to music or podcasts. None of them reports using it for studying, with the occasional use of emails or the eventual check of BlackBoard (the Bocconi e-learning platform) for announcements or last-minute new material for classes.

Most of the respondents declared not liking the amount of time they spend on their smartphone, labeling it "too much". Some even mentioned the words "dependent" or "absorbed". Some of the students were very aware of their use, as they checked regularly their screen statistics and had a fairly precise idea of their habits. When asked about desired changes in their smartphone use, only few of them did not have a wish; most of them declared they would like to use it less ("I would use it less if I had a choice", one student said); some wanted to use it better by learning to exploit some unexplored features; a couple stated that they would like to see a change in the way it is used by others, namely the fact that they feel obliged to always have it handy as friends expect them to be always reachable and that people nowadays prefer communicating through a screen instead of meeting in person. Some students have mentioned using anti-smartphone techniques; some respondents in fact declared that while studying they turn their smartphone's airplane mode on, or they leave it in another room or out of sight; a few others named another distraction-blocking app, Forest, that they used in the past but that they stopped using after it started charging fees. Other strategies involved setting specific time limits for particular apps; in some cases, when the time is up users could either receive a (possibly ignored) notification or being prevented from accessing the app again during that day.

Almost all the respondents declared that in their families the smartphone is not widely used, and it does not constitute a problem in their relationships; those who named having younger siblings said that the latter use their phones even more than they do, but that during meals or family gatherings this does not happen. Only two people reported differently; one said that the members of their family used it heavily, and it may have happened even during meals if there were some tensions and there was the need to avoid dialogue; another one said that during occasions such as watching TV together, they had noticed that everyone had the almost mindless habit of checking the phone and eventually scrolling through it.

When it came to friends' usage, reported behaviors were quite different. Some said that their friends were not so dependent, others said their friends were very heavy users. Most of them reported being annoyed by the fact that people sometimes distance themselves to answer messages or to scroll through social media, but most also agreed that this behavior is acceptable if it happens not too often and while in big groups. Some said that their friends always have their smartphone close by and that they show compulsive behaviors; some people get really absorbed while using it and do not understand anymore what is going on around them.

Talking about classmates at Bocconi, almost everybody made friends while randomly talking in class; most friendships were born at the math pre-courses, others at the beginning of regular classes, some during team projects. Some students met their current friends thanks to events (such as dinners, happy hours) organized via Facebook groups. Most of the respondents said that these friendships have had a profound impact on their current study habits and attitudes; some learned the value of cooperation by studying together, some others were challenged in their mental framework by meeting people with very different ways of approaching issues. The most recurrent answers were about yearning for excellence, perseverance and organization, and finding a balance between academic achievements and leisure. The positive encouragement sometimes translated also into concrete help while studying, and into psychological support through tough times. Some students even chose their friends on the basis of such characteristics, for example distinguishing between people who were very focused and therefore excellent study buddies, and others that were more relaxed and were therefore better companions for social events.

Study habits are very different, according to personal characteristics and objectives. All respondents attend lectures, and most take notes; those who do not take notes do it for different reasons: either they do it for classes that require qualitative reasoning and understanding general concepts, and therefore they are better off just following the line of thought; or they get distracted if they take notes, because they focus more on the precise word rather than on the general message; or they feel that the lecture's content is redundant with the materials (e.g. slides). Notes are sometimes hand-written (on paper or tablets), sometimes typed-in on slides or in Word files, sometimes hand-written in class and then typed-in later; students recognize that typed notes are neater and have the advantage of being easy to modify. Both notes and other materials, such as slides and books, are sometimes kept digital and sometimes printed, for reasons related both to study efficiency per se (e.g. seeing the pages, highlighting, writing down other notes, having a computer in front is distracting) and to health-related concerns (e.g. studying long hours in front of a screen makes their eyes burn). As for the location, many students prefer studying at home alone, others at the library or in public spaces both alone or in groups; habits change also according to study phases, for example most students prefer being alone when they need to first absorb contents and then being around others when it comes to discussing doubts or making summaries, others instead before the exams need to focus and want to be home where they cannot be disturbed by anybody, others do not mind and adapt to the present needs and where they currently are. Music is also very differently used; some people need absolute silence, some others use music in order to isolate from the outside chaos and create a "controlled" noisy environment; many people say that they listen to music only when doing some forms of "active" studying, such as math exercises or essay writing, but prefer silence when ri-elaborating concepts. Many students report studying with their smartphone handy, even if some say it is on mute.

At this point of the interview, most students had already said the word "distraction", "distracting", or "disruptive" associated to their smartphones (or sometimes to their laptops), some while talking about their own smartphone usage, others when describing their study habits. When asked to state their thoughts about why students get distracted, different opinions arose. Most of the respondents mentioned as primary reason the fact that classes or topics may not be interesting for some students, and sometimes professors are not able to capture the attention. Some students mentioned the fact of having a smartphone or a laptop handy, and therefore having the chance of finding quick entertainment or quick answers to doubts made them more likely to drift away, or simply the habit of checking for notifications and messages. One respondent said that most students lack the ability to self-motivate and end up most of the time procrastinating the start of some activities. One student mentioned that their tendency to get distracted was to be attributed to anxiety: whenever they felt that a problem was too difficult or that they needed to concentrate too much, and were sometimes afraid of not being able to solve it, then they were more likely to seek distractions. Another student mentioned FOMO (Fear Of Missing Out): social media exposes students to constant flows of images from other people's lives, and students do not want to feel left out from this constant stream; others mentioned the need to constantly feel connected. Some respondents seemed to think that both in class and while studying with others, using their smartphone was a "polite" way of seeking distractions, as it was not damaging others' attention. When answering the question some students did not focus on digital distractions and seemed more concerned about environmental distractions, such as what other people do in class or in public study places, flatmates, family, etc; in fact, they blamed distractions mostly on their companies. One students specifically referred to distractions as a signal that students are not able to distinguish the short term benefit that comes from a moment of relax, and the fact that even short breaks are more disruptive than what is usually thought. Some others also mentioned the fact that distractions are usually linked to relaxed moments, while in periods of stress or need for concentration they were not an issue. Most students said that in general, both in class and while studying, they believed that the majority of distractions come from smartphones; nonetheless, some of them reported that personally they had bigger problems with environmental distractions, e.g. those coming from having people moving around or friends talking.

Another interesting picture arises from the current situation. Due to the COVID-19 outbreak, students have been forced to follow lectures and take exams online, and to avoid meeting with classmates and professors; most respondents at the time of the interview were home with their families, mostly out of Milan. In this context, following classes online and home alone is very different from going to campus (sometimes commuting for long hours) and paying attention while in front of the teacher and surrounded by classmates. Distraction patterns are also very different; most respondents report being more distracted by their families, and some by their laptops when watching videos. Nonetheless, some students reported being less prone to distractions when following online classes, mostly due to the fact that they could self-manage when to watch them (if recorded), or to the fact that they did not have classmates or friends they could talk to. Almost all students had very little experience of live-streamed classes, as most Bocconi courses were just uploading videos; some students were still following the courses of the universities they were supposed to be in exchange at, and therefore were following live classes at US times (in the evening). When I asked them about their preferences for live or recorded classes, their answers were possibly biased by two factors: first, the fact that recorded classes were those they were more accustomed to, and therefore they could be either more keen on them (and prefer them) or not being able to see the cons of live classes (and dislike more recorded classes); second, the fact that live classes were mostly so by choice, and were therefore influenced by teaching styles. The latter factor includes the fact some Bocconi live classes were part of recorded courses but were “special classes”, for example collective summaries or with guest speakers. Preferences about live or recorded classes were quite varied. Many students preferred recorded classes as this allowed them to schedule them flexibly and to be more efficient at taking notes, even if sometimes being alone in front of a screen with the possibility of pausing the class or going back made them more relaxed about taking breaks; other students instead declared being more prone to distractions with live classes, because their pace was more natural, and therefore more boring or repetitive at some points. Some students instead said that live classes were more entertaining and it was more difficult to get distracted, in particular if the webcam had to be switched on. One positive feature of live classes was the chance of interacting with the professor to ask for explanations, and one student mentioned that they liked having a scheduled appointment they could look forward to. One negative aspect of recorded lectures is the fact that for some students the rhythm was more unnatural, both faster and more boring if the professor was just reading and not speaking as if in class. Some students mentioned the fact that following recorded classes is making them more efficient because in this way they have the chance to take better notes, in terms of completeness and order (in particular, to integrate them with the slides on the spot, instead of later), and to integrate the phases of class attendance and studying; in fact, if students cannot directly ask for clarifications, what they did was to mostly look up for their answers on the material, and cover their preparation while taking more notes.

When it comes to distraction, following lectures at home changes patterns. For some people, the sources of distraction increase, as they include the family, the cozy environment, and possibly the laptop (in particular for those who before took notes by hand and studied on printed material). When asked about how they were getting distracted, most students reported still using the smartphone a lot, in particular for messaging and social media, while some said that for news or searches or videos they had switched from the smartphone to the laptop. A few said that they only used their smartphone for relaxing because they were keeping the Bocconi webpage open full-screen on the laptop, whole some said that they were actually using more the laptop also for WhatsApp. In general, almost all respondents said that since the beginning of the lockdown their use of the smartphone has increased, in particular for communication purposes. And what about peer interactions? Most respondents still had normal interactions with the closest friends at Bocconi, while some declared that their level of communication had decreased or shrunk to academic-only content. Almost all students said that their contacts with people they were less acquainted with had basically disappeared, if not for team-work related purposes. Some students had difficulties answering, as in this semester they were supposed to be in exchange and are therefore taking non-Bocconi courses; one students instead said that the biggest change they noticed was their change in the interactions with professors during lectures: the other students were generally interacting less, and in order to fill this void the respondent said they were more keen on sharing their opinion.

Quotes from the interviews

Here are some quotes from the interviews, translated in English. I use "I" as Interviewer to denote myself, and "R" as Respondent to refer to the student.

* * *

R: [...] for sure it [*the smartphone*] is a very very useful device, but sometimes I'd like to be freer from it. I try to distance myself from my smartphone a little bit... because I can see that in a certain way it is forcing me to be constantly connected, and people want me to constantly answer to messages, to be always there...

* * *

I: But apart from your smartphone, more in general, why do you think that students get distracted? Both in class and while studying.

R: I think... I think we could refer to the "short term benefit" mechanism – clearly the sacrifice of paying attention becomes more and more burdensome the longer one pays attention to the class, in particular if the topic is boring or difficult or complicated, and so the extra minute of concentration takes more effort than the previous one, in a certain way... while the desire for relax, either from distractions or from checking one's smartphone or whatever, even staring at the corner of the whiteboard, prevails. And therefore – clearly one needs to be very rational and determined in order to acknowledge the importance of staying focused, but I think that distractions stem from the fact that students think "nothing happens, it doesn't matter... nothing happens if I drift away, so, I can..."... maybe, I don't know.

I: So you think it's this balance of self control, being tired, being myopic about costs and benefits...?

R: One is not really able to evaluate the two – the difference between two future scenarios, one in which they got distracted and another one in which they didn't... So, it's this inability, which however – I think this difference is there for sure. This creates the incentive for distractions to arise.

* * *

I: Is there something you would change in this relationship ? [*with your smartphone*]

R: Mmm yes, maybe... I have a healthy relationship but I feel like I have to check it – not use it, but simply check it, if there are messages, if there is something, every set amount of time... So I would extend this amount of time actually, instead of 20 minutes I would make it one hour, two hours.

I: But do you check for messages because, for example, if you get a message you know that the other person is expecting an immediate answer? I mean, do you feel the pressure to answer within a certain amount of time?

R: I don't feel forced to answer, it's more about knowing if – I don't know, I want to know if there is somebody or something that could help me out of my current moment of study, let's say, it's like a self-excuse, it's like I'm making up my own justification for a break... I mean, I have the excuse to take a break, maybe the three minutes to answer a message... but no, no pressure, in fact if I had an exam tomorrow I would not have my smartphone, I would hide it and not see it.

Appendix to Chapter 2

B.1 The Institutional Setting

Table B.1: Average changes to other high schools in Veneto, a.y. 2007/08.

	Track				
	General	*Technical*	*Vocational*	*Art*[a]	**Average**
% changes in the 1^{st} year	3.3	2.1	2.2	6.3	2.7

Percentage of changes to other high schools in the first year of enrolment. Veneto, a.y. 2007/08.
[a]: Art schools were absorbed by the General/Technical track in a.y. 2009/10.

Table B.2: High school graduates and university enrollment decisions.

	Still enrolled	Graduated, continuing	Graduated, not studying	Drop out	Never enrolled
Arts	24.9	4.7	5.6	7.2	57.7
General track (*liceo*)	57.3	18.9	9.8	6.2	7.8
General Social Sciences	41.9	11.2	10.2	10.8	25.9
Technical track	23.5	5.8	3.8	10.7	56.2
Vocational track	11.3	1.3	2	6.3	79.1

Sample of students who graduated from high school in 2011, interviewed in 2015.
Percentage values by track of university enrollment status.
Liceo includes: Humanities, Languages, Math & Science.
Arts includes both the *liceo* and the technical track.

Source: Istat, "I percorsi di studio e lavoro dei diplomati e dei laureati: Indagine 2015 su diplomati e laureati 2011", September 29, 2016 (Table 2, page 4). Available at www.istat.it.

Some extracts of articles that deal with the problem of wrong high school choice and dropouts.

Scuola24 — *Il quotidiano della Formazione, dell'Università e della Ricerca* — Il Sole 24 ORE

26 Feb 2015

FAMIGLIE E STUDENTI

Troppe volte si sbaglia la scelta delle superiori

Una scelta poco consapevole

Gli studenti pentiti della propria scelta tendono ad aumentare ad un anno dal diploma. L'errore nella scelta è più diffuso tra gli istituti professionali: ad un anno dal diploma il 48% opterebbe per un altro indirizzo; negli istituti tecnici questa percentuale scende al 40,6% e per le scuole artistiche o pedagogiche è al 40,4%. I liceali farebbero una scelta diversa solo nel 29,8% dei casi.

la Repubblica

Un diplomato su due ammette: "Ho sbagliato scuola"

14 febbraio 2018

Non calano i pentiti della scelta fatta a 14 anni dell'istituto o dell'indirizzo di studi. Indagine AlmaDiploma su 80mila ragazzi usciti dalle superiori nel 2016 e 2014

Più precisamente, nell'ultimo quinquennio, dal 2013-14 al 2017-18, al primo anno gli studenti iscritti erano 612.675, mentre cinque anni dopo, al 5° anno, erano scesi a 461.120 unità: lungo il percorso hanno abbandonato anzitempo 151.555 studenti, cioè il 24,74% di quelli che erano partiti cinque anni prima. Praticamente ha abbandonato uno studente ogni quattro.

B.2 High Schools in Vicenza

Tables B.3 and B.4 present data from Eduscopio, a yearly study founded by Fondazione Agnelli which aims at evaluating how good high schools are at preparing students for their future careers[29].

The three high school tracks are evaluated in different ways. Performance in the first year of university is important mostly for students in the general track, while only half of those with a technical diploma and a fifth of those with a vocational one will continue their education. These two tracks are more focused on providing students with skills that can be immediately used on the labor market, and hence the mission of these schools is to smooth the transition into a job.

Eduscopio analyses how each cohort of students in each high school performs in the years after their diploma, according to parameters such as average first contract duration or GPA in the first-year university exam. This study is considering only first-year outcomes at university because this captures both the impact of each high school on the transition and the fact that first-year grades are strongly correlated with the following academic performance. A study by Aina, Bratti, and Lippo (2019) confirms that there is perfect correlation between Eduscopio scores in the first and in the third year of university, hence the high school effect persists.

In the following tables I select some of the indicators that I deem more appropriate for this research. In particular, I highlight discrepancies between the high school curriculum/track and the following career choices. I only report results for the 2017 cohort (i.e. the year in which students in my sample are supposed to have graduated from high school) and for the high schools that were possible choices for the students in my sample. I also add as a reference the average value for that indicator for all the same curriculum institutes present in the region of Veneto (referred to in the tables as "Average in the area").

Table B.3 presents first-year academic results of students who finished the above-mentioned high schools in summer 2017, possibly including the students that were in my analysed sample in a.y. 2011/2012.

Table B.4 presents employment results of students who finished the above-mentioned high schools in summer 2017 one year after their diploma.

[29] To see all the reports and the methodology, see eduscopio.it.

Table B.3: Data regarding academic results of students from the listed high schools in Vicenza who obtained their diploma in 2017.

	Never enrolled	Drop out[a]	Enrolled cont.[a]	Share[b] human.[c]	Share[b] scientific[d]	Share[b] medical[e]	Share[b] tech.[f]
General track (*liceo*)							
Pigafetta - Humanities	.11	.05	.84	.497	.277	.145	.081
Average in the area[g]	*.09*	*.09*	*.82*				
Lioy - Math&Sciences	.06	.1	.84	.243	.351	.16	.246
Quadri - Math&Sciences	.03	.05	.91	.165	.344	.15	.341
Average in the area[g]	*.09*	*.08*	*.83*				
Don Fogazzaro - Lang.	.21	.09	.70	.653	.272	.048	.027
Pigafetta - Lang.	.14	.04	.82	.706	.17	.079	.045
Average in the area[g]	*.22*	*.08*	*.70*				
Don Fogazzaro - Social Sc.	.21	.08	.71	.758	.15	.082	.01
Average in the area[g]	*.28*	*.09*	*.63*				
Technical track							
Boscardin - Technology	.26	.12	.63	.073	.513	.32	.094
Canova - Technology	.57	.11	.33	.127	.164	.027	.682
Rossi - Technology	.52	.05	.43	.047	.166	.01	.777
Average in the area[g]	*.53*	*.08*	*.39*				
Fusinieri - Economic sector	.56	.08	.37	.299	.61	-	.091
Piovene - Economic sector	.52	.06	.43	.452	.481	.025	.042
Average in the area[g]	*.53*	*.06*	*.41*				

[a]: after one year of university.
[b]: share of enrolled students by university area.
[c]: includes humanities, social sciences, law and politics.
[d]: includes scientific disciplines, economics and statistics.
[e]: includes medicine and healthcare.
[f]: includes technical disciplines.
[g]: average data from same curriculum in the region of Veneto.

Source: eduscopio.it.

Table B.4: Data regarding employment outcomes of students from the listed high schools in Vicenza who obtained their diploma in 2017.

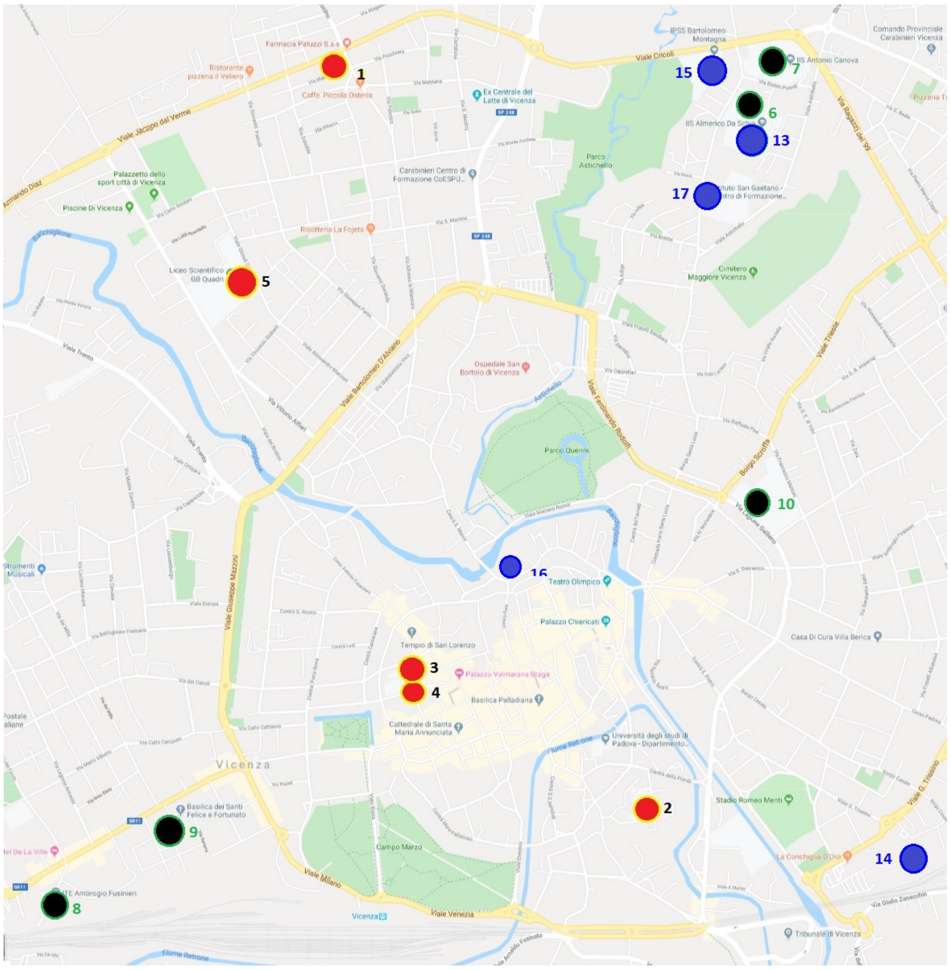
	Employment					Diploma&Job		
	Empl.[a]	Under empl.[b]	Work& Uni[c]	Uni[d]	Other[e]	Coherent Job[f]	Cross-skill Job[g]	Not coh. Job [h]
Technical track								
Boscardin - Technology	.14	.04	.17	.58	.07	.181	.222	.597
Canova - Technology	.23	.11	.13	.30	.23	.104	.182	.714
Rossi - Technology	.31	.09	.09	.39	.12	.525	.042	.432
Average in the area[i]	*.32*	*.08*	*.13*	*.35*	*.13*			
Da Schio - Economic sec.	.44	.08	.20	.13	.15	.267	.60	.133
Fusinieri - Economic sec.	.36	.08	.15	.29	.11	.507	.167	.326
Piovene - Economic sec.	.33	.09	.16	.32	.10	.216	.276	.508
Average in the area[i]	*.36*	*.09*	*.13*	*.29*	*.13*			
Vocational track								
Da Schio - Services	.39	.13	.07	.17	.24	.485	.03	.485
Lampertico - Services	.37	.19	.02	.14	.28	.526	.053	.421
Montagna - Services	.37	.12	.08	.15	.27	.609	.098	.293
Average in the area[i]	*.45*	*.15*	*.07*	*.12*	*.21*			
Lampertico - Industry	.57	.12	.05	.13	.13	.50	.099	.401
Montagna - Industry	.46	.26	.02	.04	.22	.391	.217	.391
Average in the area[i]	*.61*	*.14*	*.04*	*.05*	*.16*			

[a]: share of students who have worked at least 6 months in the last two years.
[b]: share of students who have worked less than 6 months in the last two years.
[c]: share of students working and studying at university.
[d]: share of students studying at university.
[e]: share of students who are unemployed/NEET/abroad/other.
[f]: share of students having a job coherent with their high school diploma.
[g]: share of students who have jobs which require skills that can be acquired from different high school paths.
[h]: share of students having a job not coherent with their high school diploma.
[i]: average data from same curriculum in the region of Veneto.

Source: eduscopio.it.

B.3 The Dataset: Survey Design

Figure B.1: Location of high schools in Vicenza.



Legend of the schools in Figure B.1.

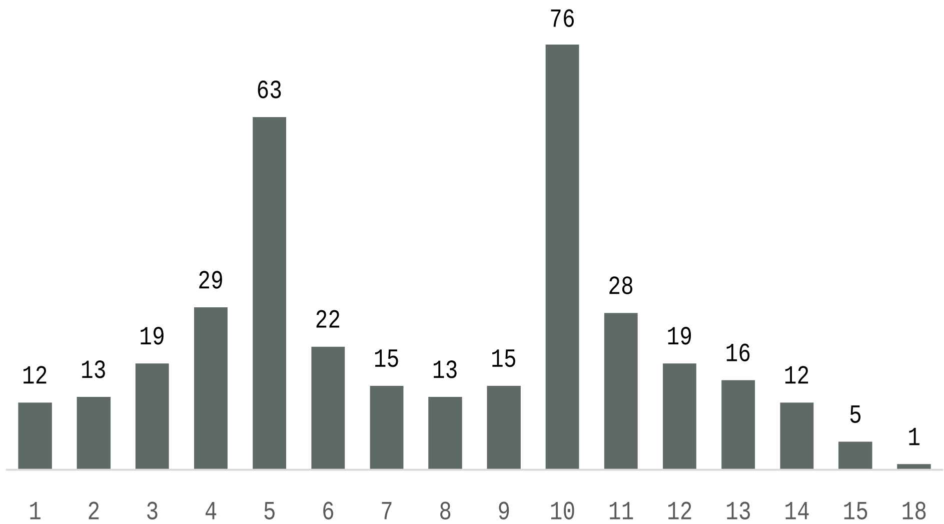
General Track	
L Citta' di Vicenza/Ex Martini	1
L Don Fogazzaro	2
L Lioy	3
L Pigafetta	4
L Quadri	5
Technical Track	
IT Boscardin	6
IT Canova	7
IT Fusinieri	8
IT Piovene	9
IT Rossi	10
Vocational Track	
IP Da Schio	13
IP Lampertico	14
IP Montagna	15
Patronato Leone XIII	16
San Gaetano	17

Table B.5: Participating students.

	Participating	out of	waves 2 & 3
Schools	10	11	
Classes	47	48	
Pupils	733	ca. 1050	358
Addresses	407		195

Pupils are considered as participating if they filled in at least one survey and we have their demographic information.

Figure B.2: Frequency of the total number of unique peers reported (outdegree), by aggregating information from Waves 2 and 3.



A high outdegree may stem from the fact that a student answers to both waves but indicates peer that cannot be unambiguously identified or even matched across the two questionnaires.

Table B.6: Children's survey attrition.

	Size of the Respondents' Sample[a] N	
Wave 1	649	100%
Wave 2	388	60%[b]
Wave 3	308	48%[b]
Wave 4	272	42%[b]

[a]: After dropping observations with item non-response.
[b]: Comparison with the first-wave N.

Table B.7: Average characteristics of respondents.

	(1)	(2)	(3)
Female, %	0.53	0.55	0.6
Foreign country of birth, %	0.14	0.12	0.10
Number of siblings	0.64	0.58	0.58
Parents co-residing, %	0.88	0.89	0.89
Mother has education college+, %	0.27	0.28	0.29
Father has education college+, %	0.27	0.26	0.26
Home-staying mother, %	0.25	0.25	0.26
Blue-collar father, %	0.29	0.25	0.23
Observations	580-739	406-539	338-408

Col. 1: answering to at least one of the 4 waves.
Col. 2: answering to at least one of the relevant waves for peers (2, 3, 4).
Col. 3: answering to the set of peers' questions at least once.

Table B.8: School choices of respondents.

	(1)	(2)
G. Humanities	6.45	6.55
G. Languages	10.75	12.41
G. Mathematics & Science	24.19	27.24
G. Art, Music & Choral	6.72	6.90
G. Social Sciences	9.68	9.66
T. Economic Sector	9.95	8.28
T. Technology Sector	16.13	14.14
V. Services	7.26	6.21
V. Industry & Crafts	4.03	4.48
V. Professional Training	4.84	4.14
Observations	372	290

Percentage of pre-enrolled in a certain curriculum

Col. 1: answering to at least one of the relevant waves for peers (2, 3, 4).
Col. 2: answering to the set of peers' questions at least once.

Figure B.3: Frequency of being reported as a peer (indegree), by aggregating information from Waves 2 and 3.

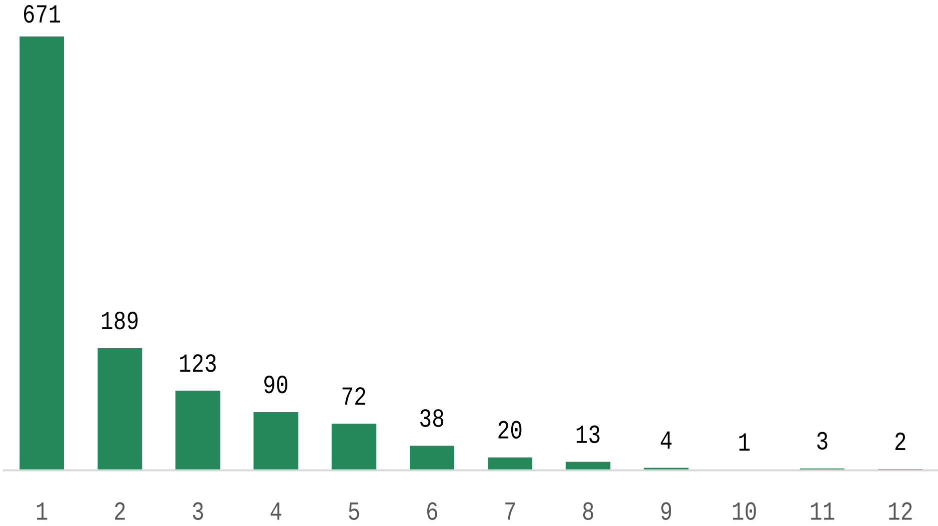


Table B.9: Length of acquaintance with each peer, as of Wave 2.

Peer	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Pre elem., > 7 y	27.8	21	23.5	16	15.5	25.7	15.2	14.7	19.7	15.3
Since elem., 2-7 y	27.1	29.2	25.8	30.7	27	25	30.4	24	25.6	40.5
Since JH, < 2 y	45.1	49.8	50.8	53.3	57.5	49.3	54.3	61.2	54.7	44.1
N [a](100%)	284	281	264	244	226	152	138	129	117	111
Same class, elem.[b]	58.3	53.9	40	44.7	41.7	42.9	41.3	40	39.6	37.1
Diff. class, elem.[b]	17.3	18.4	21.5	18.4	20.8	14.3	19	20	18.9	19.3
N (100%)	156	141	130	114	96	77	63	50	53	62
Same class, JH [c]	62.5	66.9	66.9	58.2	59.3	49.7	55.8	58.6	53.8	56.8
Diff. class, JH [c]	19.8	16.7	15.6	19.7	21.2	27	25.4	18.7	22.2	20.7
N (100%)	283	281	263	244	226	151	138	128	117	111

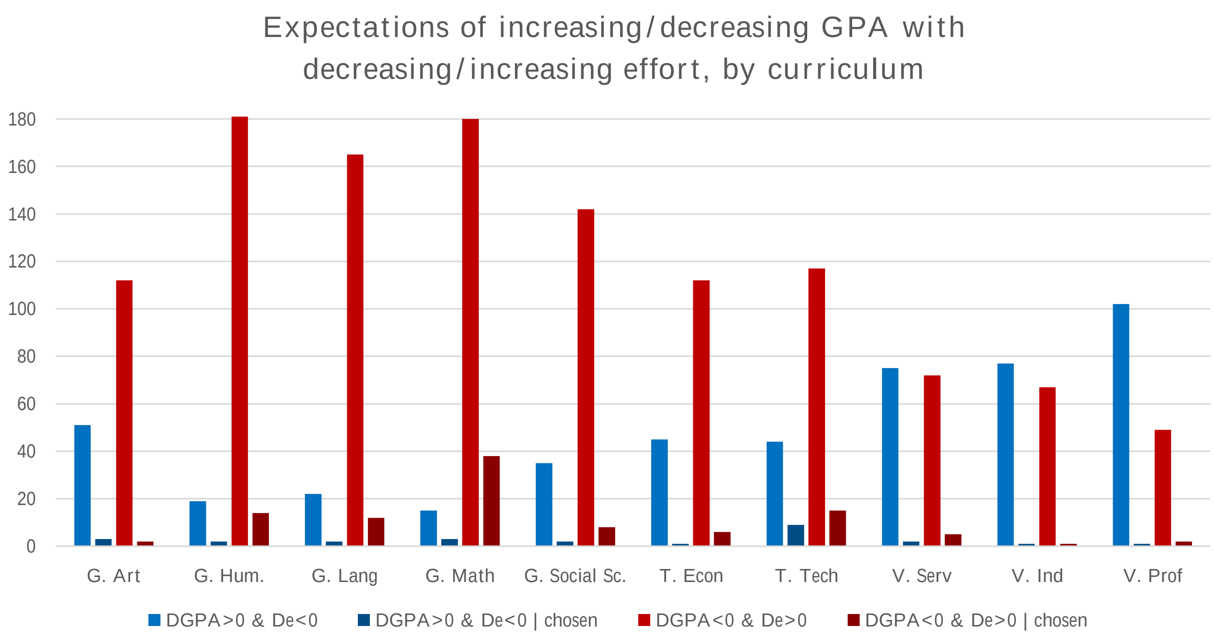
Percentage values.
[a]: Total number of individuals answering this question.
[b]: Conditional on having known each other at least since elementary school.
[c]: Conditional on having known each other at least since junior high (JH) school.

Table B.10: Frequency of students declaring having talked to friends about high school.

	(1)	(2)	(3)
Has never talked to friends about HS[a], %	0.23	0.24	0.22
Has talked to friends about HS at elem. school[a], %	0.01	0.01	0.01
Has talked to friends about HS in 6^{th} grade[a], %	0.07	0.07	0.07
Has talked to friends about HS in 7^{th} grade[a], %	0.27	0.26	0.26
Has talked to friends about HS in 8^{th} grade[a], %	0.67	0.69	0.62
Observations	560	390	321
Has talked to friends about HS n times[b,c], n	-	0.78	0.77
Has talked to friends about HS in general[b,d], %	-	0.26	0.27
Has talked to friends about a specific HS[b,d], %	-	0.24	0.24
Observations	-	216-253	191-221

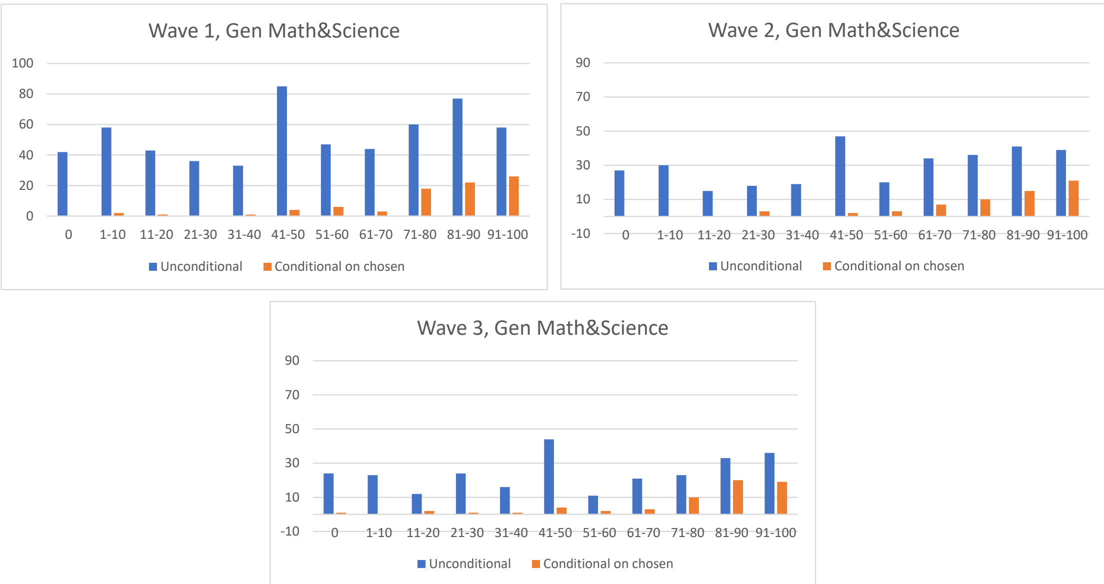
[a]: variables are dummies, collected in Wave 1.
[b]: conditional on having already talked to friends about HS.
[c]: n ranging from 0 to 3, collected in Waves 2 and 3.
[d]: variables are dummies, collected in Waves 2 and 3.

Figure B.4: Frequency of the expected relationship between varying GPA and effort, by curriculum.



For each curriculum there are 4 columns of two colors. Blue represent the situation of a decreasing GPA (Δ GPA $<$ 0) associated with higher effort (Δ e $>$ 0) exerted in high school than in the present. Red represents the opposite situation, increasing GPA with a decrease in effort. The two bars of the same color but different intensity represent respectively the whole sample (lighter shade) *vs* conditional on choosing that curriculum (darker shade).

Figure B.5: Frequency of the expected probability of completing high school in the regular time (5 years) for the Math&Sciences General curriculum, for the three waves.



In each graph observations have been divided into 10 blocks representing e.g. the number of people who answered a number between 1% and 10%. The two columns represent the unconditional number of observations (in blue) and the number of observations conditional on the fact that in Wave 4 these students declare to have chosen this curriculum.

B.4 Results

Table B.11: Marginal effects of the baseline case and with the introduction of GX.

	Baseline		Additional GX	
General				
Share of peers in G	.963***	.463	.884**	.277
	(.319)	(2.341)	(.362)	(1.684)
Share of peers in T	-.626***	-.405	-.631**	-.247
	(.224)	(1.261)	(.272)	(.864)
Share of peers in V	-.337***	-.058	-.254**	-.030
	(.128)	(3.551)	(.119)	(2.476)
Technical				
Share of peers in G	-.626***	-.405	-.631**	-.247
	(.224)	(1.261)	(.272)	(.864)
Share of peers in T	.702***	.417	.689**	.253
	(.248)	(.581)	(.294)	(.441)
Share of peers in V	-.076**	-.012	-.058**	-.006
	(.031)	(.722)	(.029)	(.480)
Vocational				
Share of peers in G	-.337***	-.058	-.254**	-.030
	(.128)	(3.551)	(.119)	(2.476)
Share of peers in T	-.076**	-.012	-.058**	-.006
	(.031)	(.722)	(.029)	(.480)
Share of peers in V	413***.	.070	.312**	.035
	(.155)	(4.273)	(.146)	(2.956)
School FE	no	yes	no	yes

By track

Table B.12: ESTIMATION RESULTS WITH A REDUCED AND A FULL LIST OF SCHOOL FEATURES, WITHOUT EXPECTATIONS.

	Short list		**Full list**	
	(1)	(2)	(3)	(4)
	β	β	β	β
Prob. Like	.067***	.067***	.046***	.047***
	(.007)	(.008)	(.009)	(.010)
Prob. Apt			.014	.015
			(.010)	(.011)
Prob. Trained			.022**	.020**
			(.009)	(.010)
Flexibility Uni/Work Both	-.002***	-.002**	.003	.004
	(.001)	(.001)	(.004)	(.004)
Flexibility Uni/Work Uni			.001	.000
			(.003)	(.003)
Flexibility Uni/Work Work			-.005	-.006
			(.004)	(.005)
Flexibility Field Humanities			-.000	-.000
			(.000)	(.001)
Flexibility Field Sciences			.000	.000
			(.001)	(.001)
Flexibility Field Law			-.001	-.001
			(.001)	(.001)
Technical vs General				
Female	-.093	-.177	-.039	-.137
	(.328)	(.340)	(.336)	(.348)
Foreign born	.309	.248	.356	.257
	(.702)	(.751)	(.755)	(.807)
No. siblings	.064	.030	-.031	-.032
	(.243)	(.255)	(.256)	(.270)
Mother with edu hs+	-.259	-.416	-.359	-.541
	(.394)	(.415)	(.405)	(.429)
Father with edu hs+	.749*	.892**	.731*	.871**
	(.398)	(.416)	(.410)	(.433)
7^{th} grade GPA	-.761***	-.988***	-.719***	-.930***
	(.227)	(.255)	(.236)	(.262)
Vocational vs General				
Female	-.341	-.384	-.304	-.327
	(.382)	(.407)	(.393)	(.418)
Foreign born	1.104*	1.168	1.297*	1.365*
	(.661)	(.738)	(.706)	(.777)
No. siblings	-.036	-.100	-.031	-.091
	(.287)	(.312)	(.296)	(.322)
Mother with edu hs+	-.346	-.635	-.522	-.825
	(.468)	(.507)	(.492)	(.534)
Father with edu hs+	.825*	.885*	.766	.829
	(.479)	(.519)	(.505)	(.544)
7^{th} grade GPA	-.888***	-1.129	-.663**	-.873***
	(.279)	(.312)	(.295)	(.330)
N	374	374	374	374
Pseudo R^2	.369	.402	.369	.402
School FE	no	yes	no	yes

Standard errors in parentheses. * p< 10%, ** p< 5%, *** p< 1%.

School-specific predictors: *prob. like:* reported subjective probability of liking the subjects taught; *prob. apt:* reported subjective probability of having the appropriate set of skills; *prob. trained:* reported subjective probability of having an adequate preparation; *flexibility uni/work both:* reported subjective probability of flexible choice between both work or university afterwards; *flexibility uni/work uni:* reported subjective probability of being able to choose only university afterwards; *flexibility uni/work work:* reported subjective probability of being able to choose only work afterwards; *flexibility field K:* reported subjective probability of being able to choose a K major at university. **Predictors:** *female:* dummy=1 if student is female; *foreign born:* dummy=1 if student is foreign-born; *no. siblings:* number of siblings (between 0 and 3); *mother with edu hs+:* dummy=1 if student's mother has at least high school education; *father with edu hs+:* dummy=1 if student's father has at least high school education; *7^{th}-grade GPA:* student's GPA in the 7th grade end-of-year report (between 6 and 10).

Table B.13: Comparison between three different aggregations of the relevant school features.

	Average		Minimum		High rank	
	(1)	(2)	(3)	(4)	(5)	(6)
	β	β	β	β	β	β
Share of peers	3.838*	3.507	5.455***	3.782*	3.167	4.860
	(2.135)	(2.715)	(1.609)	(1.958)	(2.431)	(3.016)
Prob. Like	.073***	.073***	.012*	.016**	.053***	.061***
	.010	(.010)	(.006)	(.007)	(.008)	(.010)
Flexibility Uni/Work Both	-.001	-.001	-.002***	-.002***	-.001	-.001
	(.000)	(.001)	(.001)	(.001)	(.001)	(.001)
Technical vs General						
Female	.836	.614	.614	.331	.047	.107
	(.609)	(.731)	(.484)	(.526)	(.671)	(.878)
Foreign born	-.367	-.304	-.754	-.139	-.087	.180
	(1.169)	(1.312)	(.961)	(1.036)	(1.248)	(1.470)
No. siblings	.503	.730	.457	.518	.501	.984*
	(.404)	(.471)	(.334)	(.357)	(.472)	(.585)
Mother with edu hs+	-.362	-.279	-.016	.185	-.454	-.859
	(.584)	(.635)	(.459)	(.487)	(.661)	(.805)
Father with edu hs+	.977*	1.135*	.836*	.966**	1.120*	1.217
	(.557)	(.589)	(.447)	(.471)	(.660)	(.779)
7^{th} grade GPA	-.502	-.542	-.774***	-.837**	-.590	-.835
	(.334)	(.443)	(.268)	(.333)	(.366)	(.509)
Vocational vs General						
Female	.881	.811	.676	.394	.421	.477
	(.665)	(.811)	(.549)	(.615)	(.773)	(.991)
Foreign born	-.571	-.665	-.136	.368	.198	-.091
	(1.167)	(1.376)	(.775)	(.927)	(1.362)	(1.526)
No. siblings	.371	.407	.433	.433	.431	1.111
	(.433)	(.497)	(.352)	(.391)	(.565)	(.699)
Mother with edu hs+	-.432	-.567	-.371	-.436	-.677	-.846
	(.672)	(.771)	(.535)	(.595)	(.791)	(.945)
Father with edu hs+	1.279*	1.391*	.574	.714	1.751**	1.971*
	(.675)	(.771)	(.536)	(.604)	(.842)	(1.040)
7^{th} grade GPA	-.607	-.912*	-.854***	-1.215***	-.515	-.941
	(.391)	(.545)	(.333)	(.452)	(.424)	(.653)
N	224	224	224	224	224	224
Pseudo R^2	.491	.545	.268	.341	.603	.669
School FE	no	yes	no	yes	no	yes

Standard errors in parentheses. * p< 10%, ** p< 5%, *** p< 1%.

School-specific predictors: *prob. like:* reported subjective probability of liking the subjects taught; *flexibility uni/work both:* reported subjective probability of flexible choice between both work or university afterwards. **Predictors:** *female:* dummy=1 if student is female; *foreign born:* dummy=1 if student is foreign-born; *no. siblings:* number of siblings (between 0 and 3); *mother with edu hs+:* dummy=1 if student's mother has at least high school education; *father with edu hs+:* dummy=1 if student's father has at least high school education; *7^{th}-grade GPA:* student's GPA in the 7th grade end-of-year report (between 6 and 10).

Table B.14: Marginal effects of three different aggregations of the relevant school features.

	Average	**Minimum**	**High rank**
General			
Share of peers in G	.408*	.937***	.293
	(.235)	(.274)	(.236)
Share of peers in T	-.277*	-609.***	-.209
	(.165)	(.196)	(.171)
Share of peers in V	-.131	-.328***	-.084
	(.081)	(.116)	(.072)
Technical			
Share of peers in G	-.277*	-.609***	-.209
	(.165)	(.196)	(.171)
Share of peers in T	.289*	.669***	.216
	(.173)	(.213)	(.177)
Share of peers in V	-.012	-.060**	-.007
	(.009)	(.024)	(.007)
Vocational			
Share of peers in G	-.131	-.328***	-.084
	(.081)	(.116)	(.072)
Share of peers in T	-.012	-.060**	-.007
	(.009)	(.024)	(.007)
Share of peers in V	.143	.388***	.091
	(.089)	(.135)	(.078)
School FE	no	no	no

By track, no school fixed effects

Table B.15: Marginal effects of expected GPA and effort.

	Effort	**Effort & Performance**	**Differential**	**Relevant**
General				
Share of peers in G	.791***	.624***	.747***	.607***
	(.249)	(.227)	(.219)	(.219)
Share of peers in T	-.535***	-.420***	-.477***	-.396***
	(.177)	(.161)	(.153)	(.151)
Share of peers in V	-.256***	-.204***	-.270***	-.210***
	(.092)	(.082)	(.091)	(.083)
Technical				
Share of peers in G	-.535***	-.420***	-.477***	-.397***
	(.178)	(.161)	(.153)	(.151)
Share of peers in T	.600***	.469***	.537***	.443***
	(.197)	(.178)	(.170)	(.167)
Share of peers in V	-.065***	-.049***	-.060***	-.047***
	(.025)	(.021)	(.022)	(.020)
Vocational				
Share of peers in G	-.256***	-.204***	-.270***	-.210***
	(.092)	(.082)	(.091)	(.083)
Share of peers in T	-.065***	-.049***	-.060***	-.047***
	(.025)	(.021)	(.022)	(.020)
Share of peers in V	.321***	.254***	.330***	.257***
	(.114)	(.101)	(.109)	(.101)
School FE	no	no	no	

By track, no school fixed effects
Columns refer to (1), (2), (3), (4) as in table (7).

Table B.16: Comparison of results introducing expected GPA and effort, without expectations.

	Effort		Effort & Performance		Differential	
	(1)	(2)	(3)	(4)	(5)	(6)
	β	β	β	β	β	β
Exp. tot hours studying	.271***	.273***	.273***	.276***		
	(.068)	(.067)	(.068)	(.067)		
Exp. GPA for studying <1h			-.030	-.039		
			(.113)	(.118)		
Exp. GPA for studying 1<h<2			-.033	-.036		
			(.072)	(.073)		
Exp. GPA for studying 2<h<3			.075	.081		
			(.063)	(.064)		
Exp. GPA for studying>3h			.018	.008		
			(.049)	(.049)		
Δ exp. tot hours					-.091	-.089
					(.064)	(.067)
Δ exp. GPA for studying <1h					.545**	.590***
					(.220)	(.223)
Δ exp. GPA for studying 1<h<2					-.252	-.203
					(.234)	(.200)
Δ exp. GPA for studying 2<h<3					-.360	-.473*
					(.253)	(.276)
Δ exp. GPA for studying>3h					.118	.095
					(.123)	(.119)
Technical vs General						
Female	-.112	-.069	-.126	-.078	-.130	-.090
	(.088)	(.094)	(.089)	(.096)	(.090)	(.096)
Foreign born	.070	.073	.067	.070	.084	.085
	(.069)	(.071)	(.069)	(.071)	(.069)	(.070)
No. siblings	-.088**	-.095**	-.092**	-.098**	-.083*	-.086*
	(.043)	(.045)	(.043)	(.045)	(.042)	(.044)
Mother with edu hs+	-.085	-.061	-.086	-.058	-.125	-.094
	(.153)	(.155)	(.155)	(.155)	(.147)	(.147)
Father with edu hs+	.091	.070	.097	.071	.138	.109
	(.146)	(.147)	(.147)	(.148)	(.139)	(.139)
7^{th} grade GPA	-.063*	-.072*	-.063*	-.072*	-.075**	-.084**
	(.037)	(.038)	(.037)	(.038)	(.037)	(.038)
Vocational vs General						
Female	-.052	.009	-.058	.000	-.079	-.023
	(.102)	(.109)	(.103)	(.110)	(.104)	(.110)
Foreign born	.083	.069	.083	.070	.099	.089
	(.077)	(.080)	(.077)	(.080)	(.076)	(.079)
No. siblings	-.109**	-.106**	-.109**	-.105**	-.085*	-.076
	(.050)	(.051)	(.050)	(.051)	(.048)	(.049)
Mother with edu hs+	.162	.272*	.162	.273*	.098	.176
	(.138)	(.143)	(.139)	(.143)	(.127)	(.135)
Father with edu hs+	-.054	-.137	-.053	-.139	-.014	-.073
	(.120)	(.124)	(.120)	(.124)	(.110)	(.118)
7^{th} grade GPA	-.131***	-.154***	-.131***	-.153***	-.132***	-.152***
	(.038)	(.043)	(.038)	(.043)	(.038)	(.042)
N	374	374	374	374	374	374
Pseudo R^2	.101	.153	.104	.156	.077	.132
School FE	no	yes	no	yes	no	yes

Standard errors in parentheses. * p< 10%, ** p< 5%, *** p< 1%.

School-specific predictors: *exp. tot hours studying:* expected amount of study hours; *exp. GPA for studying X:* expected GPA for each amount X of daily study hours; Δ *exp. tot hours:* expected change in study hours with respect to 8th grade; Δ *exp. GPA for studying X:* expected change in GPA with respect to 8th grade for each amount X of daily study hours. **Predictors:** *female:* dummy=1 if student is female; *foreign born:* dummy=1 if student is foreign-born; *no. siblings:* number of siblings (between 0 and 3); *mother with edu hs+:* dummy=1 if student's mother has at least high school education; *father with edu hs+:* dummy=1 if student's father has at least high school education; *7^{th}-grade GPA:* student's GPA in the 7th grade end-of-year report (between 6 and 10).

Table B.17: Marginal effects across different weighted networks, including only the relevant covariates.

	Unweighted	**Equal weights**	**Proport. weights**
General			
Share of peers in G	.574***	.445**	.356*
	(.211)	(.199)	(.187)
Share of peers in T	-.383**	-.317**	-.251*
	(.151)	(.149)	(.137)
Share of peers in V	-.191**	-.128**	-.105*
	(.078)	(.063)	(.059)
Technical			
Share of peers in G	-.383**	-.317**	-.251*
	(.152)	(.149)	(.137)
Share of peers in T	.403**	.328**	.261*
	(.160)	(.155)	(.142)
Share of peers in V	-.020*	-.011	-.009
	(.011)	(.007)	(.006)
Vocational			
Share of peers in G	-.191**	-.128**	-.105*
	(.078)	(.063)	(.059)
Share of peers in T	-.020*	-.011	-.009
	(.011)	(.007)	(.006)
Share of peers in V	.211**	.140**	.114*
	(.087)	(.070)	(.065)
School FE	no	no	no

By track, no school fixed effects

Table B.18: Comparison of results across different weighted networks, including only the relevant covariates, with bootstrapped standard errors.

	Unweighted		**Equal weights**		**Proport. weights**	
	(1)	(2)	(3)	(4)	(5)	(6)
Share of peers	4.881**	5.229	4.499*	3.693**	3.550*	3.505
	(2.040)	(7.712)	(2.515)	(3.672)	(1.999)	(3.441)
Exp. tot hours studying	-.025	-.006	-.041	.027	-.031	.021
	(.181)	(.255)	(.243)	(.301)	(.181)	(.318)
Δ exp. GPA for studying <1h	.240	.221	.195	.146	.191	.159
	(.288)	(.803)	(.263)	(.518)	(.171)	(.453)
Δ exp. GPA for studying 2<h<3	-.276	-.225	-.219	-.167	-.225	-.179
	(.370)	(.860)	(.274)	(.661)	(.163)	(.478)
Prob. Like	.065***	.065	.071***	.073*	.072***	.073**
	(.019)	(.092)	(.012)	(.044)	(.021)	(.029)
Flexibility Uni/Work Both	-.001	-.001	-.002**	-.002	-.002	-.002
	(.001)	(.002)	(.001)	(.003)	(.001)	(.002)
Technical vs General						
Female	.724	.596	.902	.501	.792	.505
	(.622)	(1.618)	(.678)	(1.238)	(.714)	(.839)
Foreign born	.075	.171	.148	.187	.155	.178
	(.461)	(1.055)	(.744)	(2.304)	(.427)	(.819)
No. siblings	-.026	-.088	-.036	-.096	-.046	-.093
	(.140)	(.589)	(.227)	(.357)	(.128)	(.362)
Mother with edu hs+	-.482	-.553	-.652	-.769	-.587	-.745
	(.505)	(.905)	(.589)	(1.334)	(.372)	(.607)
Father with edu hs+	.568	.576	.663	.736	.602	.717
	(.557)	(.717)	(.447)	(1.029)	(.395)	(.643)
7^{th} grade GPA	-.058	-.022	-.060	-.022	-.068	-.026
	(.129)	(.328)	(.141)	(.728)	(.166)	(.192)
Vocational vs General						
Female	.706	.809	.727	.734	.691	.729
	(.750)	(3.324)	(.823)	(2.327)	(.905)	(.973)
Foreign born	.260	.303	.254	.382	.277	.363
	(.563)	(2.446)	(1.050)	(.2.429)	(.857)	(1.192)
No. siblings	-.201*	-.223	-.247	-.272	-.244	-.265
	(.328)	(.358)	(.158)	(.427)	(.222)	(.275)
Mother with edu hs+	.211	.159	.251	.174	.230	.159
	(.420)	(1.203)	(.645)	(1.334)	(.405)	(1.177)
Father with edu hs+	-.117	-.130	-.080	-.145	-.076	-.126
	(.894)	(1.616)	(.896)	(1.944)	(.752)	(1.169)
7^{th} grade GPA	-.041	-.025	-.068	-.076	-.077	-.071
	(.104)	(.791)	(.146)	(.771)	(.142)	(.613)
N	224	224	211	211	211	211
Pseudo R^2	.484	.522	.487	.528	.481	.525
School FE	no	yes	no	yes	no	yes
Bootstrap std errors	yes	yes	yes	yes	yes	yes

Standard errors in parentheses. * p< 10%, ** p< 5%, *** p< 1%.

School-specific predictors: *exp. tot hours studying:* expected amount of study hours; Δ *exp. GPA for studying X:* expected change in GPA with respect to 8th grade for each amount X of daily study hours; *prob. like:* reported subjective probability of liking the subjects taught; *flexibility uni/work both:* reported subjective probability of flexible choice between both work or university afterwards. **Predictors:** *female:* dummy=1 if student is female; *foreign born:* dummy=1 if student is foreign-born; *no. siblings:* number of siblings (between 0 and 3); *mother with edu hs+:* dummy=1 if student's mother has at least high school education; *father with edu hs+:* dummy=1 if student's father has at least high school education; *7^{th}-grade GPA:* student's GPA in the 7th grade end-of-year report (between 6 and 10).

Table B.19: Estimation of results with all the relevant covariates, with and without middle school fixed effects.

	(1)		(2)	
	Male	**Female**	**Male**	**Female**
	β	β	β	β
Share of peers	7.482***	3.779	10.225**	5.645
	(2.634)	(2.791)	(4.935)	(4.082)
Exp. tot hours studying	.037	-.106	.028	-.055
	(.174)	(.143)	(.215)	(.195)
Δ exp. GPA for studying <1h	.256	.186	.554	.028
	(.283)	(.332)	(.393)	(.310)
Δ exp. GPA for studying 2<h<3	-.218	-.309	-.254	-.155
	(.316)	(.417)	(.429)	(.376)
Prob. Like	.045***	.095***	.051***	.101***
	(.013)	(.018)	(.016)	(.023)
Flexibility Uni/Work Both	-.000	-.003**	.000	-.003**
	(.001)	(.001)	(.001)	(.002)
Technical vs General				
Foreign born	.975	.675	1.348	1.189
	(.858)	(1.171)	(1.342)	(1.723)
No. siblings	-.040	-.036	.323	-.146
	(.166)	(.131)	(.325)	(.196)
Mother with edu hs+	-1.327	-.226	-2.465*	-.398
	(836.)	(.483)	(1.405)	(.632)
Father with edu hs+	.453	.311	1.012	.529
	(.384)	(.483)	(.956)	(.642)
7^{th} grade GPA	-.004	-.119	-.083	-.379
	(.094)	(.120)	(.143)	(.294)
Vocational vs General				
Foreign born	2.141	.213	22.603	.055
	(1.904)	(.497)	(6662)	(1.108)
No. siblings	.021	-.298*	-.065	-.363
	(.513)	(.153)	(.615)	(.241)
Mother with edu hs+	-.990	.535	-1.791	1.096
	(.958)	(.520)	(2.053)	(1.119)
Father with edu hs+	-.153	-.180	-.462	-.161
	(.465)	(.220)	(1.831)	(.260)
7^{th} grade GPA	.072	-.152	.152	-.418
	(.126)	(.116)	(.207)	(.324)
N	261	411	261	411
Pseudo R^2	.767	.758	.826	.802
School FE	no	no	yes	yes

Standard errors in parentheses. * p< 10%, ** p< 5%, *** p< 1%.

School-specific predictors: *exp. tot hours studying:* expected amount of study hours; Δ *exp. GPA for studying X:* expected change in GPA with respect to 8th grade for each amount X of daily study hours; *prob. like:* reported subjective probability of liking the subjects taught; *flexibility uni/work both:* reported subjective probability of flexible choice between both work or university afterwards. **Predictors:** *foreign born:* dummy=1 if student is foreign-born; *no. siblings:* number of siblings (between 0 and 3); *mother with edu hs+:* dummy=1 if student's mother has at least high school education; *father with edu hs+:* dummy=1 if student's father has at least high school education; *7^{th}-grade GPA:* student's GPA in the 7th grade end-of-year report (between 6 and 10).

Table B.20: Marginal effects of choice only, and choice with beliefs.

	Actual Choice		Choice & Expectation	
General				
Actual Share of peers in G	.413***	.327	.259***	.172
	(.090)	(1.315)	(.062)	(.403)
Expected in G			.171***	.130
			(.033)	(.293)
Actual Share of peers in T	-.299***	-.312	-.180***	-.163
	(.066)	(.475)	(.044)	(.167)
Expected in T			-.119***	-.124
			(.024)	(.099)
Actual Share of peers in V	-.114***	-.014	-.079***	-.009
	(.030)	(1.772)	(.022)	(.512)
Expected in V			-.052***	-.007
			(.013)	(.387)
Technical				
Actual Share of peers in G	-.299***	-.312	-.180***	-.163
	(.066)	(.475)	(.044)	(.167)
Beliefs in G			-.119***	-.124
			(.024)	(.099)
Actual Share of peers in T	.320***	.315	.191***	.165
	(.071)	(.228)	(.046)	(.123)
Beliefs in T			.127***	.125**
			(.026)	(.050)
Actual Share of peers in V	-.021***	-.002	-.011***	-.001
	(.006)	(.264)	(.003)	(.071)
Beliefs in V			-.007***	-.001
			(.002)	(.054)
Vocational				
Actual Share of peers in G	-.114***	-.014	-.079***	-.009
	(.030)	(1.772)	(.022)	(.512)
Beliefs in G			-.052***	-.006
			(.013)	(.387)
Actual Share of peers in T	-.021***	-.002	-.011***	-.001
	(.006)	(.264)	(.003)	(.071)
Beliefs in T			-.007***	-.001
			(.002)	(.054)
Actual Share of peers in V	.135***	.017	.090***	.010
	(.036)	(2.036)	(.025)	(.583)
Beliefs in V			.059***	.007
			(.014)	(.441)
School FE	no	yes	no	yes

By track

Table B.21: Marginal effects of baseline case and different weighted networks.

	Unweighted	**Equal weights**	**Proport. weights**
General			
Share of peers in G	.963***	.479***	.494***
	(.319)	(.124)	(.130)
Share of peers in T	-.626***	-.333***	-.344***
	(.224)	(.094)	(.099)
Share of peers in V	-.337***	-.145***	-.149***
	(.128)	(.052)	(.054)
Technical			
Share of peers in G	-.626***	-.333***	-.344***
	(.224)	(.094)	(.099)
Share of peers in T	.702***	.364***	.375***
	(.248)	(.101)	(.106)
Share of peers in V	-.076**	-.030***	-.031***
	(.031)	(.011)	(.012)
Vocational			
Share of peers in G	-.337***	-.145***	-.149***
	(.128)	(.052)	(.054)
Share of peers in T	-.076**	-.030***	-.031***
	(.031)	(.011)	(.012)
Share of peers in V	413***.	.175***	.181***
	(.155)	(.062)	(.064)
School FE	no	no	no

By track, no school fixed effects

Analysis of variance (least squares used to fit a linear model).

	Unweighted				**Equal weights**				**Proport. weights**			
	Partial SS	F	Partial SS	F	Partial SS	F	Partial SS	F	Partial SS	F	Partial SS	F
Model	61.021	76.58***	60.091	29.45***	57.23	71.56***	56.59	27.69***	56.98	71.04***	56.77	27.83***
Share of peers	25.408	191.32***	24.183	177.77***	24.17	181.32***	23.24	170.52***	23.919	178.93***	23.414	172.19***
Exp. tot hours studying	.000	.00	.008	.06	.011	.08	.000	.00	.008	.06	.000	.00
Δ exp. GPA for studying <1h	.161	1.21	.181	1.33	.137	1.03	.160	1.17	.139	1.04	.158	1.16
Δ exp. GPA for studying 2<h<3	.178	1.34	.205	1.51	.137	1.03	.164	1.21	.140	1.05	.162	1.19
Prob. Like	8.247	60.62***	6.664	50.18***	6.405	48.06***	8.34	61.18***	6.577	49.2***	8.184	60.18
Flexibility Uni/Work Both	.027	.21	.000	.00	.003	.03	.020	.14	.002	.01	.017	.12
Residual	88.312		89.242		83.44		84.077		83.686		83.899	
Total	149.33		149.33		140.67		140.67		140.67		140.67	
N	224		224		211		211		211		211	
Root MSE	.364		.369		.365		.369		.366		.369	
R^2	.409		.402		.407		.402		.405		.404	
Adj-R^2	.403		.389		.401		.388		.399		.389	
School FE	no		yes		no		yes		no		yes	

F stat reported in column "F", with significance value attached: * p< 10%, ** p< 5%, *** p< 1%.

Table B.22: Summary statistics of node characteristics – Simulated Network.

	Mean	**Std. Dev.**	**Min**	**Max**
Female	.52	.49	0	1
Foreign-Born	.14	.31	0	1
Have Co-residing Parents	.88	.29	0	1
Have Older Siblings	.64	.68	0	1
Have Mother with Education College+	.27	.39	0	1
Have Father with Education College+	.26	.38	0	1
Have Stay-at-Home Mother	.25	.39	0	1
Have Blue-Collar Father	.29	.40	0	1
7^{th} grade GPA	7.65	.83	6	9.8
N. obs.	766			

Table B.23: Summary statistics of fraction of all potential edges sharing the same characteristics – Simulated Network.

Same Gender	.47
Both Foreign-Born	.57
Both Have Co-residing Parents	.52
Both Have Older Siblings	.36
Both Have Mothers with Education College+	.41
Both Have Fathers with Education College+	.41
Both Have Stay-at-Home Mothers	.44
Both Have Blue-Collar Fathers	.40
Same[a] 7^{th} grade GPA	.50
N. obs.	585,990

[a]: within one standard deviation.

Table B.24: LOGISTIC REGRESSION OF LINK FORMATION – SIMULATED NETWORK.

Same Gender	1.478***
	(.060)
Both Foreign-Born	.616***
	(.061)
Both Have Co-residing Parents	.244***
	(.056)
Both Have Older Siblings	.061
	(.049)
Both Have Mothers with Education College+	-.041
	(.056)
Both Have Fathers with Education College+	.040
	(.057)
Both Have Stay-at-Home Mothers	.139***
	(.052)
Both Have Blue-Collar Fathers	.323***
	(.052)
Same[a] 7^{th} grade GPA[a]	.207***
	(.048)
N. obs.	585,990
McFadden's pseudo R^2	0.0501

[a]: within one standard deviation.
Standard errors in parentheses.
Statistical significance: *** p<0.01; ** p<0.05; * p<0.1.

Appendix to Chapter 3

C.1 Motivating Quotes

Schooling decisions are sequential not only to economists but also to parents who know the option value of the right high school. This is true both in tracking systems like the Italian one, where the contents taught and the methodology of teaching can affect the probability of later enrolling to (and succeeding in) university, but also in the US where the quality of a school can impact the chances of admission to a good college afterwards. Choosing the right high school is perceived as a stepping stone to college and/or to work. The following quotes represent how this is true both in Italy and in the US, and both to parents and children.

> *American 8th grader during high school choice in NYC*: "[I put on the application form] Specialized High School A because of [its] rigorous curriculum and they offer a lot of college credits [...] most people who go to college after that came back and said that Specialized High School A was much harder than college. And I thought that it would be good to prepare myself for college [...]" Source: Sattin-Bajaj (2014)
>
> *Mother of two 8th graders during high school choice in NYC*: "If I didn't like the colleges they [the high school's graduates] got into, we wouldn't put it [on the application form]. We [she and her husband] grew up on Long Island, in Levittown. There were not great schools. That affected our colleges, so I wanted our daughters to have more options." Source: Sattin-Bajaj (2014)
>
> *Older brother of an Italian 9th grader who had just made high school track choice*: "If someone studies Humanities in a general-track high school, but after 5 years he no longer wishes to go to college, what can he do? And after studying art in a general-track high school? Because, when one is 14, he

> makes a choice thinking that perhaps he will go to college afterwards... But, after 5 years, he might change his mind. [Had he attended a technical- or vocational-track high school] He could go to work, if he becomes fed up with school." Source: Istituto IARD (2001)

In making this choice, parents have stronger preferences and are more future-oriented than children. It is therefore natural that in their role of primary decision makers they try to shape their child's choice set even when they want to convey the idea that it is indeed their son or daughter who is actually making the choice. The next quotes provide anecdotal evidence of how parents try to meddle with presenting the "right" options, and how they state they did not interfere with the process because it was headed towards they direction they liked the most.

> *Mother of two 8th graders during high school choice in NYC*: "Kind of a joint process. We [she and her husband] did a lot of work getting information. We stayed on top of fairs, blogs, visits. But when we took them to see fairs, we let them choose; it was up to them to decide which schools they wanted to list. [on the application form]" Source: Sattin-Bajaj (2014)
>
> *One of the two daughters of the NYC mother above*: "My parents did a really good job showing me what the choices were." Source: Sattin-Bajaj (2014)
>
> *Father of 8th grader during high school choice in NYC*: "It was pretty equal in the sense that I made it clear to them that this was going to be their choice; but I also made it clear that I was going to tell them what I thought. I probably would have been more interventionist if I had disagreed with their choices. My theory of child-rearing is that if they are deciding between two very good choices, it's their decision." Source: Sattin-Bajaj (2014)

C.2 Institutional Setting

Table C.1: Supplied curricula in the city of Vicenza in the a.y. 2011/12.

Track	**Curriculum**
General	Humanities
General	Languages
General	Mathematics & Science
General	Art
General	Music & Choral
General	Social Sciences
Technical	Economic Sector
Technical	Technology Sector
Vocational	Services
Vocational	Industry & Crafts
Vocational	Professional Training

High school graduates and university enrollment decisions.

	Still enrolled	Graduated, continuing	Graduated, not studying	Drop out	Never enrolled
General track (*liceo*)	57.3	18.9	9.8	6.2	7.8
General Social Sciences	41.9	11.2	10.2	10.8	25.9
Vocational track	11.3	1.3	2	6.3	79.1
Technical track	23.5	5.8	3.8	10.7	56.2
Arts	24.9	4.7	5.6	7.2	57.7

Sample of students who graduated from high school in 2011, interviewed in 2015.
Percentage values by track of university enrollment status.
Liceo includes: Humanities, Languages, Math & Science.
Arts includes both the *liceo* and the technical track.

Source: Istat, "I percorsi di studio e lavoro dei diplomati e dei laureati: Indagine 2015 su diplomati e laureati 2011", September 29, 2016 (Table 2, page 4). Available at www.istat.it.

Table C.2: AVERAGE CHANGES TO OTHER HIGH SCHOOLS IN VENETO, A.Y. 2007/08.

	Track				
	General	*Technical*	*Vocational*	*Art*[a]	**Average**
% changes in the 1^{st} year	3.3	2.1	2.2	6.3	2.7

Percentage of changes to other high schools in the first year of enrolment.
Veneto, a.y. 2007/08.
[a]: Art schools were absorbed by the General/Technical track in a.y. 2009/10.

C.3 Survey Questions

Eliciting Ranked-first and Top-three alternatives

Question before the choice (Wave 1): (to children) Which curriculum would you choose today? *Presented with a three-row table, where rows were named "first choice", "second choice", "third choice", and children had to write down their favorite options.*
(to parents) Which curriculum would you choose today for your child? *Presented with a three-row table, where rows were named "first choice", "second choice", "third choice", and parent(s) had to write down their favorite options.*

Question before the choice (Waves 2 and 3): (to children) Which curriculum would you choose today? *Presented with a list of all ten alternatives and children had to attribute a number from 1 (favorite) to 10 (least favorite).*
(to parents) Which curriculum would you choose today for your child? *Presented with a list of all ten alternatives and parent(s) had to attribute a number from 1 (favorite) to 10 (least favorite).*

Question at choice (Wave 4): Write down the names of schools and curricula that you wrote in your pre-enrollment choice. *Presented with a three-row table, where rows were named "first choice", "second choice", "third choice".*

Eliciting Considered Alternatives

Question before the choice (Waves 1 to 3): (to children & parents) Have you ever *(Wave 1)* / in the last month since the last survey *(Waves 2 and 3)* thought about the school choice? Can you name the specific school/curriculum you thought about?
For each of the following people [a list followed], if you ever *(Wave 1)* / in the last month since the last survey *(Waves 2 and 3)* talked with them about the school choice can you name the specific school/curriculum you discussed?
Have you ever *(Wave 1)* / in the last month since the last survey *(Waves 2 and 3)* searched for information on leaflets/websites/experts about a specific school/curriculum?

Question at choice (Wave 4): Write down all the names of schools and curricula that were considered for your pre-enrollment choice.
Question at choice (Wave 4): Check all curricula you did not want to consider for the choice. *Presented with a list of all ten alternatives and children had to check them if they had not been allowed to choose them.*

Eliciting Perceptions of Parental Vetoing

Question before the choice (Waves 1 to 3): (to children) Would your parents accept [sub-track K], if you were to propose it as your own choice?
(to parents) Would you accept [sub-track K], if your child were to propose it to you as their own choice?

- Percent chance that they would accept it, if you were to ask them WITHOUT motivating your choice: chance $\in \{0, 100\}$
- Percent chance that they would accept it, if you were to ask them MOTIVATING your choice: chance $\in \{0, 100\}$

Presented with a list of all ten alternatives and the two columns for the percent chances of accepting motivated/unmotivated options.

Question at choice (Wave 4): Check all curricula you were not allowed to choose from. *Presented with a list of all ten alternatives and children had to check them if they had not been allowed to choose them.*

Eliciting Perceived Awareness of Choice Alternatives

Question before the choice (Waves 1 to 3): (to children & parents) What high school curricula do you know or have you heard the name of? Please mark one. *Presented with a list of all ten alternatives, and for each the following options:*
◯ I know it
◯ I have heard the name only
◯ I have never heard of it
Interpretation:
• 'I have never heard of [sub-track K]': unawareness about existence of K
• 'I have heard [sub-track K]'s name only': awareness about existence of K, but limited knowledge about characteristics of K
• 'I know [sub-track K]': awareness about existence of K and refined knowledge about characteristics of K

Eliciting perception of influence and weight of specific factors in the choice

Table C.3: Question about the influence and weight that each of these factors should have, as reported by Child in Wave 4.

Factors	Parents According to your parent(s), this factor ... ... should have a ___influence	 ... should have a ___weight
Follow your interests and preferences for specific subjects	Good Bad Neither good nor bad I don't know/remember, I haven't been told	Heavy Light None I don't know/remember, I haven't been told
Follow your own aptitude/talent for specific subjects	Good Bad Neither good nor bad I don't know/remember, I haven't been told	Heavy Light None I don't know/remember, I haven't been told
Consider your preparation at the end of junior high	Good Bad Neither good nor bad I don't know/remember, I haven't been told	Heavy Light None I don't know/remember, I haven't been told
Consider your future study effort	Good Bad Neither good nor bad I don't know/remember, I haven't been told	Heavy Light None I don't know/remember, I haven't been told
Consider your future effort in non-curricular activities	Good Bad Neither good nor bad I don't know/remember, I haven't been told	Heavy Light None I don't know/remember, I haven't been told
Follow your study/work objectives	Good Bad Neither good nor bad I don't know/remember, I haven't been told	Heavy Light None I don't know/remember, I haven't been told
Keep both job and study opportunities open	Good Bad Neither good nor bad I don't know/remember, I haven't been told	Heavy Light None I don't know/remember, I haven't been told
Keep field of studies opportunities open	Good Bad Neither good nor bad I don't know/remember, I haven't been told	Heavy Light None I don't know/remember, I haven't been told
Consider how far the school is from home	Good Bad Neither good nor bad I don't know/remember, I haven't been told	Heavy Light None I don't know/remember, I haven't been told
Consider your friends' choices	Good Bad Neither good nor bad I don't know/remember, I haven't been told	Heavy Light None I don't know/remember, I haven't been told
Consider your family's preferences	Good Bad Neither good nor bad I don't know/remember, I haven't been told	Heavy Light None I don't know/remember, I haven't been told
Consider your teachers' suggestions	Good Bad Neither good nor bad I don't know/remember, I haven't been told	Heavy Light None I don't know/remember, I haven't been told

For each factor, children had to report whether they thought their parent(s) considered this factor to have a good/bad/no influence on the choice, and should have a heavy/light/no weight in affecting it, or whether these factors had not been discussed.

C.4 At-choice Choice Sets

Table C.4: Positive and negative forces at play as reported at the moment of choice – Waves 3 and 4, Child. Number of Curricula (range: 0 to 10), by Gender.

	Factors	Median	Mean	StdDev	Min	Max	N
Positive forces							
Considered at choice[a,b]	M	1	1.55	.74	1	4	87
	F	2	1.93	.93	1	4	134
Suggested by mom[b]	M	1	.89	1.01	0	5	93
	F	1	1.38	1.40	0	6	141
Suggested by dad[b]	M	1	.83	1.01	0	5	93
	F	1	1.23	1.27	0	6	141
Suggested by teacher (orientation)[b]	M	1	.61	1.11	0	10	93
	F	1	.86	.96	0	5	141
Suggested by other teacher[b]	M	0	.35	.52	0	2	93
	F	0	.53	.81	0	4	141
Present in ranking[b]	M	10	8.39	3.11	1	10	89
	F	10	8.66	2.89	1	10	132
Present in ranking[c]	M	10	8.74	2.96	1	10	84
	F	10	9.13	2.45	1	10	117
Aware of it[c,d]	M	10	9.73	.72	7	10	89
	F	10	9.49	1.16	5	10	124
Thought about it in the previous month[c]	M	1	.58	.62	0	2	90
	F	1	.99	.73	0	3	124
Talked about it in the previous month, with mom[c]	M	0	.38	.59	0	2	90
	F	0	.53	.64	0	3	124
Talked about it in the previous month, with dad[c]	M	0	.32	.56	0	2	90
	F	0	.34	.55	0	2	124
Talked about it in the previous month, with both parents[c]	M	0	.3	.57	0	2	90
	F	0	.39	.60	0	3	124
Talked about it in the previous month, with teacher[c]	M	0	.22	.49	0	2	90
	F	0	.19	.44	0	2	124
Negative forces							
Mom suggested against[b]	M	1	1.88	2.66	0	9	93
	F	1	1.67	2.22	0	9	141
Dad suggested against[b]	M	0	1.54	2.46	0	9	93
	F	1	1.48	2.19	0	9	141
Teacher (orientation) suggested against	M	0	.99	2.35	0	9	93
	F	0	.64	1.62	0	9	141
Other teacher suggested against	M	0	.67	1.91	0	9	93
	F	0	.35	1.07	0	9	141
Not allowed by parents[b]	M	0	1.83	2.38	0	8	93
	F	0	1.25	1.95	0	7	141
Child did not want to consider it[b]	M	7	6.32	2.84	0	10	93
	F	7	5.94	3.04	0	10	141

[a]: Open question. Student had to write down the name of schools considered for the choice and their respective curricula.
[b]: As of wave 4, after pre-enrollment decision has been submitted. N = 241.
[c]: As of wave 3, only for those who declare that their pre-enrollment decision has been submitted. N = 216.
N = 103 observations who answered both to wave 3 and 4.
[d]: "Awareness" refers to having declared that one curriculum is either known or the child has heard of it.

Table C.5: POSITIVE AND NEGATIVE FORCES AT PLAY AS REPORTED AT THE TIME OF CHOICE – WAVES 3 AND 4, CHILD. SHARES (RANGE: 0 TO 1).

	Curricula										
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**N**
Final pre-enrollment choices											
Choice distribution, share (row sums to 100%)	.065	.065	.113	.249	.085	.105	.16	.07	.04	.05	354
Choice distribution, share (row sums to 100%)[a]	.066	.062	.112	.278	.091	.133	.12	.046	.046	.046	241
Choice distribution, share (row sums to 100%)[b]	.079	.074	.12	.264	.083	.046	.176	.079	.032	.046	216
Choice distribution, share (row sums to 100%)[b]	.097	.078	.126	.35	.097	.049	.117	.029	.029	.029	103
Factors											
Positive forces											
Considered at choice[a,c]	.16	.15	.26	.40	.16	.17	.16	.08	.09	.07	241
Suggested by mom[a]	.13	.13	.23	.31	.10	.09	.12	.03	.02	.03	238
Suggested by dad[a]	.08	.13	.16	.31	.09	.10	.13	.02	.02	.02	238
Suggested by teacher (orientation)[a]	.06	.08	.10	.22	.06	.05	.08	.06	.02	.03	238
Suggested by other teacher[a]	.06	.04	.06	.13	.02	.02	.07	.03	.02	.01	238
Present in ranking (top 3)[a]	.39	.38	.47	.64	.42	.33	.37	.20	.13	.13	187-202
Present in ranking (all)[a]	.82	.80	.81	.84	.81	.81	.81	.79	.78	.78	241
Present in ranking (top 3)[b]	.38	.39	.57	.68	.49	.29	.45	.24	.15	.15	181-200
Present in ranking (all)[b]	.86	.84	.86	.86	.83	.84	.85	.83	.83	.84	216
Aware of it[b,d]	.99	.99	.99	.99	.98	.94	.96	.90	.88	.91	216
Thought about it in previous month[b]	.03	.09	.12	.05	.24	.07	.04	.08	.05	.02	216
Talked about it in previous month, with mom[b]	.02	.05	.09	.05	.13	.03	.02	.04	.03	.02	216
Talked about it in previous month, with dad[b]	.02	.04	.05	.02	.08	.02	.02	.04	.02	.02	216
Talked about it in previous month, with both parents[b]	.02	.04	.05	.04	.09	.03	.02	.03	.02	.01	216
Talked about it in previous month, with teacher[b]	.02	.02	.04	.01	.05	.01	.0	.02	.01	.01	216
All curricula allowed[a]					.09						214
Child wanted to consider all[a]					.58						214
Negative forces											
Mom suggested against[a]	.20	.19	.14	.14	.14	.16	.16	.16	.20	.24	238
Dad suggested against[a]	.17	.16	.13	.13	.11	.15	.13	.15	.17	.20	238
Teacher (orientation) suggested against	.10	.07	.07	.07	.06	.06	.07	.09	.08	.10	238
Other teacher suggested against	.06	.04	.02	.06	.02	.03	.04	.06	.06	.07	238
Not allowed by parents[a]	.15	.09	.11	.14	.12	.14	.14	.17	.16	.22	241
Child did not want to consider it[a]	.67	.73	.68	.51	.66	.70	.64	.73	.77	.73	214
Perc. families with at least one negative force[e]	.76	.74	.70	.61	.71	.73	.71	.78	.81	.83	241
Perc. families with all negative forces[f]	.01	.02	.02	.01	.01	.01	.01	.02	.02	.02	241

Variables are coded as dummies. Numbers represent the share for which *dummy* = 1 out of total N of non-missing answers.

[a]: As of wave 4, after pre-enrollment decision has been submitted. N = 241.
[b]: As of wave 3, only for those who declare that their pre-enrollment decision has been submitted. N = 216.
[c]: Open question. Student had to write down the name of schools considered for the choice and their respective curricula.
N = 103 observations who answered both to wave 3 (early pre-enrollment) and 4.
[d]: "Awareness" refers to having declared that one curriculum is either known or the child has heard of it.
[e]: Out of the 241 respondents to wave 4, this represents for each alternative if any of the four above-mentioned negative dummies is =1.
[f]: Out of the 241 respondents to wave 4, this represents for each alternative if all the four above-mentioned negative dummies are =1.

Curricula
General track: 1 Art, Music & Choral; 2 Humanities; 3 Languages; 4 Mathematics & Science; 5 Social Sciences
Technical track: 6 Economic Sector; 7 Technology Sector
Vocational track: 8 Services; 9 Industry & Crafts; 10 Professional Training

Table C.6: Positive and negative forces at play as reported at the moment of choice – Waves 3 and 4, Child. Shares (range: 0 to 1), by Track.

	Tracks			
	General	**Technical**	**Vocational**	**N**
Final pre-enrollment choices				
Choice distribution, share (row sums to 100%)	.58	.26	.16	354
Choice distribution, share (row sums to 100%)[a]	.61	.25	.14	241
Choice distribution, share (row sums to 100%)[b]	.62	.22	.16	216
Choice distribution, share (row sums to 100%)[b]	.75	.16	.09	103
Factors				
Positive forces				
Considered at choice[b,c]	.69	.30	.20	241
Suggested by mom[a]	.51	.19	.07	241
Suggested by dad[a]	.48	.20	.07	241
Suggested by teacher (orientation)[a]	.40	.12	.09	241
Suggested by other teacher[a]	.27	.08	.06	241
Present in ranking (top 3)[a]	.81	.45	.24	241
Present in ranking (all)[a]	.90	.85	.81	241
Present in ranking (top 3)[b]	.81	.45	.24	216
Present in ranking (all)[b]	.90	.87	.85	216
Aware of it[b,d]	.47	.46	.44	216
Thought about it in the previous month[b]	.87	.87	.87	216
Talked about it in the previous month, with mom[b]	.28	.05	.08	216
Talked about it in the previous month, with dad[b]	.19	.04	.07	216
Talked about it in the previous month, with both parents[b]	.22	.04	.06	216
Talked about it in the previous month, with teacher[b]	.13	.01	.05	216
Negative forces				
Mom suggested against[a]	.44	.21	.27	241
Dad suggested against[a]	.37	.18	.22	241
Teacher (orientation) suggested against	.19	.07	.12	241
Other teacher suggested against	.13	.04	.10	241
Not allowed by parents[a]	.29	.18	.27	241
Child did not want to consider it[a]	.84	.73	.75	241

Variables are coded as dummies. Numbers represent the share for which *dummy* = 1 (accounting for any curriculum in a track).

[a]: As of wave 4, after pre-enrollment decision has been submitted. N = 241
[b]: As of wave 3, only for those who declare that their pre-enrollment decision has been submitted. N =216
[c]: Open question. Student had to write down the name of schools considered for the choice and their respective curricula.
[d]: "Awareness" refers to having declared that one curriculum is either known or the child has heard of it.

Curricula
General track: Art, Music & Choral; Humanities; Languages; Mathematics & Science; Social Sciences
Technical track: Economic Sector; Technology Sector
Vocational track: Services; Industry & Crafts; Professional Training

Table C.7: Positive and negative forces at play as reported at the moment of choice – Waves 3 and 4, Child. Shares (range: 0 to 1), by Gender.

	Gender	Curricula 1	2	3	4	5	6	7	8	9	10	N
Final pre-enrollment choices												
Choice distribution,	M	.07	.03	.06	.30	.02	.06	.26	.07	.08	.05	145
share (row sums to 100%)	F	.06	.09	.15	.22	.13	.12	.08	.07	.01	.05	200
Δ	(F-M)	-.01	.06	.09	-.08	.11	.06	-.18	0	-.07	0	
Factors: *Positive forces*												
Considered at choice[a,b]	M	.13	.09	.17	.41	.04	.10	.19	.12	.15	.05	93
	F	.18	.20	.31	.40	.24	.20	.13	.06	.05	.07	141
Suggested by mom[b]	M	.10	.05	.13	.30	.04	.03	.15	.03	.02	.03	93
	F	.15	.18	.30	.33	.14	.12	.11	.03	.02	.03	138
Δ	(F-M)	.05	.13	.17	.03	.10	.09	-.04	0	0	0	
Suggested by dad[b]	M	.05	.07	.12	.25	.05	.05	.14	.02	.02	.04	93
	F	.09	.17	.19	.36	.12	.14	.13	.03	.03	.01	138
Δ	(F-M)	.04	.10	.07	.11	.07	.09	-.01	.01	.01	-.03	
Suggested by teacher (orientation)[b]	M	.05	.01	.02	.21	.01	.05	.12	.06	.03	.03	93
	F	.07	.13	.15	.23	.09	.05	.06	.06	.01	.03	138
Suggested by other teacher[b]	M	.03	0	.02	.14	0	.01	.07	.04	.01	.02	93
	F	.07	.07	.09	.13	.03	.02	.07	.03	.02	.01	138
Present in ranking (top 3)[b]	M	.36	.34	.33	.67	.37	.38	.49	.22	.19	.17	72-81
	F	.40	.40	.55	.63	.45	.31	.26	.19	.08	.11	109-120
Present in ranking (all)[b]	M	.78	.78	.81	.87	.78	.82	.83	.80	.78	.77	93
	F	.85	.82	.82	.82	.84	.81	.80	.79	.77	.78	141
Present in ranking (top 3)[c]	M	.27	.27	.51	.75	.44	.34	.62	.25	.23	.18	71-83
	F	.46	.47	.62	.63	.52	.26	.32	.23	.09	.14	105-115
Present in ranking (all)[c]	M	.81	.81	.82	.84	.79	.81	.86	.81	.81	.79	90
	F	.89	.86	.89	.86	.85	.86	.85	.84	.84	.87	124
Aware of it[c,d]	M	.99	.99	.99	.99	.99	.94	.99	.91	.90	.93	90
	F	1	.99	1	.99	.98	.94	.94	.89	.85	.89	124
Thought about it in previous month[c]	M	.02	.03	.02	.05	.24	0	.02	.14	.01	.09	90
	F	.04	.13	.19	.06	.23	.13	.06	.04	.02	.02	124
Talked about it in previous month, with mom[c]	M	.02	.02	.03	.05	.14	0	.01	.04	.01	.03	90
	F	.02	.07	.13	.04	.11	.05	.02	.03	.05	.01	124
Talked about it in previous month, with dad[c]	M	.02	.02	.03	.04	.09	0	.01	.05	.01	.03	90
	F	.02	.06	.06	.01	.07	.03	.02	.02	.03	.01	124
Talked about it in previous month, with both[c]	M	.03	.01	.02	.04	.1	0	.01	.04	.01	.02	90
	F	.02	.06	.08	.03	.09	.05	.02	.02	.02	0	124
Talked about it in previous month, with teacher[c]	M	.02	.01	.01	.02	.08	0	.01	.03	.01	.02	216
	F	.02	.02	.06	0	.03	.02	0	.02	.02	.01	216
All curricula allowed[b]	M					.06						49
	F					.11						63
Child wanted to consider all[b]	M					.55						84
	F					.61						125
Factors: *Negative forces*												
Mom suggested against[b]	M	.27	.20	.18	.13	.15	.17	.19	.16	.21	.20	93
	F	.17	.18	.12	.16	.14	.15	.14	.17	.20	.26	138
Dad suggested against[b]	M	.17	.19	.16	.11	.13	.15	.15	.15	.17	.15	93
	F	.17	.14	.12	.14	.11	.15	.13	.15	.17	.23	138
Teacher (orientation) suggested against	M	.14	.10	.09	.04	.09	.10	.10	.11	.12	.12	93
	F	.07	.06	.06	.09	.05	.04	.04	.08	.06	.09	138
Other teacher suggested against	M	.09	.07	.05	.04	.04	.05	.06	.07	.10	.07	93
	F	.04	.02	.01	.07	.01	.01	.02	.04	.04	.07	138
Not allowed by parents[b]	M	.19	.14	.19	.18	.16	.19	.15	.19	.19	.23	93
	F	.12	.06	.06	.11	.11	.12	.14	.16	.14	.23	141
Child did not want to consider it[b]	M	.75	.82	.70	.55	.74	.71	.63	.65	.70	.74	84
	F	.62	.67	.66	.49	.61	.69	.66	.77	.82	.74	125
Perc. families with at least one negative force[e]	M	.82	.84	.76	.66	.77	.77	.71	.75	.78	.83	93
	F	.72	.67	.66	.59	.67	.72	.72	.81	.84	.83	141
Perc. families with all negative forces[f]	M	.02	.03	.03	.01	.03	.02	.02	.02	.03	.02	93
	F	-	.01	.01	.01	-	.01	.01	.01	.02	.02	141

Variables are coded as dummies. Numbers represent the share for which *dummy* = 1 out of total N of non-missing answers.
[a]: Open question. Student had to write down the name of schools considered for the choice and their respective curricula.
[b]: As of wave 4, after pre-enrollment decision has been submitted. N = 241.
[c]: As of wave 3, only for those who declare that their pre-enrollment decision has been submitted. N = 216.
N = 103 observations who answered both to wave 3 and 4.
[d]: "Awareness" refers to having declared that one curriculum is either known or the child has heard of it.
[e]: Out of the 241 respondents to wave 4, this represents for each alternative if any of the four above-mentioned negative dummies is =1.
[f]: Out of the 241 respondents to wave 4, this represents for each alternative if all the four above-mentioned negative dummies are =1.

Curricula
General track: 1 Art, Music & Choral; 2 Humanities; 3 Languages; 4 Mathematics & Science; 5 Social Sciences
Technical track: 6 Economic Sector; 7 Technology Sector
Vocational track: 8 Services; 9 Industry & Crafts; 10 Professional Training

Table C.8: Share of answers to the question "Which of the following best describes the way in which the choice of the best high school curriculum for you has been carried out in your family?" – Wave 4, Child, by Gender.

Style of choice					
Style A					
Common decision (%)			*Who had the last word?* (%)		
	M	**F**		**M**	**F**
Talked and reached a common agreement	35	37	Child	64	68
			Father	16	10
			Mother	4	15
			Other relative	8	-
Style B					
One person decided after listening to others: who? (%)			*Of which, listened to... (%)*		
	M	**F**		**M**	**F**
Child	48	50	Father	68	59
			Mother	65	73
			Other relative	35	32
			Teacher	5	36
Father	3	2	Child	50	50
			Mother	100	-
			Other relative	-	50
			Teacher	50	-
Mother	3	-	Child	-	-
			Father	-	-
			Other relative	-	-
			Teacher	-	-
Parents	8	6	Child	67	57
			Other relative	17	29
			Teacher	5	14
Other relative	-	-			
Teacher	-	1	Child	-	100
			Father	-	100
			Mother	-	100
Style C					
One person decided without listening to others: who? (%)					
	M	**F**			
Child	-	4			
Mother	1	-			
Father	1	-			
N	71 (100%)	112 (100%)			

Share of answers to the question "Who submitted the pre-enrollment form?" – Wave 4, Child, N=238.

	Mode				
Who submitted?	Missing	Don't recall	Paper&Pencil	Online	
Don't recall	-	2.5	0.8	-	3.4
Child alone	0.4	-	10	0.4	10.9
Child with parent(s)	0.4	0.8	63.5	2.9	67.5
Parent(s)	-	0.8	13	2.1	16
Somebody else	-	-	2.1	-	2.1
Total	0.8	4.2	89.5	5.5	100%

In a.y. 2011/12 the pre-enrollment form could be submitted either online or on paper, without constraints; nonetheless the form needed to be signed by one parent, as the law requires that an adult figure takes the responsibility for the minor.

Figure C.1: Frequency of answers to the question "Which is your favorite style of choice? Rank the choices so that 1 is your favorite and 3 is your least favorite option" – Wave 4, Child.

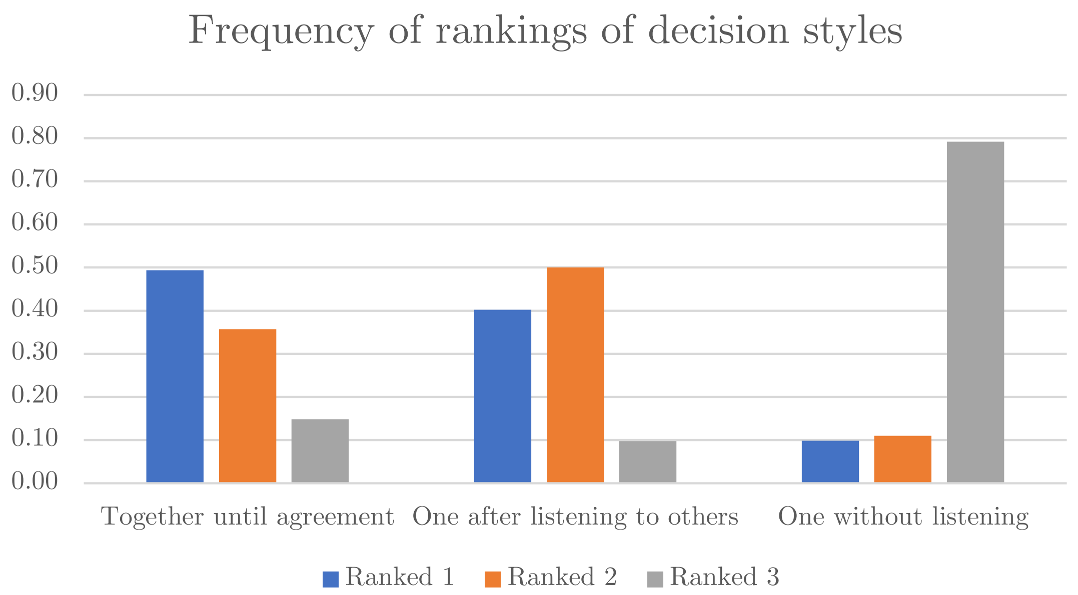


Table C.9: DISTRIBUTION OF THE AT-THE-MOMENT-OF-CHOICE CHOICE SET – WAVE 3, IF PRE-ENROLLED, AND WAVE 4, FAMILY OUTCOME. NUMBER OF CURRICULA (RANGE: 0 TO 10), BY CHILD'S GENDER, CHILD'S 7^{th} GRADE GPA.

		Mean	Std Dev	Min	p10	p50	p90	Max	N
Overall									
Actual choice									
Ranked-first alternative		1	0						354
Top-three alternative(s)		1.28	.56	1	1	1	2	3	354
Consideration set		1.67	.92	1	1	1	3	5	241
Feasibility sets									
Agency sets									
Implicit parental veto, lb[a]		7.66	2.78	0	3	9	10	10	238
Implicit parental veto, ub[a]		8.02	3.11	0	3	10	10	10	239
Explicit parental veto		8.80	1.94	3	5	10	10	10	241
Awareness set		9.95	.34	6	10	10	10	10	238
Distribution by Gender									
Chosen alternative(s)									
Ranked-first alternative	M	1	0						145
	F	1	0						200
Top-three alternative(s)	M	1.2	.45	1	1	1	2	3	145
	F	1.34	.62	1	1	1	2	3	200
Consideration set	M	1.56	.73	1	1	1	3	4	93
	F	1.72	1.02	1	1	1	3	5	141
Feasibility set									
Agency set									
Implicit parental veto, lb[a]	M	7.39	3.04	1	3	9	10	10	98
	F	7.81	2.58	0	4	9	10	10	138
Implicit parental veto, ub[a]	M	7.42	3.41	0	1	10	10	10	98
	F	8.50	2.75	0	5	10	10	10	139
Explicit parental veto	M	8.49	2.16	3	5	10	10	10	93
	F	8.96	1.79	3	6	10	10	10	141
Awareness set	M	9.95	.41	6	10	10	10	10	98
	F	9.95	.28	8	10	10	10	10	138
Distribution by Child's GPA									
Chosen alternative(s)									
Ranked-first alternative	GPA <p25	1	0						72
	GPA p25-p75	1	0					1	115
	GPA>p75	1	0					1	76
Top-three alternative(s)	GPA <p25	1.22	.51	1	1	1	2	3	72
	GPA p25-p75	1.30	.57	1	1	1	2	3	115
	GPA>p75	1.28	.55	1	1	1	2	3	76
Consideration set	GPA <p25	1.45	.75	1	1	1	2.5	4	40
	GPA p25-p75	1.65	.91	1	1	1	3	5	75
	GPA>p75	1.73	.90	1	1	2	3	5	56
Feasibility sets									
Agency sets									
Implicit parental veto, lb[a]	GPA <p25	7.58	3.3.	0	1	9	10	10	55
	GPA p25-p75	7.40	2.65	1	3	8	10	10	88
	GPA>p75	7.73	2.58	1	4	9	10	10	63
Implicit parental veto, ub[a]	GPA <p25	8.13	3.19	0	1	10	10	10	55
	GPA p25-p75	7.51	3.44	0	1	10	10	10	89
	GPA>p75	8.65	2.33	1	5	10	10	10	63
Explicit parental veto	GPA <p25	9.18	1.63	3	7.5	10	10	10	40
	GPA p25-p75	8.67	2.08	3	5	10	10	10	75
	GPA>p75	8.75	1.95	4	5	10	10	10	56
Awareness set	GPA <p25	9.96	.27	8	10	10	10	10	55
	GPA p25-p75	9.98	.15	9	10	10	10	10	88
	GPA>p75	9.95	.28	8	10	10	10	10	63

Gender: "M" male, "F" female.
7^{th} grade GPA: "<p25" below 7.10/10 (25^{th} percentile), "p25-p75" between 7.1 and 8.6, ">p75" above 8.6.
[a]: *lb*: lower bound; *ub*: upper bound.

Table C.10: Distribution of the at-the-moment-of-choice choice set – Wave 3, if Pre-Enrolled, and Wave 4, Family Outcome. Number of Curricula (range: 0 to 10), by Parental Education.

		Mean	Std Dev	Min	p10	p50	p90	Max	N
Distribution by Parents' Education									
Father									
Chosen alternative(s)									
Ranked-first alternative	Elementary or middle school	1	0						58
	High school	1	0						130
	College or more	1	0						79
Top-three alternative(s)	Elementary or middle school	1.28	.52	1	1	1	2	3	58
	High school	1.22	.50	1	1	1	2	3	130
	College or more	1.32	.63	1	1	1	2	3	79
Consideration set	Elementary or middle school	1.52	.78	1	1	1	3	4	29
	High school	1.59	.88	1	1	1	3	5	91
	College or more	1.82	.95	1	1	2	3	4	51
Feasibility sets									
Agency sets									
Implicit parental veto, lb[a]	Elementary or middle school	8.08	2.83	1	3	10	10	10	50
	High school	7.41	2.84	0	3	9	10	10	98
	College or more	7.43	2.76	1	3	8	10	10	63
Implicit parental veto, ub[a]	Elementary or middle school	8.42	3.03	0	4	10	10	10	50
	High school	7.92	3.21	0	1	10	10	10	98
	College or more	7.94	3.09	0	3	10	10	10	64
Explicit parental veto	Elementary or middle school	9.45	1.21	5	7	10	10	10	29
	High school	8.87	1.92	3	6	10	10	10	91
	College or more	8.18	2.23	3	5	9	10	10	51
Awareness set	Elementary or middle school	9.98	.14	9	10	10	10	10	50
	High school	9.97	.22	8	10	10	10	10	98
	College or more	9.95	.28	8	10	10	10	10	63
Mother									
Chosen alternative(s)									
Ranked-first alternative	Elementary or middle school	1	0						50
	High school	1	0						139
	College or more	1	0						83
Top-three alternative(s)	Elementary or middle school	1.2	.49	1	1	1	2	3	50
	High school	1.28	.56	1	1	1	2	3	139
	College or more	1.26	.54	1	1	1	2	3	83
Consideration set	Elementary or middle school	1.48	.68	1	1	1	2	3	31
	High school	1.63	.97	1	1	1	3	5	84
	College or more	1.76	.86	1	1	2	3	4	59
Feasibility sets									
Agency sets									
Implicit parental veto, lb[a]	Elementary or middle school	7.68	3.12	0	3	10	10	10	41
	High school	7.84	2.68	1	3	9	10	10	108
	College or more	7.09	2.81	1	3	7	10	10	65
Implicit parental veto, ub[a]	Elementary or middle school	8.29	3.34	0	1	10	10	10	41
	High school	8.29	2.90	0	4	10	10	10	108
	College or more	7.5	3.29	0	2	9	10	10	66
Explicit parental veto	Elementary or middle school	9.26	1.73	4	8	10	10	10	31
	High school	8.75	1.92	3	6	10	10	10	84
	College or more	8.58	2.11	3	5	10	10	10	59
Awareness set	Elementary or middle school	10	0						41
	High school	9.97	.21	8	10	10	10	10	108
	College or more	9.94	.30	8	10	10	10	10	65

[a]: *lb*: lower bound; *ub*: upper bound.

Table C.11: Composition of each set at the moment of choice – Family Outcome. For each track, ratio of curricula covered over total number of available curricula (total number of curricula: 5 for the General Track, 2 for the Technical Track, 3 for the Vocational Track).

	At Choice			
	G.	**T.**	**V.**	**N**
Chosen alternative(s)				
Ranked-first alternative(s)	.11	.13	.05	354
Top-three alternative(s)	.15	.15	.07	354
Consideration set	.2	.20	.09	241
Feasibility sets				
Agency sets				
Implicit parental veto, lb[a]	.28	.31	.33	238
Implicit parental veto, ub[a]	.98	.99	.99	239
Explicit parental veto	.90	.89	.84	241
Awareness set	1	1	.99	238

G.: General Track; T.: Technical Track; V.: Vocational Track.
[a]: *lb*: lower bound; *ub*: upper bound.

Table C.12: Poisson regressions of the at-the-moment-of-choice number of tracks included in each choice set on child's and parents' characteristics – Wave 3, if Pre-Enrolled, and Wave 4, Family Outcome. Significance level of coefficients reported.

	Family outcome						
	Ranked-First Alt.	**Top-Three Alt.**	**Consid. Set**	**Agency Set, implicit lb**	**Agency Set, implicit ub**	**Agency Set, explicit**	**Awareness Set**
After the choice							
Female student	-	.024	.092	.091	-.027*	-.009	-.003
		(.035)	(.061)	(.197)	(.016)	(.027)	(.003)
Foreign-born student	-	.012	-.135***	.518*	.028	-.058	-.021
		(.087)	(.052)	(.260)	(.019)	(.050)	(.020)
Lives with both parents	-	.085	.216**	.261	.018	-.053	-.001
		(.076)	(.103)	(.350)	(.013)	(.063)	(.001)
Stay-at-home mother	-	.032	.027	.293	-.000	-.044	-.008
		(.042)	(.067)	(.210)	(.019)	(.037)	(.007)
Blue-collar father	-	.016	-.084	.381*	-.050	.052*	.006
		(.046)	(.054)	(.211)	(.036)	(.028)	(.006)
Has older siblings	-	-.071**	.013	-.102	.003	.001	.004
		(.034)	(.063)	(.199)	(.016)	(.031)	(.004)
7^{th}-grade GPA,	-	.015	.119	.562**	.022	.060**	.003
lower 25perc		(.052)	(.097)	(.239)	(.019)	(.029)	(.003)
7^{th}-grade GPA,	-	-.041	-.003	.237	.002	-.045	.004
upper 25perc		(.035)	(.065)	(.229)	(.018)	(.036)	(.004)
Sample size	239	239	156	194	195	156	194

lb: lower bound; *ub*: upper bound.

Significance levels: [***] significant at 1%; [**] significant at 5%; [*] significant at 10%.

Predictors: *female student:* dummy=1 if student is female; *foreign-born student:* dummy=1 if student is foreign-born; *lives with both parents:* dummy=1 if student lives with both parents; *stay-at-home mother:* dummy=1 if student has a stay-at-home mother; *blue-collar father:* dummy=1 if student's father works in a blue-collar occupation; *has older siblings:* dummy=1 if student has older siblings (between 1 and 3); *7^{th}-grade GPA, lower 25 percentile:* dummy=1 if student's GPA in the 7th grade end-of-year report (between 6 and 10) is in the bottom quartile of the distribution; *7^{th}-grade GPA, upper 25 percentile:* dummy=1 if student's GPA in the 7th grade end-of-year report (between 6 and 10) is in the upper quartile of the distribution.

C.5 Before-the-choice Choice Set Evolution

Figure C.2: Probability of accepting a choice today, with or without motivation – Wave 1, Child & Parent.

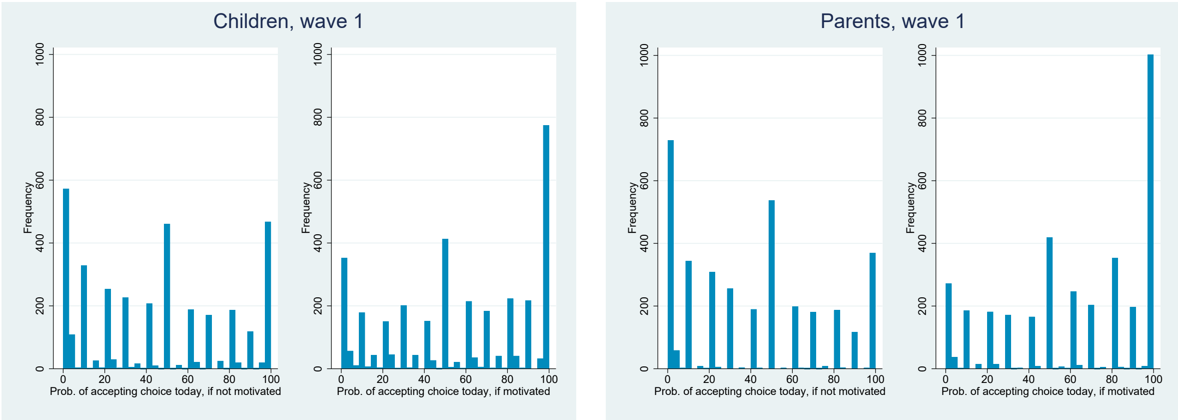


Figure C.3: Probability of accepting a choice today, with or without motivation – Wave 2, Child & Parent.

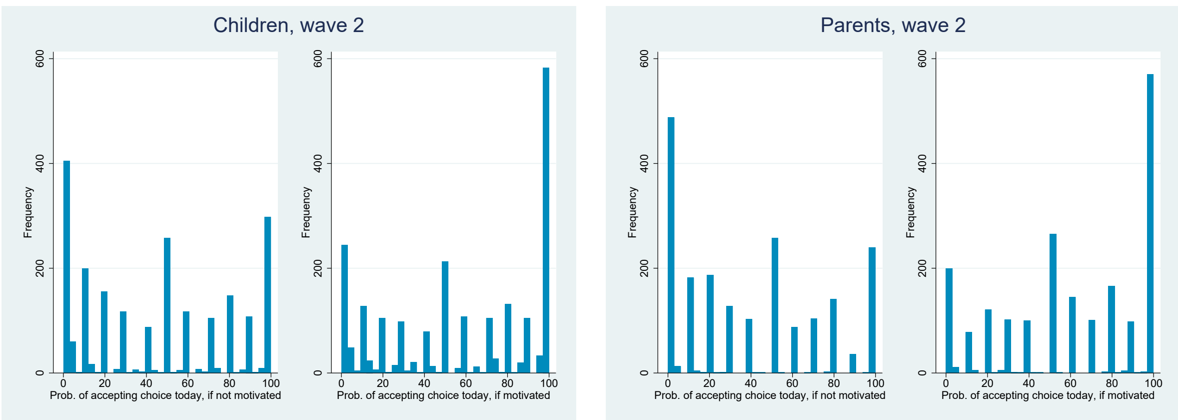


Figure C.4: Probability of accepting a choice today, with or without motivation – Wave 3, Child & Parent.

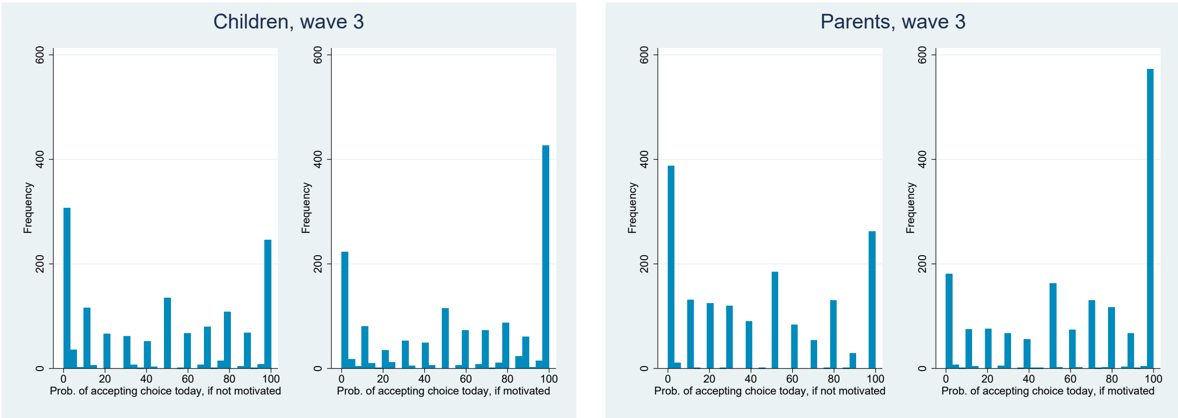


Figure C.5: Probability of accepting a choice today, with or without motivation – Wave 3, if already pre-enrolled, Child & Parent.

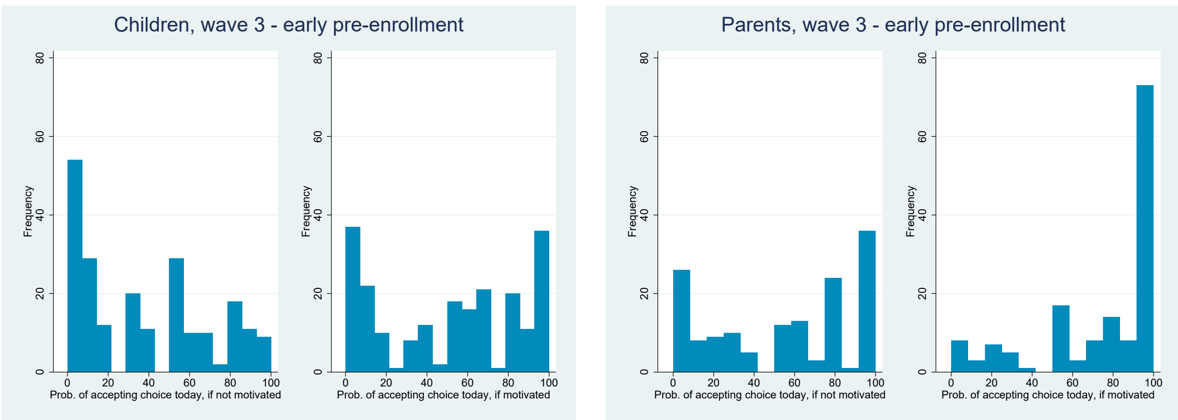


Figure C.6: Number of curricula the child reported: "Feeling sure parents would allow" (prob in 90-100%) (top-left panel); "Feeling sure parents would not allow" (prob in 0-10%) (top-right panel); "Feeling unsure whether parents would allow" (prob in 11-89%) (bottom-left panel); or "Having no idea whether parents would allow" (bottom-right panel), *without* any motivation – Wave 1, Child, N=489.

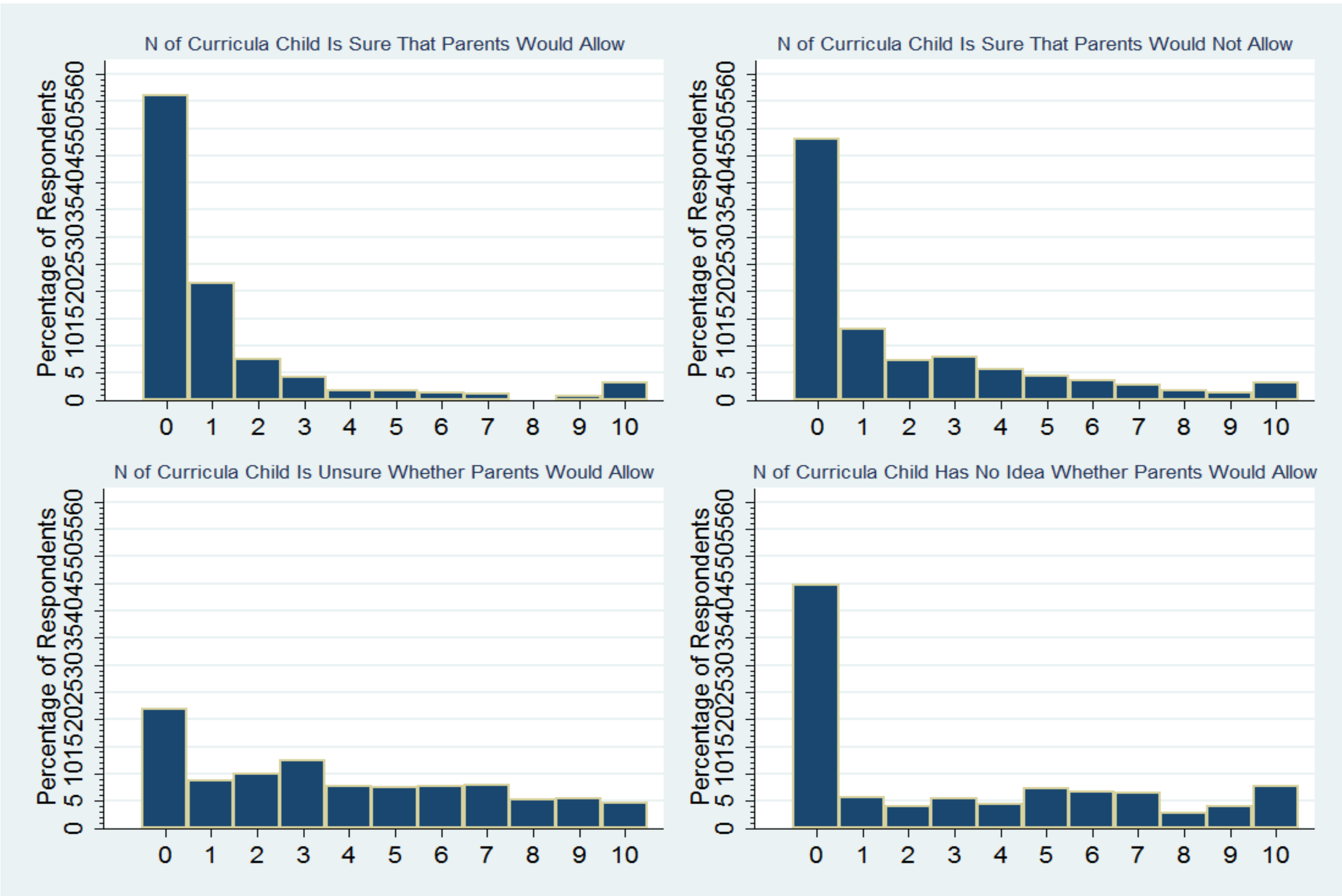


Figure C.7: Number of curricula the child's parent(s) reported: "Feeling sure they would allow" (prob in 90-100%) (top-left panel); "Feeling sure they would not allow" (prob in 0-10%) (top-right panel); "Feeling unsure whether they would allow" (prob in 11-89%) (bottom-left panel); or "Having no idea whether they would allow" (bottom-right panel), *without* any motivation – Wave 1, Parent, N=389.

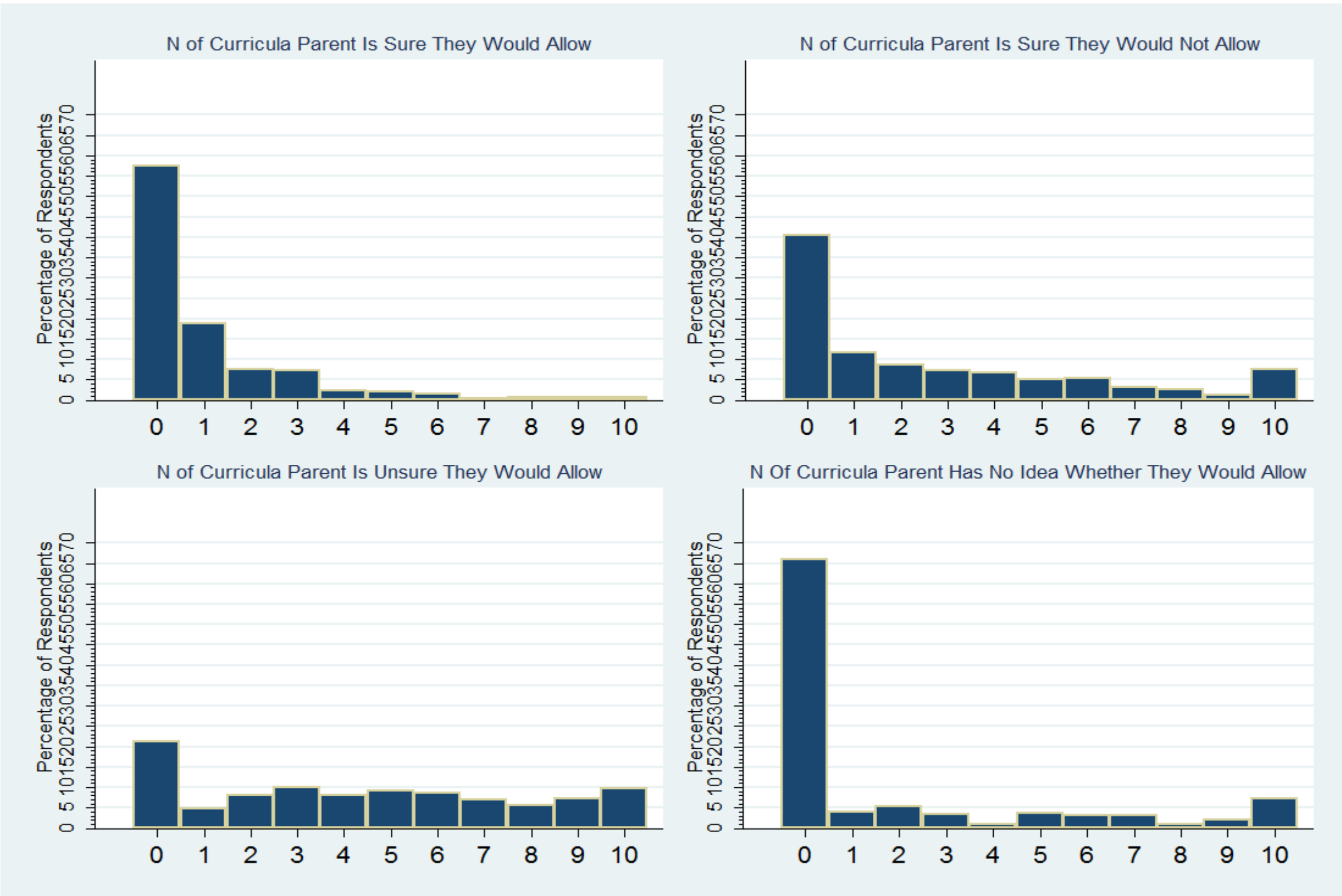


Figure C.8: Number of curricula the child reported: "Feeling sure parents would allow" (prob in 90-100%) (top-left panel); "Feeling sure parents would not allow" (prob in 0-10%) (top-right panel); "Feeling unsure whether parents would allow" (prob in 11-89%) (bottom-left panel); or "Having no idea whether parents would allow" (bottom-right panel), *with* some motivation – Wave 1, Child, N=488.

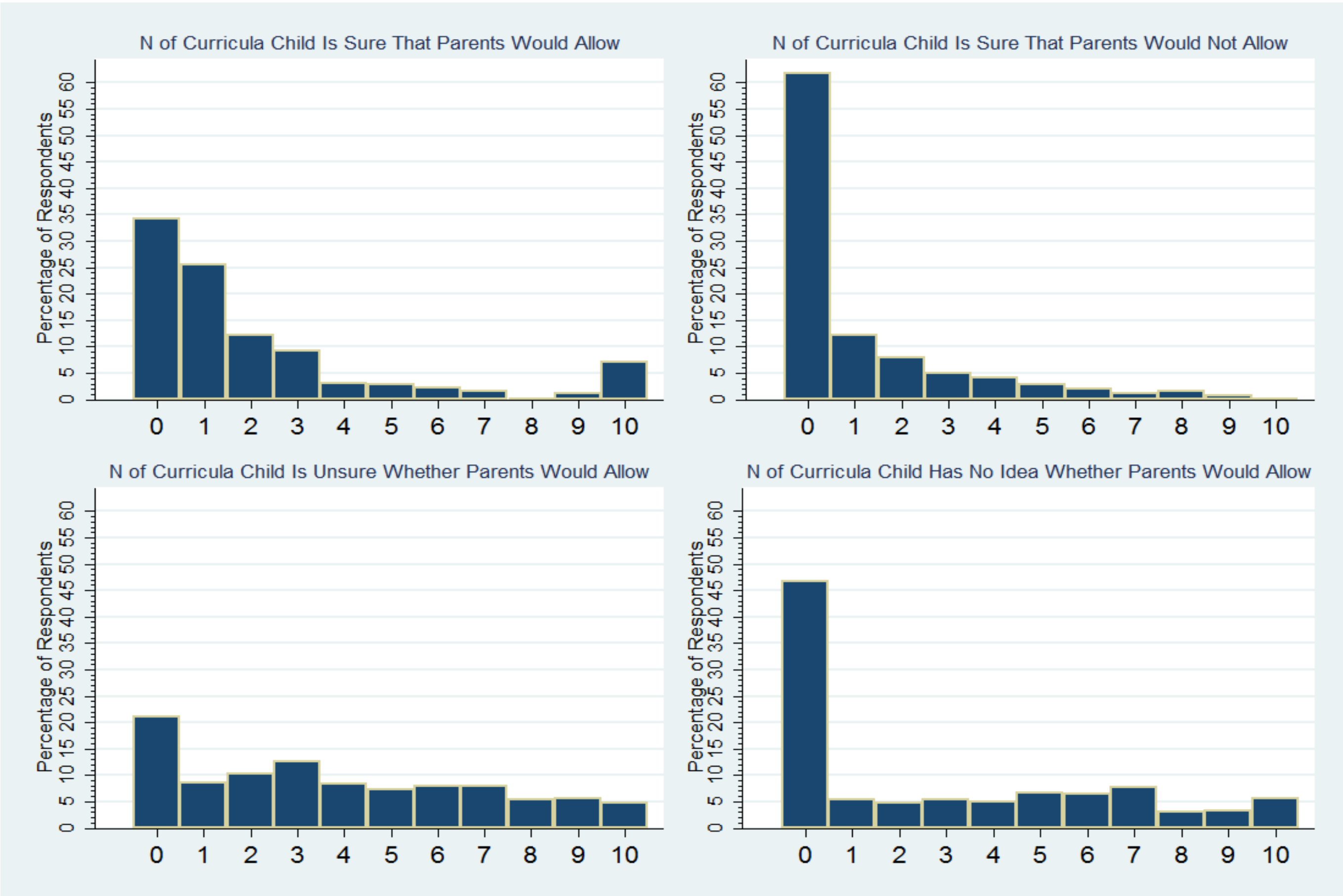


Figure C.9: Number of curricula the child's parent(s) reported: "Feeling sure they would allow" (prob in 90-100%) (top-left panel); "Feeling sure they would not allow" (prob in 0-10%) (top-right panel); "Feeling unsure whether they would allow" (prob in 11-89%) (bottom-left panel); or "Having no idea whether they would allow" (bottom-right panel), *with* some motivation – Wave 1, Parent, N=399.

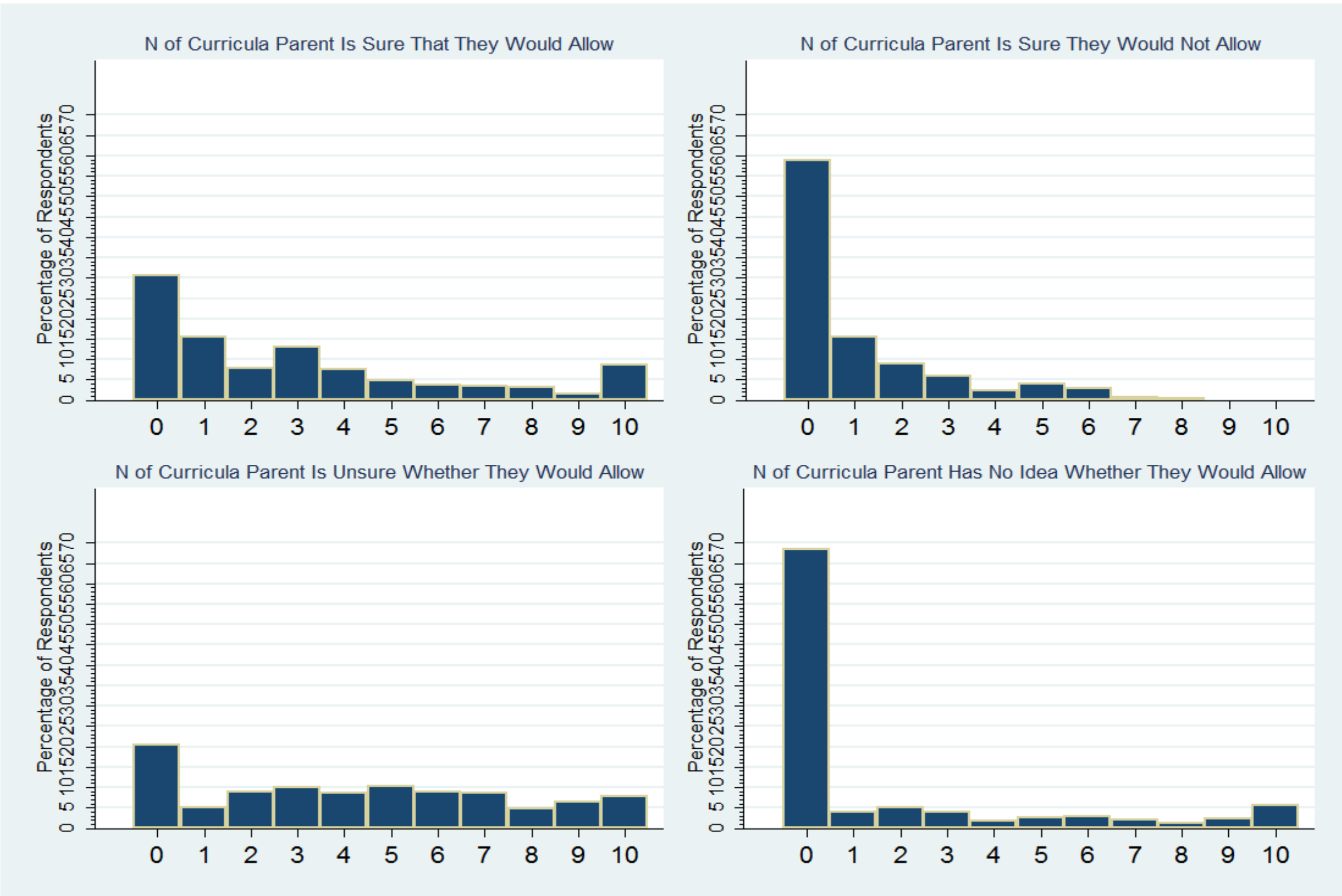


Table C.13: Before-the-choice choice set – Waves 1 and 2, Child. Number of alternatives (Range: 0 to 10). Matched Answers Across Waves, Before & At Choice.

Wave 1

Set	Mean	Std. Dev.	p10	p50	p90	Mean Prob.	Std. Dev.	N
Stated preferred alternative(s)								
Ranked-first alternative(s)	1	0	-	-	-	74.45[a]	23.22	177
Top-three alternative(s)	2.64	.62	2	3	3	40.53[b]	18.61	177
Consideration set(s)								
Active consideration set	3.50	1.00	2	4	5			117
Feasibility sets								
Agency sets								
Implicit parental veto, lb[c]	4.75	2.75	2	4	10	63.18	20.70	164
Implicit parental veto, ub[c]	6.21	2.93	3	6	10	52.34	23.27	193
Awareness set	8.71	1.66	6	9	10			173

Wave 2

Set	Mean	Std. Dev.	p10	p50	p90	Mean Prob.	Std. Dev.	N
Stated preferred alternative(s)								
Ranked-first alternative(s)[d]	1.07	.33	1	1	1	78.02[a]	25.52	177
Top-three alternative(s)[d]	3.20	1.17	3	3	4	32.47[b]	13.66	177
Consideration set(s)								
Active consideration set	3.85	1.16	3	4	5			117
Cumulative consideration set, ub[c]	4.69	1.24	3	4	6			129
Feasibility sets								
Agency sets								
Implicit parental veto, lb[c]	5.14	2.86	2	5	10	67.46	22.16	164
Implicit parental veto, ub[c]	6.33	2.88	3	6	10	58.26	24.69	193
Awareness set	9.50	1.10	8	10	10			173

At Choice

Set	Mean	Std. Dev.	p10	p50	p90			N
Chosen alternative(s)								
Ranked-first alternative(s)	1	0						177
Top-three alternative(s)	1.26	.55	1	1	2			177
Consideration set	1.67	.93	1	1	3			117
Feasibility sets								
Agency sets								
Implicit parental veto, lb[c]	6.57	3.18	10	10	10			164
Implicit parental veto, ub[c]	7.66	3.10	3	10	10			193
Explicit parental veto	8.875	1.91	5	10	10			128
Awareness set	9.94	.39	10	10	10			173

[a]: Mean probability that the first-ranked alternative would be chosen today.
[b]: Mean probability that the first three ranked alternatives would be chosen today.
[c]: *lb*: lower bound; *ub*: upper bound.
[d]: Ties allowed.

Table C.14: Before-the-choice choice set – Waves 1 and 2, Parent. Number of alternatives (Range: 0 to 10). Matched Answers Across Waves, Before & At Choice.

Wave 1

Set	Mean	Std. Dev.	p10	p50	p90	Mean Prob.	Std. Dev.	N
Stated preferred alternative(s)								
Ranked-first alternative(s)	1	-				67.87[a]	26.22	166
Top-three alternative(s)	2.76	.72	2	3	3	40.04[b]	17.85	166
Consideration set(s)								
Active consideration set	3.61	1.15	2	4	5			109
Feasibility sets								
Agency sets								
Implicit parental veto, lb[c]	5.68	2.55	2	6	9	60.86	22.65	154
Implicit parental veto, ub[c]	6.47	3.09	2	7	10	53.33	22.75	174
Awareness set	8.99	1.90	6	10	10			162

Wave 2

Set	Mean	Std. Dev.	p10	p50	p90	Mean Prob.	Std. Dev.	N
Stated preferred alternative(s)								
Ranked-first alternative(s)[c]	1.14	.48	1	1	1	37[a]	30.98	166
Top-three alternative(s)[c]	3.73	2.20	3	3	7	12.74[b]	18.83	166
Consideration set(s)								
Active consideration set	4.11	2.08	3	4	6			109
Cumulative consideration set, ub[c]	5.05	1.88	3	5	7			109
Feasibility sets								
Agency sets								
Implicit parental veto, lb[c]	5.49	2.90	1	5	10	64.84	21.08	154
Implicit parental veto, ub[c]	6.62	3.13	3	7	10	57.17	23.02	174
Awareness set	9.33	1.70	8	10	10			162

At Choice

Set	Mean	Std. Dev.	p10	p50	p90			N
Chosen alternative(s)								
Ranked-first alternative(s)	1	-						166
Top-three alternative(s)	1.28	.56	1	1	2			166
Consideration set	1.60	.83	1	1	3			109
Feasibility sets								
Agency sets								
Implicit parental veto, lb[c]	6.62	3.20	4	10	10			154
Implicit parental veto, ub[c]	7.63	3.10	10	10	10			174
Explicit parental veto	8.96	1.87	5	10	10			115
Awareness set	9.93	.40	10	10	10			162

[a]: Mean probability that the first-ranked alternative would be chosen today.
[b]: Mean probability that the first three ranked alternatives would be chosen today.
[c]: *lb*: lower bound; *ub*: upper bound.
[d]: Ties allowed.

Table C.15: DISTRIBUTION OF TIES – WAVES 2 AND 3, CHILD & PARENT.

	Child		
	Ranked First	**Ranked Second**	**Ranked Third**
Wave 2			
No ties, %	91.94	91.64	88.96
One tie, %	5.07	4.95	5.52
More than one tie, %	2.99	3.41	5.52
N	335	323	308
Wave 3			
No ties, %	79.07	83.33	76.19
One tie, %	13.95	14.29	7.14
More than one tie, %	6.98	2.38	16.67
N	43	42	42

	Parent		
	Ranked First	**Ranked Second**	**Ranked Third**
Wave 2			
No ties, %	87.63	87.5	86.36
One tie, %	8.48	5.47	4.55
More than one tie, %	3.89	7.03	9.09
N	283	256	242
Wave 3			
No ties, %	93.94	93.75	93.10
One tie, %	3.03	3.13	3.45
More than one tie, %	3.03	3.13	3.45
N	33	32	29

Table C.16: Distribution of the before-the-choice choice set – Wave 1, Child. Number of Curricula (range: 0 to 10), by Child's Gender, Child's 7^{th} Grade GPA.

		Child, Wave 1							
		Mean	Std Dev	Min	p10	p50	p90	Max	N
Overall									
Stated preferred alternative(s)									
Ranked-first alternative		1	0						287
Top-three alternative(s)		2.57	.67	1	1	3	3	3	287
Consideration set(s)									
Active consideration set		3.34	.99	1	2	3	5	8	287
Feasibility sets									
Agency sets									
Implicit parental veto, lb[c]		4.72	2.75	1	2	4	10	10	253
Implicit parental veto, ub[c]		5.86	3.02	1	2	5	10	10	315
Awareness set		8.76	1.62	3	6	9	10	10	345
Distribution by Gender									
Stated preferred alternative(s)									
Ranked-first alternative	M	1	0						111
	F	1	0						176
Top-three alternative(s)	M	2.54	.72	1	1	3	3	3	111
	F	2.58	.64	1	2	3	3	3	176
Consideration set(s)									
Active consideration set	M	3.18	.90	1	2	3	4	5	111
	F	3.45	1.04	1	2	3	5	8	176
Feasibility sets									
Agency sets									
Implicit parental veto, lb[c]	M	4.77	3.01	1	1	4	10	10	107
	F	4.68	2.55	1	2	4	10	10	146
Implicit parental veto, ub[c]	M	5.91	3.07	1	2	5	10	10	129
	F	5.82	2.99	1	2	5	10	10	186
Awareness set	M	8.60	1.82	3	6	9	10	10	142
	F	8.87	1.45	5	7	9	10	10	203
Distribution by Child's GPA									
Stated preferred alternative(s)									
Ranked-first alternative	GPA <p25	1	0						46
	GPA p25-p75	1	0						142
	GPA>p75	1	0						84
Top-three alternative(s)	GPA <p25	2.35	.79	1	1	3	3	3	46
	GPA p25-p75	2.62	.64	1	2	3	3	3	142
	GPA>p75	2.61	.66	1	2	3	3	3	84
Consideration set(s)									
Active consideration set	GPA <p25	2.93	.90	1	2	3	4	5	46
	GPA p25-p75	3.38	.93	1	2	3	4	5	142
	GPA>p75	3.53	1.09	2	2	3	5	8	84
Feasibility sets									
Agency sets									
Implicit parental veto, lb[c]	GPA <p25	4	2.90	1	1	3	10	10	35
	GPA p25-p75	5	2.74	0	2	4	10	10	131
	GPA>p75	4.73	2.70	1	2	4	10	10	81
Implicit parental veto, ub[c]	GPA <p25	5.21	3.25	1	1	4	10	10	57
	GPA p25-p75	6.18	2.99	1	3	5	10	10	157
	GPA>p75	6.28	2.79	1	3	6	10	10	85
Awareness set	GPA <p25	8.61	1.62	3	6	9	10	10	66
	GPA p25-p75	8.92	1.45	4	7	10	10	10	162
	GPA>p75	8.84	1.53	5	6	10	10	10	86

Gender: "M" male, "F" female.
7^{th} grade GPA: "<p25" below 7.10/10 (25^{th} percentile), "p25-p75" between 7.1 and 8.6, ">p75" above 8.6.
[a]: *lb*: lower bound; *ub*: upper bound.

Table C.17: DISTRIBUTION OF THE BEFORE-THE-CHOICE CHOICE SET – WAVE 1, CHILD. NUMBER OF CURRICULA (RANGE: 0 TO 10), BY PARENTAL EDUCATION.

		Child, Wave 1							
Distribution by Parents' Education									
Father									
		Mean	**Std Dev**	**Min**	**p10**	**p50**	**p90**	**Max**	**N**
Stated preferred alternative(s)									
Ranked-first alternative	Elementary or middle school	1	0						60
	High school	1	0						135
	College or more	1	0						78
Top-three alternative(s)	Elementary or middle school	2.67	.60	1	2	3	3	3	60
	High school	2.50	.74	1	1	3	3	3	135
	College or more	2.65	.55	1	2	3	3	3	78
Consideration set(s)									
Active consideration set	Elementary or middle school	3.38	.92	2	2	3	5	5	60
	High school	3.30	1.12	1	2	3	5	8	135
	College or more	3.45	.77	2	2	4	4	5	78
Feasibility sets									
Agency sets									
Implicit parental veto, lb[c]	Elementary or middle school	4.53	3.07	0	1	3	10	10	55
	High school	4.80	2.71	1	2	4	9	10	123
	College or more	4.69	2.49	1	2	4	9	10	67
Implicit parental veto, ub[c]	Elementary or middle school	5.67	3.00	1	2	5	10	10	67
	High school	6.29	3.08	1	2	6	10	10	150
	College or more	5.56	2.82	1	3	5	10	10	82
Awareness set	Elementary or middle school	9.26	1.05	6	8	10	10	10	74
	High school	8.86	1.53	4	7	10	10	10	161
	College or more	8.46	1.69	3	6	9	10	10	83
Mother									
Stated preferred alternative(s)									
Ranked-first alternative	Elementary or middle school	1	0						48
	High school	1	0						142
	College or more	1	0						85
Top-three alternative(s)	Elementary or middle school	2.37	.76	1	1	3	3	3	48
	High school	2.64	.64	1	2	3	3	3	142
	College or more	2.58	.64	1	2	3	3	3	85
Consideration set(s)									
Active consideration set	Elementary or middle school	3.19	1.08	1	2	3	5	5	48
	High school	3.43	.95	1	2	3	5	5	142
	College or more	3.33	1.02	1	2	3	4	8	85
Feasibility sets									
Agency sets									
Implicit parental veto, lb[c]	Elementary or middle school	4.28	3.02	0	1	3	10	10	39
	High school	4.80	2.76	1	2	4	10	10	128
	College or more	4.77	2.57	1	2	4	10	10	79
Implicit parental veto, ub[c]	Elementary or middle school	5.67	3.22	1	1	5	10	10	55
	High school	6.08	2.94	1	3	6	10	10	155
	College or more	5.83	3.03	1	2	5	10	10	91
Awareness set	Elementary or middle school	9.21	1.21	5	7	10	10	10	63
	High school	8.81	1.61	3	6	10	10	10	167
	College or more	8.62	1.54	3	6	9	10	10	92

Gender: "M" male, "F" female.
7^{th} grade GPA: "<p25" below 7.10/10 (25^{th} percentile), "p25-p75" between 7.1 and 8.6, ">p75" above 8.6.
[a]: *lb*: lower bound; *ub*: upper bound.

Table C.18: Distribution of the before-the-choice choice set – Wave 2, Child. Number of Curricula (range: 0 to 10), by Child's Gender, Child's 7^{th} Grade GPA.

		Child, Wave 2							
		Mean	**Std Dev**	**Min**	**p10**	**p50**	**p90**	**Max**	**N**
Overall									
Stated preferred alternative(s)									
Ranked-first alternative		1.13	.67	1	1	1	1	5	111
Top-three alternative(s)		3.47	1.69	1	3	3	4	10	287
Consideration set(s)									
Active consideration set		4.08	1.69	1	3	4	5	10	287
Feasibility sets									
Agency sets									
Implicit parental veto, lb[c]		4.80	2.84	1	1	4	10	10	253
Implicit parental veto, ub[c]		6.24	2.92	1	3	6	10	10	315
Awareness set		9.49	1.12	4	8	10	10	10	345
Distribution by Gender									
Stated preferred alternative(s)									
Ranked-first alternative	M	1.14	.54	1	1	1	1	5	176
	F	1.13	.59	1	1	1	1	5	287
Top-three alternative(s)	M	3.65	1.99	1	3	3	5	10	111
	F	3.35	1.46	1	3	3	4	10	176
Consideration set(s)									
Active consideration set	M	4.22	1.95	1	3	4	7	10	111
	F	3.99	1.51	1	3	4	5	10	176
Feasibility sets									
Agency sets									
Implicit parental veto, lb[c]	M	5.07	2.98	1	1	5	10	10	107
	F	4.60	2.72	1	2	4	10	10	146
Implicit parental veto, ub[c]	M	6.29	3	1	3	6	10	10	129
	F	6.20	2.86	1	3	6	10	10	186
Awareness set	M	9.49	1.04	4	8	10	10	10	142
	F	9.49	1.18	4	8	10	10	10	203
Distribution by Child's GPA									
Stated preferred alternative(s)									
Ranked-first alternative	GPA <p25	1.46	1.22	1	1	1	2	5	46
	GPA p25-p75	1.09	.39	1	1	1	1	4	142
	GPA>p75	1.05	.26	1	1	1	1	3	84
Top-three alternative(s)	GPA <p25	4.13	2.51	1	3	3	9	10	46
	GPA p25-p75	3.51	1.75	1	3	3	4	10	142
	GPA>p75	3.07	.46	1	3	3	3	6	84
Consideration set(s)									
Active consideration set	GPA <p25	4.56	2.40	1	3	4	9	10	46
	GPA p25-p75	4.11	1.76	1	3	4	5	10	142
	GPA>p75	3.86	.78	1	3	4	4	7	84
Feasibility sets									
Agency sets									
Implicit parental veto, lb[c]	GPA <p25	3.49	2.95	1	1	2	9	10	35
	GPA p25-p75	4.95	2.82	1	2	4	10	10	131
	GPA>p75	5.20	2.64	1	2	5	10	10	81
Implicit parental veto, ub[c]	GPA <p25	5.65	3.02	1	3	5	10	10	57
	GPA p25-p75	6.36	2.96	1	3	6	10	10	157
	GPA>p75	6.71	2.63	3	3	7	10	10	85
Awareness set	GPA <p25	9.62	.99	4	9	10	10	10	66
	GPA p25-p75	9.47	1.13	4	8	10	10	10	162
	GPA>p75	9.45	1.11	5	7	10	10	10	86

Gender: "M" male, "F" female.
7^{th} grade GPA: "<p25" below 7.10/10 (25^{th} percentile), "p25-p75" between 7.1 and 8.6, ">p75" above 8.6.
[a]: *lb*: lower bound; *ub*: upper bound.

Table C.19: Distribution of the before-the-choice choice set – Wave 2, Child. Number of Curricula (range: 0 to 10), by Parental Education.

		Child, Wave 2							
Distribution by Parents' Education									
Father									
		Mean	**Std Dev**	**Min**	**p10**	**p50**	**p90**	**Max**	**N**
Stated preferred alternative(s)									
Ranked-first alternative	Elementary or middle school	1.28	1.03	1	1	1	1	5	60
	High school	1.10	.44	1	1	1	1	5	135
	College or more	1.05	.27	1	1	1	1	3	78
Top-three alternative(s)	Elementary or middle school	3.67	2.22	1	2	3	8.5	10	60
	High school	3.35	1.34	1	3	3	4	10	135
	College or more	3.37	1.55	1	3	3	4	10	78
Consideration set(s)									
Active consideration set	Elementary or middle school	4.28	2.14	1	2	4	8.5	10	60
	High school	3.98	1.41	1	3	4	5	10	135
	College or more	4.04	1.61	1	3	4	5	10	78
Feasibility sets									
Agency sets									
Implicit parental veto, lb[c]	Elementary or middle school	4.96	3.20	1	1	4	10	10	55
	High school	4.89	2.66	1	2	4	10	10	123
	College or more	4.39	2.69	1	1	4	10	10	67
Implicit parental veto, ub[c]	Elementary or middle school	6.55	3.19	1	3	7	10	10	67
	High school	6.28	2.80	1	3	6	10	10	150
	College or more	5.89	2.92	1	3	5	10	10	82
Awareness set	Elementary or middle school	9.77	.56	8	9	10	10	10	74
	High school	9.43	1.21	4	8	10	10	10	161
	College or more	9.45	1.16	4	8	10	10	10	83
Mother									
Stated preferred alternative(s)									
Ranked-first alternative	Elementary or middle school	1.37	1.14	1	1	1	2	5	48
	High school	1.12	.47	1	1	1	1	5	142
	College or more	1.01	.11	1	1	1	1	2	85
Top-three alternative(s)	Elementary or middle school	4.27	2.70	1	3	3	10	10	48
	High school	3.28	1.23	1	3	3	4	10	142
	College or more	3.22	1.25	1	3	3	3	10	85
Consideration set(s)									
Active consideration set	Elementary or middle school	4.81	2.52	1	3	4	10	10	48
	High school	3.91	1.34	1	3	4	5	10	142
	College or more	3.89	1.37	1	3	4	5	10	85
Feasibility sets									
Agency sets									
Implicit parental veto, lb[c]	Elementary or middle school	4.49	3.23	1	1	3	10	10	39
	High school	4.91	2.81	1	2	4	10	10	128
	College or more	4.68	2.65	1	2	4	10	10	79
Implicit parental veto, ub[c]	Elementary or middle school	6.49	3.24	1	3	7	10	10	55
	High school	6.15	2.87	1	3	6	10	10	155
	College or more	6.18	2.81	1	3	6	10	10	91
Awareness set	Elementary or middle school	9.78	.66	7	9	10	10	10	63
	High school	9.51	.99	4	8	10	10	10	167
	College or more	9.31	1.43	4	7	10	10	10	92

Gender: "M" male, "F" female.
7^{th} grade GPA: "<p25" below 7.10/10 (25^{th} percentile), "p25-p75" between 7.1 and 8.6, ">p75" above 8.6.
[a]: *lb*: lower bound; *ub*: upper bound.

Table C.20: Distribution of the before-the-choice choice set – Wave 1, Parent. Number of Curricula (range: 0 to 10), by Child's Gender, Child's 7^{th} Grade GPA.

		Parent, Wave 1 Mean	Std Dev	Min	p10	p50	p90	Max	N
Overall									
Stated preferred alternative(s)									
Ranked-first alternative		1	0						264
Top-three alternative(s)		2.78	.70	1	2	3	3	5	264
Consideration set(s)									
Active consideration set		3.57	1.08	1	2	4	5	7	264
Feasibility sets									
Agency sets									
Implicit parental veto, lb[c]		5.45	2.65	1	2	5	10	10	235
Implicit parental veto, ub[c]		6.20	3.09	1	3	6	10	10	274
Awareness set		8.88	2.0	1	6	10	10	10	302
Distribution by Gender									
Stated preferred alternative(s)									
Ranked-first alternative	M	1	0						112
	F	1	0						152
Top-three alternative(s)	M	2.76	.71	1	2	3	3	4	112
	F	2.79	.69	1	2	3	3	5	152
Consideration set(s)									
Active consideration set	M	3.63	1.11	1	2	4	5	7	112
	F	3.53	1.06	1	2	3	5	6	152
Feasibility sets									
Agency sets									
Implicit parental veto, lb[c]	M	5.05	2.65	1	2	5	9	10	103
	F	5.76	2.62	1	3	5	10	10	132
Implicit parental veto, ub[c]	M	6.13	3.10	1	2	6	10	10	115
	F	6.25	3.11	1	3	6	10	10	159
Awareness set	M	8.85	2.16	1	5	10	10	10	126
	F	8.90	1.88	1	6	10	10	10	176
Distribution by Child's GPA									
Stated preferred alternative(s)									
Ranked-first alternative	GPA <p25	1	0						50
	GPA p25-p75	1	0						125
	GPA>p75	1	0						78
Top-three alternative(s)	GPA <p25	2.74	.66	1	2	3	3	4	50
	GPA p25-p75	2.83	.66	1	2	3	3	5	125
	GPA>p75	2.74	.71	1	2	3	3	4	78
Consideration set(s)									
Active consideration set	GPA <p25	3.34	.96	1	2	3	4.5	5	50
	GPA p25-p75	3.66	.98	1	3	4	5	6	125
	GPA>p75	3.70	1.23	1	2	4	5	7	78
Feasibility sets									
Agency sets									
Implicit parental veto, lb[c]	GPA <p25	4.05	2.50	1	1	3	8	10	38
	GPA p25-p75	5.53	2.67	1	2	5	10	10	113
	GPA>p75	6.12	2.42	1	3	6	10	10	76
Implicit parental veto, ub[c]	GPA <p25	5.31	2.96	1	3	4	10	10	51
	GPA p25-p75	6.19	3.11	1	3	6	10	10	132
	GPA>p75	7.05	2.92	1	3	8	10	10	79
Awareness set	GPA <p25	8.39	2.40	2	4	10	10	10	57
	GPA p25-p75	9.02	1.77	1	7	10	10	10	144
	GPA>p75	9.40	1.37	3	8	10	10	10	82

Gender: "M" male, "F" female.
7^{th} grade GPA: "<p25" below 7.10/10 (25^{th} percentile), "p25-p75" between 7.1 and 8.6, ">p75" above 8.6.
[[a]]: *lb*: lower bound; *ub*: upper bound.

Table C.21: DISTRIBUTION OF THE BEFORE-THE-CHOICE CHOICE SET – WAVE 1, PARENT. NUMBER OF CURRICULA (RANGE: 0 TO 10), BY PARENTAL EDUCATION.

		Parent, Wave 1							
Distribution by Parents' Education									
Father									
		Mean	**Std Dev**	**Min**	**p10**	**p50**	**p90**	**Max**	**N**
Stated preferred alternative(s)									
Ranked-first alternative	Elementary or middle school	1	0						55
	High school	1	0						130
	College or more	1	0						69
Top-three alternative(s)	Elementary or middle school	2.78	.66	1	2	3	3	4	55
	High school	2.75	.73	1	2	3	3	5	130
	College or more	2.90	.60	1	2	3	3	5	69
Consideration set(s)									
Active consideration set	Elementary or middle school	3.53	.94	1	2	3	5	5	55
	High school	3.51	1.18	1	2	3	5	7	130
	College or more	3.84	.92	2	3	4	5	6	69
Feasibility sets									
Agency sets									
Implicit parental veto, lb[c]	Elementary or middle school	5.67	3.26	1	2	5	10	10	45
	High school	5.48	2.61	1	2	5	10	10	118
	College or more	5.39	2.22	1	3	5	8	10	67
Implicit parental veto, ub[c]	Elementary or middle school	5.74	3.38	1	2	4.5	10	10	58
	High school	6.26	3.09	1	2	6	10	10	134
	College or more	6.79	2.78	1	3	7.5	10	10	72
Awareness set	Elementary or middle school	8.52	2.55	1	4	10	10	10	67
	High school	9.10	1.62	3	7	10	10	10	142
	College or more	9.22	1.43	3	8	10	10	10	76
Mother									
Stated preferred alternative(s)									
Ranked-first alternative	Elementary or middle school	1	0						42
	High school	1	0						137
	College or more	1	0						76
Top-three alternative(s)	Elementary or middle school	2.67	.85	1	1	3	3	5	42
	High school	2.79	.66	1	2	3	3	4	137
	College or more	2.83	.64	1	2	3	3	5	76
Consideration set(s)									
Active consideration set	Elementary or middle school	3.17	1.08	1	2	3	5	6	42
	High school	3.65	1.09	1	2	4	5	7	137
	College or more	3.72	1.0	2	2	4	5	6	76
Feasibility sets									
Agency sets									
Implicit parental veto, lb[c]	Elementary or middle school	5.44	2.86	1	2	5	10	10	32
	High school	5.54	2.77	1	2	5	10	10	123
	College or more	5.36	2.33	1	3	5	8	10	75
Implicit parental veto, ub[c]	Elementary or middle school	5.61	3.53	1	1	4.5	10	10	46
	High school	6.54	3.09	1	3	7	10	10	140
	College or more	6.13	2.81	1	3	6	10	10	79
Awareness set	Elementary or middle school	8.58	2.42	1	4	10	10	10	55
	High school	8.88	2.04	1	6	10	10	10	149
	College or more	9.31	1.19	5	8	10	10	10	84

Gender: "M" male, "F" female.
7^{th} grade GPA: "<p25" below 7.10/10 (25^{th} percentile), "p25-p75" between 7.1 and 8.6, ">p75" above 8.6.
[a]: *lb*: lower bound; *ub*: upper bound.

Table C.22: Distribution of the before-the-choice choice set – Wave 2, Parent. Number of Curricula (range: 0 to 10), by Child's Gender, Child's 7^{th} Grade GPA.

		Parent, Wave 2							
		Mean	**Std Dev**	**Min**	**p10**	**p50**	**p90**	**Max**	**N**
Overall									
Stated preferred alternative(s)									
Ranked-first alternative		1.18	.61	1	1	1	2	6	264
Top-three alternative(s)		3.92	2.40	1	3	3	10	10	264
Consideration set(s)									
Active consideration set		4.41	2.34	1	3	4	10	10	264
Feasibility sets									
Agency sets									
Implicit parental veto, lb[c]		5.35	2.85	1	2	5	10	10	235
Implicit parental veto, ub[c]		6.48	3.15	1	3	7	10	10	274
Awareness set		9.26	1.78	1	8	10	10	10	302
Distribution by Gender									
Stated preferred alternative(s)									
Ranked-first alternative	M	1.28	.76	1	1	1	2	6	112
	F	1.10	.45	1	1	1	1	5	152
Top-three alternative(s)	M	4.15	2.65	1	3	3	10	10	112
	F	3.75	2.18	1	3	3	7	10	152
Consideration set(s)									
Active consideration set	M	4.68	2.57	1	3	4	10	10	112
	F	4.21	2.14	1	3	4	7	10	152
Feasibility sets									
Agency sets									
Implicit parental veto, lb[c]	M	5.58	2.84	1	2	5	10	10	103
	F	5.17	2.86	1	1	5	10	10	132
Implicit parental veto, ub[c]	M	6.54	3.24	1	3	7	10	10	115
	F	6.43	3.09	1	3	6	10	10	159
Awareness set	M	9.25	1.89	1	7	10	10	10	126
	F	9.27	1.71	1	8	10	10	10	176
Distribution by Child's GPA									
Stated preferred alternative(s)									
Ranked-first alternative	GPA <p25	1.24	.59	1	1	1	2	4	50
	GPA p25-p75	1.22	.74	1	1	1	2	6	125
	GPA>p75	1.05	.27	1	1	1	1	3	78
Top-three alternative(s)	GPA <p25	4.44	3.23	1	1	3	10	10	50
	GPA p25-p75	3.94	2.30	1	3	3	10	10	125
	GPA>p75	3.5	1.63	1	3	3	5	10	78
Consideration set(s)									
Active consideration set	GPA <p25	4.76	3.15	1	1	4	10	10	50
	GPA p25-p75	4.4	2.23	1	3	4	10	10	125
	GPA>p75	4.17	1.65	1	3	4	10	10	78
Feasibility sets									
Agency sets									
Implicit parental veto, lb[c]	GPA <p25	4.53	3.13	1	1	4	9	10	38
	GPA p25-p75	5.12	2.73	1	2	5	9	10	113
	GPA>p75	6.01	2.72	1	3	6	10	10	76
Implicit parental veto, ub[c]	GPA <p25	5.84	3.57	1	1	5	10	10	51
	GPA p25-p75	6.60	3.09	1	3	6.5	10	10	132
	GPA>p75	6.68	2.88	1	3	7	10	10	79
Awareness set	GPA <p25	9.10	2.29	1	6	10	10	10	57
	GPA p25-p75	9.33	1.66	1	8	10	10	10	144
	GPA>p75	9.52	1.07	5	8	10	10	10	82

Gender: "M" male, "F" female.
7^{th} grade GPA: "<p25" below 7.10/10 (25^{th} percentile), "p25-p75" between 7.1 and 8.6, ">p75" above 8.6.
[a]: *lb*: lower bound; *ub*: upper bound.

Table C.23: DISTRIBUTION OF THE BEFORE-THE-CHOICE CHOICE SET – WAVE 2, PARENT. NUMBER OF CURRICULA (RANGE: 0 TO 10), BY PARENTAL EDUCATION.

		Parent, Wave 2							
Distribution by Parents' Education									
Father									
		Mean	**Std Dev**	**Min**	**p10**	**p50**	**p90**	**Max**	**N**
Stated preferred alternative(s)									
Ranked-first alternative	Elementary or middle school	1.29	.85	1	1	1	2	6	55
	High school	1.16	.61	1	1	1	1	5	130
	College or more	1.12	.32	1	1	1	2	2	69
Top-three alternative(s)	Elementary or middle school	4.04	2.78	1	1	3	10	10	55
	High school	4.07	2.47	1	3	3	10	10	130
	College or more	3.58	1.67	1	3	3	6	10	69
Consideration set(s)									
Active consideration set	Elementary or middle school	4.34	2.78	1	1	3	10	10	55
	High school	4.62	2.36	1	3	4	10	10	130
	College or more	4.14	1.63	1	3	4	6	10	69
Feasibility sets									
Agency sets									
Implicit parental veto, lb[c]	Elementary or middle school	5.18	3.12	1	1	4	10	10	45
	High school	5.34	2.84	1	2	5	10	10	118
	College or more	5.57	2.69	1	3	5	10	10	67
Implicit parental veto, ub[c]	Elementary or middle school	6.21	3.46	1	2	5.5	10	10	58
	High school	6.57	3.05	1	3	7	10	10	134
	College or more	6.68	3.02	1	3	7	10	10	72
Awareness set	Elementary or middle school	9.06	2.32	1	6	10	10	10	67
	High school	9.42	1.48	2	8	10	10	10	142
	College or more	9.38	1.28	4	8	10	10	10	76
Mother									
Stated preferred alternative(s)									
Ranked-first alternative	Elementary or middle school	1.31	1.00	1	1	1	2	6	42
	High school	1.21	.60	1	1	1	2	5	137
	College or more	1.04	.20	1	1	1	1	2	76
Top-three alternative(s)	Elementary or middle school	3.98	2.60	1	2	3	10	10	42
	High school	4.20	2.66	1	2	3	10	10	137
	College or more	3.37	1.36	1	3	3	4	10	76
Consideration set(s)									
Active consideration set	Elementary or middle school	4.40	2.57	1	2	4	10	10	42
	High school	4.65	2.59	1	2	4	10	10	137
	College or more	4	1.39	1	3	4	5	10	76
Feasibility sets									
Agency sets									
Implicit parental veto, lb[c]	Elementary or middle school	5.5	3.24	1	1	5	10	10	32
	High school	5.47	2.91	1	2	5	10	10	123
	College or more	5.08	2.51	1	2	5	9	10	75
Implicit parental veto, ub[c]	Elementary or middle school	5.96	3.33	1	2	5	10	10	46
	High school	6.82	3.14	1	3	7	10	10	140
	College or more	6.20	2.97	1	3	6	10	10	79
Awareness set	Elementary or middle school	9.2	2.10	1	8	10	10	10	55
	High school	9.30	1.77	1	8	10	10	10	149
	College or more	9.38	1.32	4	8	10	10	10	84

Gender: "M" male, "F" female.
7^{th} grade GPA: "<p25" below 7.10/10 (25^{th} percentile), "p25-p75" between 7.1 and 8.6, ">p75" above 8.6.
[a]: *lb*: lower bound; *ub*: upper bound.

Table C.24: Composition of each set before the choice and at the moment of choice – Waves 1 and 2, Child & Parent. For each track, ratio of curricula covered over total number of available curricula (total number of curricula: 5 for the General Track, 2 for the Technical Track, 3 for the Vocational Track).

	Evolution								**At Choice**			
	Wave 1				**Wave 2**							
	G.	**T.**	**V.**	**N**	**G.**	**T.**	**V.**	**N**	**G.**	**T.**	**V.**	**N**
Child												
Chosen alternative(s)												
Ranked-first alternative(s)	.13	.10	.05	287	.14	.13	.05	287	.14	.10	.03	177
Top-three alternative(s)	.33	.28	.11	287	.44	.36	.19	287	.18	.12	.04	177
Consideration set	.41	.35	.20	287	.50	.41	.26	287	.24	.17	.05	117
Feasibility sets												
Agency sets												
Implicit parental veto, lb[a]	.60	.49	.27	253	.61	.46	.28	253	.19	.22	.26	147
Implicit parental veto, ub[a]	.66	.60	.45	315	.71	.64	.47	315	.97	.98	.98	170
Explicit parental veto									.90	.91	.86	126
Awareness set	.95	.88	.74	345	.99	.95	.88	345	.99	.99	.99	173
Parent												
Chosen alternative(s)												
Ranked-first alternative(s)	.13	.10	.04	264	.14	.14	.07	264	.13	.10	.04	166
Top-three alternative(s)	.33	.31	.16	264	.48	.38	.24	264	.17	.13	.05	166
Consideration set	.43	.38	.22	264	.53	.45	.29	264	.21	.17	.06	109
Feasibility sets												
Agency sets												
Implicit parental veto, lb[a]	.65	.60	.33	235	.65	.56	.33	235	.19	.23	.24	136
Implicit parental veto, ub[a]	.67	.68	.50	274	.72	.68	.50	274	.80	.98	.98	154
Explicit parental veto									.91	.92	.88	113
Awareness set	.91	.90	.83	302	.96	.93	.87	302	.99	.99	.99	162

G.: General Track; T.: Technical Track; V.: Vocational Track.
[a]: *lb*: lower bound; *ub*: upper bound.

Table C.25: Predictors of the number of tracks included in each child's set before the choice – Waves 1 and 2, Child.

	Child					
	Ranked-First Alt.	**Top-Three Alt.**	**Consid. Set**	**Agency Set, lb**	**Agency Set, ub**	**Awareness Set**
Wave 1						
Female student	-	-.111*	-.095	-.034	-.010	-.003
		(.063)	(.061)	(.051)	(.078)	(.021)
Foreign-born student	-	-.245**	-.306*	-.104	-.123	-.149*
		(.122)	(.160)	(.120)	(.144)	(.088)
Lives with both parents	-	.030	.060	-.029	.085	-.039
		(.106)	(.105)	(.083)	(.118)	(.039)
Stay-at-home mother	-	.114	.054	.037	.088	.017
		(.077)	(.072)	(.057)	(.080)	(.023)
Blue-collar father	-	.045	.114	.104*	.092	-.011
		(.077)	(.078)	(.058)	(.104)	(.028)
Has older siblings	-	.035	.093	.005	-.027	-.023
		(.065)	(.063)	(.052)	(.081)	(.022)
7^{th}-grade GPA,	-	.094	.133*	.195***	.058	.014
lower 25perc		(.091)	(.071)	(.053)	(.104)	(.030)
7^{th}-grade GPA,	-	-.135*	-.069	.031	-.029	-.031
upper 25perc		(.069)	(.072)	(.061)	(.083)	(.023)
Sample size	158	158	158	171	149	174
Wave 2						
Female student	.001	-.023***	-.146**	.082	-.138*	.016
	(.027)	(.055)	(.062)	(.057)	(.072)	(.019)
Foreign-born student	.056	.133	.097	-.126	-.154	-.071
	(.083)	(.131)	(.138)	(.126)	(.166)	(.063)
Lives with both parents	-.025	-.041	-.035	-.130	-.040	.011
	(.019)	(.080)	(.107)	(.107)	(.131)	(.007)
Stay-at-home mother	.017	.123*	.094	.028	.005	-.032
	(.030)	(.066)	(.070)	(.065)	(.083)	(.027)
Blue-collar father	.042	-.065	.011	.031	.114	.029**
	(.049)	(.075)	(.080)	(.070)	(.090)	(.014)
Has older siblings	-.034	.034	.104*	.032	.050	.016
	(.025)	(.056)	(.063)	(.056)	(.073)	(.016)
7^{th}-grade GPA,	.010	.108	.080	-.021	-.122	.026
lower 25perc	(.045)	(.070)	(.070)	(.072)	(.121)	(.015)
7^{th}-grade GPA,	-.016	-.196***	-.225***	-.069	-.019	-.018
upper 25perc	(.023)	(.061)	(.167)	(.065)	(.078)	(.020)
Sample size	158	158	158	171	149	174

lb: lower bound; *ub*: upper bound.

***

Significance levels: [***] significant at 1%; [**] significant at 5%; [*] significant at 10%.

Predictors: *female student:* dummy=1 if student is female; *foreign-born student:* dummy=1 if student is foreign-born; *lives with both parents:* dummy=1 if student lives with both parents; *stay-at-home mother:* dummy=1 if student has a stay-at-home mother; *blue-collar father:* dummy=1 if student's father works in a blue-collar occupation; *has older siblings:* dummy=1 if student has older siblings (between 1 and 3); *7^{th}-grade GPA, lower 25 percentile:* dummy=1 if student's GPA in the 7th grade end-of-year report (between 6 and 10) is in the bottom quartile of the distribution; *7^{th}-grade GPA, upper 25 percentile:* dummy=1 if student's GPA in the 7th grade end-of-year report (between 6 and 10) is in the upper quartile of the distribution.

Table C.26: PREDICTORS OF THE NUMBER OF TRACKS INCLUDED IN EACH PARENT'S SET BEFORE THE CHOICE – WAVES 1 AND 2, PARENT.

	Parent					
	Ranked-First Alt.	**Top-Three Alt.**	**Consid. Set**	**Agency Set, lb**	**Agency Set, ub**	**Awareness Set**
Wave 1						
Female student	-	-.094	-.104	-.027	-.022	-.032*
		(.065)	(.065)	(.055)	(.061)	(.018)
Foreign-born student	-	-.041	-.002	-.008	-.120	-.114
		(.128)	(.132)	(.140)	(.179)	(.078)
Lives with both parents	-	.000	-.066	.079	-.021	.014
		(.098)	(.104)	(.087)	(.098)	(.024)
Stay-at-home mother	-	.192**	.097	.099	.043	.013
		(.076)	(.073)	(.061)	(.076)	(.020)
Blue-collar father	-	-.061	-.049	-.071	-.070	-.035
		(.088)	(.083)	(.075)	(.095)	(.031)
Has older siblings	-	.004	.077	-.019	-.041	.012
		(.066)	(.066)	(.058)	(.068)	(.020)
7^{th}-grade GPA,	-	.055	.007	-.081	-.149*	-.028
lower 25perc		(.088)	(.089)	(.083)	(.089)	(.034)
7^{th}-grade GPA,	-	-.202***	-.202***	-.017	-.035	-.002
upper 25perc		(.070)	(.071)	(.059)	(.066)	(.018)
Sample size	147	147	154	139	160	
Wave 2						
Female student	-.102**	-.133*	-.078	-.088	-.148*	-.046**
	(.044)	(.071)	(.069)	(.061)	(.077)	(.019)
Foreign-born student	.017	.212	.131	.089	-.062	-.016
	(.090)	(.132)	(.127)	(.105)	(.181)	(.061)
Lives with both parents	.007	-.107	-.103	-.045	-.062	-.037
	(.055)	(.101)	(.102)	(.107)	(.122)	(.043)
Stay-at-home mother	.001	.006	-.030	.045	.099	-.070**
	(.050)	(.075)	(.077)	(.067)	(.087)	(.035)
Blue-collar father	-.010	-.033	.054	-.096	-.011	.067***
	(.061)	(.089)	(.081)	(.086)	(.110)	(.023)
Has older siblings	-.035	.003	.073	-.101	-.043	.025
	(.039)	(.071)	(.069)	(.066)	(.078)	(.020)
7^{th}-grade GPA,	.063	.114	.132	.010	-.101	-.005
lower 25perc	(.070)	(.091)	(.089)	(.083)	(.131)	(.033)
7^{th}-grade GPA,	-.068*	-.100	-.113	-.156**	-.072	.039
upper 25perc	(.038)	(.079)	(.076)	(.071)	(.078)	(.025)
Sample size	147	147	147	154	139	160

lb: lower bound; *ub*: upper bound.

Significance levels: [***] significant at 1%; [**] significant at 5%; [*] significant at 10%.

Predictors: *female student:* dummy=1 if student is female; *foreign-born student:* dummy=1 if student is foreign-born; *lives with both parents:* dummy=1 if student lives with both parents; *stay-at-home mother:* dummy=1 if student has a stay-at-home mother; *blue-collar father:* dummy=1 if student's father works in a blue-collar occupation; *has older siblings:* dummy=1 if student has older siblings (between 1 and 3); *7^{th}-grade GPA, lower 25 percentile:* dummy=1 if student's GPA in the 7th grade end-of-year report (between 6 and 10) is in the bottom quartile of the distribution; *7^{th}-grade GPA, upper 25 percentile:* dummy=1 if student's GPA in the 7th grade end-of-year report (between 6 and 10) is in the upper quartile of the distribution.