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“Tanto canto sem cantor”

Contents

Introduction

This thesis covers the themes of migration and conflict, and it does so through the lens of political economy.

Migration policy is shaping the political debate in Europe and the US. High attention to the issue and emergency rhetoric have resulted in the centrality of Border Enforcement in the public discourse. This has imposed strong ethical challenges for policy-makers, made even more relevant by the dare conditions of human migration from the South to the North of the World. My dissertation investigates migration, in Europe and in Africa. In Europe, I focus on how the accruing of high attention to migration policy has influenced policy outcomes. In Africa I analyze how and why potential migrants make dangerous traveling choices. I also look at human conflict, itself a major determinant of forced displacement and migration. In what follows, I present three chapters for my thesis. The first two relate to migration, while the third relates to conflict for natural resources.

In Chapter 1, my Job Market Paper, I study border enforcement policy in the Mediterranean Sea. Irregular migrants attempt to cross the Mediterranean Sea to reach Europe. European border enforcement has the conflicting objectives of preventing irregular migration and granting humane treatment to migrants. The former would lead policy to deter border crossings, at the cost of increasing risk for migrants; the latter would require reducing this risk. Exploiting geo-located data on the universe of rescue operations for migrants leaving Africa from Libya to reach Europe from 2014 to 2017, I show that rescue policy influences departures. Using exogenous variation coming from commercial sea traffic, I also show that policy impacts death risk for migrants. The implied trade-off is dynamic, as present policy influences future policy expectations by migrants. Further, if the policymaker is more concerned with outcomes when they get more visibility, this trade-off interacts with public attention. Using shocks to attention uncorrelated with policy and migration, I empirically find that this is the case. Then, I propose and estimate a dynamic model of policy choice and public attention. I show that past rescue policy was suboptimal in minimizing the number of migrants' deaths. I also use the estimated preferences to assess the policymakers' willingness to accept migrants' deaths to reduce migrants' arrivals.

In Chapter 2, I present the preliminary results of an ongoing RCT I am conducting in Guinea with Lucia Corno and Eliana La Ferrara. We conduct a large scale randomized experiment among 160 secondary schools in Guinea to study whether risky and irregular migration towards Europe can be reduced by the provision of information related to the risk and cost of journey and to the economic situation in the destination countries. Combining hard data and video-testimonies by migrants who settled in Europe, we study the effect of three treatments: one in which we deliver information about the risks and costs of the journey, one in which we give information about migrants economic outcomes, and a treatment pooling the two previous types of information. Preliminary results show that information affects perceptions about risks and economic outcomes, and about migration intentions. Preliminary evidence shows varying levels of persistence of change across different belief types. Also, long-term effects on migration outcomes are concentrated on the non-wealthy students.

In Chapter 3, I investigate the relationship between the ownership of a natural resource and the occurrence of armed conflict with Matteo Bizzarri and Riccardo Franceschin. We build a model of resource war to investigate the impact of a change in the resource value on the likelihood of conflict. A predator decides if to wage war against a resource holder and seize its resource. A powerful third party can intervene to back the defendant. However, it does not act as a social planner, but it maximizes its own profits. Then, the effect of a change in resource value is *a priori* unclear. On the one hand, increased resource value results in a higher incentive to predate; on the other hand, it makes for a higher incentive to intervene by the third party, increasing deterrence. We find that the probability of a conflict as a function resource value is hump-shaped under general assumptions. We test our prediction using data on interstate and civil war.

Chapter 1

Rescue on Stage: Border Enforcement and Public Attention in the Mediterranean

1.1 Introduction

Migrants move across borders with risks. High-income countries pursue contradicting policies aiming to keep migrants out while also ensuring that they are treated humanely. This results in countries facing complex trade-offs in planning border enforcement policies. Public attention and media coverage affect these trade-offs, given the relevance of irregular immigration in the political debate. Smugglers sell migrants crossings on unseaworthy boats along the maritime route connecting Libya to Italy. To avoid shipwrecks and migrants' deaths, European authorities intercept migrants trying to cross and transfer them to Italy. To deter future migrants' departures, Europe keeps rescue interceptions far from the Libyan coast. From 2014 to mid-2017, around 400,000 people left North African shores, and 12,000 drowned before reaching rescue. In the future, irregular migration pressure through the Mediterranean is bound to increase due to population growth in Africa (Hanson and McIntosh, 2016). Border enforcement decisions influence the safety of migrants in a variety of contexts around the globe. Similar migrants' sea crossings happen from Morocco to Spain, from Turkey to Greece, and from France to the UK, through the English Channel. In the US, border enforcement policies put migrants' lives in danger at the border with Mexico by shifting their routes towards more remote crossing points (Gathmann, 2008). The number of actors involved adds to the complexity of the issue; government actions impact both irregular migrants and smugglers and are subject to public opinion and media scrutiny.

In this paper, I make several key contributions to understanding these complex issues. First, I use rich high-frequency geo-referenced data on rescues to establish a negative link between present rescue distance from the Libyan coast and future migrants' departures. Second, I exploit exogenous variation shifting border enforcement and allowing me to recover the causal effect of rescue distances on migrants' safety. Third, I show that increases in public attention to migration make policy safer for migrants. Fourth, I develop a dynamic model of border enforcement and migration, where media and public attention are explicitly modeled. I estimate this model using data on rescues, migrants' deaths, and attention to describe in a rich way the dynamics induced by policy changes. Finally, I use my estimation to evaluate policy preferences and show how policymakers value migrants' safety against arrivals.

This work exploits high-frequency data on rescue operations, complete with rescue locations, to establish a negative relation between rescue distance for migrants and future departures. I find that higher rescue distances reduce migrants' departures after one week. Deiana et al. (2019) have shown that the presence of rescue operations in the Mediterranean Sea facilitates smugglers' operations. However, this is the first work to rely on high-frequency variation in the geographical scale of rescue operations to evaluate their impact, allowing me to obtain easier identification and evaluate counterfactual policy. Compared to previous work showing the effect of border closures on migration, such as Aksoy and Poutvaara (2019) and Friebel et al. (2017), this paper has the advantage of employing data on actual migration instead of migration intentions.

I examine the impact of distance on migrants' safety, using data on deadly incidents in migration collected by IOM (2017) from various media and institutional sources. I exploit variation in ships entering the Mediterranean through the Suez Canal, proxying maritime traffic, as an exogenous shock to rescue operations. I find that the death risk for migrants increases with rescue distance. This work is the first to study the relation between death probability and policy causally in this context. It provides a counterpart for sea borders to the results of Cornelius (2001) and Gathmann (2008), showing that US border enforcement increases the risk for irregular migrants along its border with Mexico.

The negative relations between distance and safety and between distance and departures imply the basic trade-off that policymakers face in this context. I show that public attention to migration influences how policymakers solve such trade-off, with increases in public attention leading to policy that is safer for migrants. In so doing, I address potential endogeneity concerns by instrumenting attention with sports events crowding out attention to migration, in the spirit of Eisensee and Strömberg (2007).[1] The result does not depend on the spurious seasonal correlation between migration and matches, as I show by including a fine-grained set of seasonal controls.

Beyond establishing a causal relationship between attention and distance, and between distance and policy outcomes–migrants' departures and safety–another major contribution of this paper is to develop a model where I explicitly take into account the behavior of the main actors, the government and the migrants, but also the smugglers and public attention. The model is estimated on the high-frequency data on migrants' rescues, deaths, and attention. Therefore, the model allows me to simulate distance and attention counterfactuals and evaluate the relative welfare loss to policymakers from migrants' arrivals and deaths. In this model, a policymaker aims at minimizing both arrivals and deaths. Migrants buy the passage from smugglers and risk being shipwrecked if coastguards do not rescue them. Smugglers and migrants forecast future policy choices based on present rescue distance so that a higher rescue distance in the present decreases the future availability of smuggling services. They also take weather conditions into account when making crossing decisions. The policymaker faces an intertemporal trade-off between the safety of migrants at sea and future migration pressure. In the estimated model, at the steady-state, the policymaker dislikes both arrivals and deaths, and she is willing to accept one migrant's death to avoid ten migrants' arrivals.

In estimating the model, I consider the potential influence of NGO rescue actors on rescue policy. This type of humanitarian organization has engaged in rescue operations throughout the sample period, alongside institutional actors. NGOs do not pursue a deterrence objective in their operations. For this reason, when analyzing the trade-off that the policymaker faces, I model NGOs as a shifter in the cost to increase rescue distance, which I estimate to be positive.

Using my structurally estimated model, I illustrate that the policy stance taken from 2014 to 2017 was suboptimal in minimizing expected migrants' deaths, which could have been reduced by decreasing or increasing distance, respectively, by increasing safety and increasing deterrence.

Shocks to public attention in the model put pressure on the government by increasing the marginal disutility from contemporaneous outcomes. Hence, attention influences the intertemporal trade-off faced by the policymaker. I show that attention shocks lead to a reduction in rescue distance; if attention increases temporarily, the policymaker accepts

[1] As an instrument, I use newsworthy soccer matches of Italian *Serie A*; I define a match to be noteworthy if contestants are among the three most popular teams in *Serie A*, based on Google Searches, and if their result is unexpected, based on odd-implied outcome probability.

more future departures to diminish migrants' present death probability. This effect is persistent for two reasons. First, attention shocks themselves are persistent. Second, attention affect distances through policy outcomes; higher attention leads to safer policy, which induces higher departures, thus increasing the incentive to save migrants quickly and avoid incidents. For this reason, the impact of attention is self-reinforcing in the short term, before fading away.

Other works have drawn a connection between policy outcomes and attention–usually in the form of media coverage–in various contexts. Eisensee and Strömberg (2007) shows that news coverage drives the US government to increase relief response to worldwide natural disasters; Durante and Zhuravskaya (2018) shows that Israeli military forces strategically time attacks on Palestinians to minimize emotional press coverage abroad; Facchini et al. (2016) find that Representatives' voting behavior in roll call votes responds to public opinion differentially based on the level of the media coverage of their activities in their constituencies. The main insights of these works come from the press; however, a recent literature has shown internet's role in shaping political behavior. Internet access has been found to depress political turnout in Germany, Italy, and the UK (see, respectively, Falck et al., [2014], Campante et al., [2018], Gavazza et al., [2019]); however, it has been found to contribute to other forms of political participation and oversight. Campante et al. (2018) find that internet facilitated the establishment of local grassroots political movements in Italy. Guriev et al. (2019) show that the expansion of 3G networks reduces trust in government by exposing corruption scandals, in turn negatively affecting incumbent parties' vote share. The aforementioned study by Gavazza et al. (2019) finds suggestive evidence that broadband diffusion coincides with lower taxes in the UK, by facilitating information diffusion among voters. In addition, in recent theoretical work, Matějka and Tabellini (2017) have shown that, in a static setting of electoral competition, individual information acquisition alters the strategic positioning of political opponents. In sum, there is empirical and theoretical evidence of complementarity between public attention and the public's preferred political outcomes, and that internet and the press facilitate the diffusion of policy-relevant information among voters. This paper models the impact of such complementarity in a dynamic policy setting. In a variety of contexts, policymaking involves an intertemporal trade-off. At the same time, public attention to a specific policy outcome is not fixed in most cases, as it evolves with outcomes themselves as well as exogenously–for example, with media coverage about competing news-relevant events. My contribution to the literature on the impact of media on policy is general since I argue that fluctuations in public attention affect the intertemporal incentives that policymakers face.

In what follows, I first delineate the context. Second, I explore the relationship between policy, outcomes, and attention. Third, I turn to the model of policy choice. Fourth, I explain my empirical approach in estimating it. Fifth, I show the model's fit and results. Finally, I conclude.

1.2 Context

In this section, I provide details on the context of irregular migration through the Central Mediterranean route and on the political and institutional framework of border enforcement policy during my period of analysis, from the end of 2014 to mid-2017.

1.2.1 The Central Mediterranean Route of Migration

Migration through the Mediterranean Sea is the result of the peculiar nature of the sea border and the different economic conditions on its northern and southern coasts. The Mediterranean divides and connects Europe and Africa. The two continents' shores face each other at distances that can go as low as the 300 KM separating West Libya from the Italian island of Lampedusa, the 75 KM from the Tunisian city of Kelibia and the Italian island of Lampedusa, or the 15 KM stretch of sea between Morocco and the UK territory of Gibraltar. Short distances and perceived high economic opportunity have pushed migrants from Africa to try crossing the Mediterranean for years. Irregular migration has been using the "Central Mediterranean" route, connecting Libya and Italy since the 1990s; however, the number of migrants' crossings increased substantially in the last half of the 2000s (Fargues and Bonfanti, 2014).

During Gaddafi's rule in Libya, human smuggling activities started to thrive; his fall, in 2011, set them free from institutional border controls (Tinti and Reitano, 2018). Higher uptake by Syrian asylum-seekers fleeing the country from 2010 prompted the development of a market for crossings on a large scale (Tinti and Reitano, 2018). In response to Libya's transformation into a major human smuggling hub, European authorities established institutional Search and Rescue (SAR) operations in the Central Mediterranean. This country's central role for border crossing attempts is apparent when looking at the geographical distribution of interceptions. Figure A.1 depicts the location of rescue interceptions from November 2014 to April 2017 in the Central Mediterranean, overlaid on a 2-d histogram of rescue frequencies in Inverse-Hyperbolic Sine units. Except for a small number of interceptions between Italy and Greece, for boats leaving from Egypt, interceptions were heavily concentrated near West Libya.

The risk for migrants encouraged an institutional effort to conduct rescue operations at sea, which reduced barriers to entry in the smuggling scheme; at the same time, deterrence emerged as a policy issue. Figure A.2 summarizes the main phases of rescue policy in the Central Mediterranean route as established by this section. In 2012 and 2013, Libyan smugglers relied on wooden vessels capable of reaching the Italian shores 300 KM away. Shipwrecks were not absent; in October 2013, a migrants' ship sank off the coast of Lampedusa, causing the death of 366 African migrants, most of whom were Eritreans. The tragedy led Italian authorities to launch the SAR operation Mare Nostrum, managed by the Italian Navy. It is possible that institutional SAR operations reaching into the Maltese and Libyan rescue areas opened the opportunity for smugglers to enter business with cheaper boats. This idea is corroborated by Deiana et al. (2019), who found that in periods where rescue operations are present in the Mediterranean Sea, weather conditions have more of an impact on departures since smugglers switch to less safe and cheaper technologies, inducing a higher number of crossings. In October 2014, Italy discontinued Mare Nostrum because of the uneven burden-sharing among European Nations. The European Border Enforcement Agency (Frontex) launched Triton Operation on November 1, 2014, and took over patrolling activities (EPSC, 2017). Officially, this was a border enforcement operation, but international conventions–such as the 1982 United Nations Convention on the Law of the Sea (UNCLOS) and the 1974 International Convention for the Safety of Life at Sea (SOLAS)–require assets employed in these operations to engage in SAR. Still, Triton's operational area was reduced to roughly 220 KM away from the Libyan coast with a view of discouraging migration. Indeed, deterrence motives are apparent both in external and internal communication on rescue operations by the agency–see, for example, Frontex (2015), a disclosed internal document compiled by the EU border enforcement agency.[2] However, EU authorities would soon have to adjust their policy to decrease the risk for migrants.

EU policy saw a significant turn in favor of migrants' safety in 2015, after two tragedies. During April, two shipwrecks claimed the lives of 1200 migrants. This event contributed to two significant policy changes. First, the mandate for Triton Operation increased to cover a larger area. Second, the EU started European Operation Sophia, conducting SAR activities inside the Libyan SAR zone (EPSC, 2017), just outside Libyan territorial waters, 22.224 KM from the Libyan coast. Hence, 2015 saw a progressive decrease in the distance of rescue operations from the Libyan coast. Figure A.3 plots the weekly

[2] The document was collected by Forensic Oceanography, a research team based within the Forensic Architecture Agency at Goldsmiths (University of London), for the project 'Death by Rescue', available at https://archive.is/5NjTU.

average distance of rescue operations from the Libyan shores, weighted by the number of migrants involved, against time. Despite the considerable weekly variation, we see a marked decrease in rescue distances, from 90-100 KM in November 2014 to 40-65 KM at the end of 2016.

In roughly mid-2017, EU and Italian border enforcement policy in the Mediterranean shifted towards contracting border enforcement provision to Libyan authorities. In March 2017, Italy and the UN-backed Libyan government of Al-Sarraj reached a deal. Libyan authorities agreed to scale up migration control in exchange for financial support and naval assets. The Italian government first committed to transferring naval assets to Libyan institutions on April 21 (Interni, 2015). After a few weeks, departures started to decrease (Villa, 2015), a sign that Libyan institutions had started border enforcement activities. In my analysis below, I focus on Triton Operation before the deal with Libya. This allows me to focus on rescue location as the main policy instrument since other border enforcement tools were absent over the period.

As I show in the remainder of the paper, the shifts in rescue distance illustrated above, as well as short-term changes, had some impact on the risk of journeys for migrants. Shipwrecks can occur during crossings. As I show in Section 1.4, a higher rescue distance set by policy induces a higher chance of incurring in deadly incidents for migrants. Also, since distance impacts the risk of shipwreck, it influences the smugglers' incentives to operate. Lower distances could turn into higher profits for smugglers in several ways. For instance, smugglers might be able to charge higher prices for their services when risk is low; outcomes of present crossings might also affect demand and prices for future crossings by influencing migrants' perceptions about the riskiness of traveling. Thus, migrants' and smugglers' beliefs about future policy will affect their decision to trade. Figure A.3 depicts the evolution of rescue distances over time; shifts in distances are considerably persistent. If migrants and smugglers are not informed about the present policy, they can base their forecasts on the past one. Indeed, in Section 1.5, I document that higher rescue distance influences future departures.

1.2.2 Commercial Ships' Rescues and Exogenous Variation in Distance

To investigate the relation between rescue distance and migrants' risk, I employ variation in commercial sea traffic, proxied by the number of ships entering the Mediterranean through the Suez Canal, as an exogenous shock to rescue distance. Commercial ships are obliged to provide rescues to boats in distress if requested. As shown in Figure A.5, the Mediterranean rescue area is located just south of a major maritime shipping hub, connecting the East and West Mediterranean, and notably routes connecting the Suez Canal with the West Mediterranean and Gibraltar. Rescue distance set by policymakers directly impacts the proportion of rescues taken up by commercial ships. Higher distances make it more likely for migrants' boats to reach the commercial route passing South of Sicily. The dashed line in Figure A.4 shows a kernel regression of the proportion of migrants saved by merchant or fishing vessels over time. In the first months of 2015, when rescue distances were high, commercial ships took up around 30% of rescues. This imposed a large financial burden of commercial shipping, mostly consisting in delays for large shipments, and leading shipowners to voice requests for intervention to EU authorities in 2015.[3] After the geographical expansion of rescue activities, the proportion of rescues by merchant ships reverted to 3-4%.

We can hypothesize that the EU and Italian authorities consider the impact of rescue operations on trade when setting policy. Shipping delays caused by rescues can create economic damage by negatively affecting trade. Further, they can represent a large cost item for the shipping industry, widely consisting of European companies: four of the five largest liner companies by cargo capacity are European (Asariotis et al., 2018). According to the European Community Shipowners' Association (ECSA, 2015), Italian and EU authorities have recognized the problem and helped reduce the burden for shipowners. Indeed, 'mitigat[ing] the risk to maritime industry activities' was among the themes discussed in 2016 at the Shared Awareness and De-confliction in the Mediterranean (SHADE MED) forum. SHADE MED was organized by NATO and European and Italian authorities; it brought together representatives of military and civilian organizations engaged in maritime security and rescue, including members of the shipping industry.[4] Authorities are likely to take these concerns more seriously when stakes are high; rescue practices should then adjust in response to variation in maritime traffic in the Mediterranean basin. In the next section, I show that this is the case by proxying maritime traffic over time with the count of ship crossings from the Red Sea to the Mediterranean Sea through the Suez Canal, an international trade hub connecting the Red Sea and the Mediterranean. Importantly, it provides a much faster sea route from South Asia to Europe than its best counterpart–circumnavigating Africa. For this reason, the Suez Canal traffic virtually consists of goods transportation only (ALEXBANK, 2018), and between 7 and 10% of world sea trade (in volume) passes through it (De Waal, 2019).

[3] A letter by the European Community Shipowners' Association and International Chamber of Shipping, addressed to EU Member States, and EU authorities in copy, is available at https://bit.ly/3jD46La.

[4] See https://bit.ly/3mtgE9U for an account of the event.

As I document in the next section, authorities respond to higher commercial traffic by 'protecting' commercial ships from rescue duties. Indeed, we see a decrease in rescue distance when maritime traffic increases, and no increase–or a decrease–in their fraction of interceptions.

1.2.3 Whose Decision: Institutional Rescuers or NGOs?

Non-Governmental Organizations (NGOs), another private rescue provider, conducted rescue activities alongside institutional actors during the sample period; however, the latter remained crucial in influencing SAR policy. The severe danger for migrants crossing the Mediterranean pushed humanitarian organizations to start engaging in migrant interceptions at different stages of Triton Operation, especially after the twin shipwrecks of April 2015. All of them focused on saving lives as their only stated objective. Even if they disagreed over deterrence objectives with NGOs, authorities could steer operations in their preferred direction in many ways. First, the responsibility to assign rescues rests with the Maritime Rescue Coordination Center of Rome, at the Italian *Ministero delle Infrastrutture*. NGO and the MRCC have worked together to manage SAR, but tension has emerged at times. In 2018, for example, NGOs accused the Italian MRCC of intentionally not sharing information with them about migrants' boats in distress to prevent non-institutional players from interfering in operations.[5] Second, as suggested in Cusumano and Pattison (2018), authorities could ask NGOs to transfer migrants from the rescue area to the Italian port, with the consequence that they have to leave the area, instead of using for that aim faster governmental assets. Third, SAR actors influence each other indirectly because if an actor forgoes its search duties in an area, another actor has to take up the task. During several operations, NGOs and their supporters have lamented the absence of institutional SAR actors needed in the rescue area and the consequent need to take action in their place.[6] Fourth, and most importantly, although strong at times, NGO interceptions almost always remained a minority fraction; Figure A.4 supports this point, showing a kernel regression of proportion intercepted by NGOs over time, in the dashed-dotted line. Therefore, NGO involvement did not make institutions incapable of conducting their preferred policy altogether; rather, we should understand NGO presence as increasing the cost of making policy less safe for migrants.

[5]The following newspaper articles document the issue: https://archive.is/tQoFU and https://archive.vn/8ds2B. They are in Italian, but I can provide an English summary if requested.

[6]The following tweets by MSF and one of its employees are examples: https://archive.vn/0yepl and https://archive.is/V4Rid.

1.2.4 Migration and SAR: Attention, Coverage, and Political Sentiment

Today, migration is a central theme for European politics. European citizens surveyed in the Eurobarometer have consistently rated migration to be among the top two policy issues in the years after the financial crisis, together with terrorism.[7] Irregular migration seems to be an even higher source of worry for voters in Europe and the US (Casarico et al., 2015).

Border enforcement is central to the platform of far-right parties that have recently gained traction in Italy and Europe. However, political attitudes are not at the heart of the connection between attention and policy changes that I analyze in this paper. During my analysis period, there was no abrupt change in the political incentives of the institutional actors involved, the Italian Navy, Coast Guard, and Frontex. Throughout the sample period, Partito Democratico, the leading national social-democratic party, remained in government–with the partial support of right-wing moderates in the high chamber, *Senato*. Also, within the same period, there is no evidence of a turnaround in Italians' opinion about migration. According to the Eurobarometer, 75% of Italian citizens had negative attitudes about migration from outside the EU in November 2014; the figure remained fairly stable over the next two years, registering a 69% in November 2016, while there was a short-lived and modest drop to 62% in May 2017.[8] Also, over the sample period, parliament voting intentions for the main nationalist anti-immigration party in Italy, Lega, always remained between 12% and 16% from the beginning of 2015 to the end of 2017.[9] As for Frontex, the agency has claimed it needed to build political support in key stakeholders (Member States and EU bodies) to sustain its ability to perform its operations (Frontex, 2016). Over the years considered in my analysis and beyond, Italy has remained among the countries most invested in SAR in the Mediterranean, suggesting that the agency focused on building support in the country.

Even though political attitudes towards migration do not seem to have changed radically during the period, public attention devoted to migration in Italy saw a significant increase. The solid line in Figure A.6 reports the value for the weekly *Google* search volume for the word '*migranti*' (i.e. migrants) over the sample period. Attention was

[7]Responses can be consulted interactively at https://archive.is/JZ71S.

[8]'Very Negative' or 'Fairly Negative' answers to the question '*Please tell me whether each of the following statements evokes a positive or negative feeling for you. Immigration of people from outside the EU.*'. Responses can be consulted interactively at https://archive.is/0Zrhk.

[9]A visualization of aggregated polls, made by *PollofPolls*, is available on *Politico*'s website, at this https://bit.ly/35GUB8X.

low at the end of 2014; it registered considerable peaks in early 2015, and it stabilized over an increasing trend until the end of the sample period. As it is clear, this trend is common to other measures of attention to migration; the dashed line in Figure A.6, reporting the number of Italian news articles about migration in the Mediterranean, closely tracks searches. It would also be legitimate to ask whether the increase in attention is driven by one particular type of voters or citizens with particular political preferences. This does not seem to be the case if we take newspaper sentiment as a (demand-driven) indicator of contemporaneous sentiment in society. Figure A.7 shows the evolution of the number of newspaper articles classified to report an overall '*Objective*', '*Positive*', or '*Negative*' sentiment, with supervised machine learning. I defer the discussion of the classification methodology to the next section. For the moment, I notice that articles of all types evolved in the same way. These facts support the idea that public attention to migration increased in Italy over the sample period, and the increase was not limited to the supporters of one political side.

Media attention is an important driver of policy initiatives across policy domains–see, for example, Eisensee and Strömberg (2007), Facchini et al. (2016), and Durante and Zhuravskaya (2018). In the Central Mediterranean route, irregular migration involves stories of migrants escaping poverty or conflict (Berry et al., 2015) and going through highly dangerous trips in dire conditions, which makes migration coverage prone to be emotionally charged. In a different context–Israeli attacks on Palestinians–Durante and Zhuravskaya (2018) claim that emotionally charged coverage, if negative, is particularly harmful to policymakers. The same mechanism may make attention to the issue even more relevant to policymakers in the Mediterranean. In sum, the political relevance of illegal migration today, coupled with the type of coverage it receives, makes border enforcement likely to interact with public attention.

As I pointed out in Section 1.2.1, border enforcement policy in the Mediterranean faces a trade-off between present migrants' safety and future migration pressure. I contend that this provides a mechanism for attention to influence policy choice. A temporary increase in attention makes contemporaneous outcomes relatively more important. Therefore, it induces the policymaker to accept more future arrivals to reduce present deaths. As I show in Section 1.6, an increase in attention, measured by Google searches about migration, results in a decrease in rescue distance. Replicating the analysis on news articles count, I find that the effect is concentrated among articles covering migration news objectively, rather than showing positive or negative sentiment. Also, I demonstrate that NGO presence reduces the impact of attention on rescue distance. NGOs focus on the humanitarian objective of SAR and counter the deterrence perspective taken by institutional actors. In this sense, public attention does not affect a trade-off for them because they simply aim to prevent shipwrecks for migrants who are at sea.

In the next section, I describe the data I will use to test my hypotheses.

1.3 Data

1.3.1 Policy and Migration Outcomes

To establish a link between policy and migration outcomes–migrants' deaths and departures–I collect information about the distance of rescue operations from the Libyan coast, the number of migrants rescued, and the number of deaths at sea in the area. As I explained in the previous section, I also use information about maritime traffic in the Mediterranean Sea, as proxied by counts of ships entering the Mediterranean through the Suez Canal, to build an instrumental variable for policy. In my analyses on the impact policy on outcomes, I use a measure of tidal conditions in the rescue area to consider the impact of weather on smugglers' operations.

Rescue Operations for Migrants' Boats from Libya

To measure rescue distance from the Libyan coast and the number of migrants rescued, I use a dataset containing the universe of SAR operations in the Central Mediterranean from November 1, 2014, to April 1, 2017, collected by Frontex (2017). A data point in the dataset is a rescue operation, and variables collected are date, coordinates of detection and interception, type of interception (institutional, NGO, or commercial ship), type of boat used by migrants, number of migrants, and, for almost all observations, country of departure. I focus on rescue operations for migrants coming from Libya to ensure the internal validity of my analysis.[10] These migrants make up 91% of irregular migrants who were rescued during SAR in the Mediterranean and disembarked to Italy (CGCCP, 2017).[11]

Restricting my analysis to Libya has the advantage of removing any potential threats coming from undetected irregular entries. Indeed, migrants who reached Italian shores autonomously (without being rescued at sea) do not appear in my data. According to CGCCP (2017), no migrant boat from Libya has reached Italian shores autonomously from 2015 to 2017. Less than 10,000 migrants reached Italian shores autonomously and were

[10] Find a complete account of my strategy in selecting boats from Libya in Section A.3.1 of the appendix.

[11] The second most important source is the route connecting Egypt-Greece-Turkey with Calabria, in Italy, with 9% of irregular migrants.

apprehended; they left from Algeria, Tunisia, Turkey, Greece, or Egypt (CGCCP, 2017). This figure might represent a partial account since migrants could have reached Italy without being detected; however, according to UNHCR (2018), most migrants arriving autonomously over the timeframe were intercepted near the Italian coast and directed to port by Italian authorities, undergoing identification. Further, we have no reason to think that the distribution of departure countries for migrants reaching Italian shores undetected should differ from the same distribution for detected ones. We can speculate that the absence of migrants reaching Italian shores autonomously from Libya is due to a combination of high traveling distances, together with the opportunity to be rescued at sea. In sum, the interception's data I use contains the universe of migrants' *departures* from Libya.

Frontex data on the type of rescuer is imprecise in registering whether a rescue was operated by NGOs or commercial ships, as I document in Section A.3.2 and A.3.3 of the appendix. I fully address this issue in the data cleaning stage by complementing Frontex data with news data about interceptions and disembarkations available in the European Media Monitor website, and data about rescues by *Médecins Sans Frontières*, one of the prominent NGOs operating in the rescue area. To check the final data quality, I compare the number of rescues by year and actor with a report by the Italian Coast Guard (CGCCP, 2017). I find only negligible discrepancies. I analyze these discrepancies in detail and explain all steps of data cleaning in the appendix.

Missing Migrants Data on Deadly Incidents

To measure the death risk for migrants, I have to complement information on migrants' arrivals with data on migrants' deaths at sea. I employ data by the Missing Migrants Project (IOM, 2017), a dataset constructed by the International Organization of Migration and accessible online. It is the most comprehensive dataset of migration incidents worldwide, and it includes information on incidents that caused one or more migrants to die or go missing. Information comes from several sources, such as media, institutions, and NGOs. It records the number of deaths and the number of missing per incident, indications of the incident's location, and source information. To use such data in this research, I extract only incidents that involved migrants leaving Africa from Libya. I explain how I classify source country in Section A.4 of the appendix.

Navigation Reports for the Suez Canal

I retrieve monthly data about the passage of ships through the Suez Canal, collected by (SCA, 2017), which I use as a proxy for maritime traffic in the Mediterranean. Importantly, this data includes the direction of the passage. So, I can construct a measure of shocks to commercial traffic in the Mediterranean Sea by focusing on North-bound ships–i.e., entering the Mediterranean Sea. Such data is only available from January 2015–included–so I collect it from that date onwards.

European Centre for Medium-Range Weather Forecasts (ECMWF)

As in Deiana et al. (2019), I proxy for weather conditions using tidal data by the European Centre for Medium-Range Weather Forecasts (ECMWF). I use forecast data on the significant height of combined wind waves and swell. This measure is commonly referred to as the significant wave height, an average of the heights of the highest tercile of the waves experienced by mariners in open waters as measured from the wave crest to trough of the preceding wave (Deiana et al., 2019). I retrieved this data for a location in the sea at the crossing between an imaginary line connecting Tripoli and Lampedusa with the limit of Libyan territorial waters, outside of which rescue interceptions can happen.

1.3.2 Attention to Migration

I employ several data sources about public attention to migration in Italy to study the relation between attention and policy. My analysis takes advantage of Google Trends data on daily searches about migration, collected with a very parsimonious word choice, as well as data on coverage of migration by newspapers, based on a more refined selection of terms. As I have shown in the previous section, the two measures are strongly correlated. Data on news articles allows me to build a measure of sentiment in media coverage of migration, useful to analyze the channel by which attention affects policy. I also collect information about newsworthy Italian soccer events, which I use as exogenous shocks to attention to migration.

Google Trends of Searches about Migration

Google Trends data contains the volume of daily searches by word, or list of words, in a given country, over time. I use such data to proxy attention to migration in Italy; in particular, I collect the volume of searches for 'migranti', chosen as a mostly neutral reference to the issue. Trends data record actual volumes with noise, and this might produce measurement error issues. To diminish such worries, I draw the time series four times and take an average, and I resort to instrumental variable estimation. Google Trends returns missing values when search volume is too low to give a precise estimate. I set those observations to 0. However, this is a minimal issue for this series. Likely due to the high attention to the issue, missing observations are only the 0.7% of daily observations for two series, and the 1.1% in the remaining two. When averaging over weeks, I have no zero-observations.

News Articles about Migration from Factiva and Data on Diffusion

Dow Jones Factiva is an online repository of digitalized news text. Its Italian chapter contains news articles from an extremely comprehensive list of printed and online sources.[12] I retrieved articles covering irregular migration to Europe through the Mediterranean by selecting articles based on the presence of at least one string referring to migration as well as a string among a list of Mediterranean toponyms. The specific list of strings is available in Section A.5 of the appendix, together with further cleaning procedures. In this way, I extracted 82,691 articles dated October 1, 2014, to August 31, 2017.

After collecting articles, I created a sentiment classification based on Kaal et al. (2014), employing supervised machine learning and logistic regression. The classification distinguishes objective from subjective articles; further, it classifies subjective articles as either positive-sentiment or negative-sentiment.[13] The classified sample consists of 2,236 rated articles, 80% of which make the training set; I use the other 20% for testing. I set hyperparameters using cross-validation. The attained balanced accuracy of the model is about 59%.

To complete my press data, I gather information about the diffusion of various sources employed. To this end, I employ data by *Accertamenti Diffusione Stampa* and *Audiweb*. These agencies research the diffusion of media sources. *Accertamenti Diffusione Stampa* obtains and audits data on the diffusion of traditional newspapers prepared by publishers, making them available in monthly chapters. Their measure of diffusion merges sales of newspapers and subscriptions. *Audiweb* researches diffusion of online sources, in partnership with the Nielsen corporation, by using a panel representative of the Italian population and website usage data. For a given month, *Audiweb* collects the total estimated digital audience of a given digital source, represented by single users. Using diffusion data for print and online media, I match 76% of the articles collected through Factiva–28% are in the printed press, and 48% are online.

[12] A complete list of newspapers in Factiva's database is available upon request to the author.

[13] The classification allows further data cleaning, by identifying articles not covering migration.

Figure A.6, referred to in the previous section, reports the evolution of Google searches about migration (solid line) and news articles about the same issue in Italy (dashed line). Their high correlation provides cross-validation for searches as an attention measure. Indeed, it suggests that a parsimonious and neutral formulation of Google Trends only tracking the word '*migranti*', Italian for 'migrants', is well correlated to other attention measures more precisely linked to irregular migration to Europe through the Mediterranean. However, Google search volume as a measure of public attention measure has some advantages. First, it likely responds less to supply shocks in the media market, which I am not interested in tracking. Second, it probably responds more quickly to shifts in public attention to events that have yet to materialize in newspaper contents, e.g., waves of attention starting in social networks.

Bet365 data on *Serie A*

To obtain exogenous variation to attention, I use *Serie A* soccer matches and their odds for the agency *Bet365*. Using odds, I back out the market-implied probability of realized outcomes and identify 'unexpected victories', which I use as an instrumental variable. I focus on the three most popular teams in Italy based on Google searches in 2014: Juventus, Inter Milan, Napoli.

I list the most important moments from the above data in Table A.1.

In the next sections, I establish a link between rescue distance and risk of death for migrants–Section 1.4–and between rescue distance and future departures–Section 1.5. In Section 1.6, I turn to the relationship between attention and distances.

1.4 Rescue Distance and Migrants' Safety

1.4.1 Methodology

Investigating the impact of rescue distance on safety requires constructing a measure of survival probability for migrants. Using IOM (2017) data, I construct d_t, counting total deaths for a given week t, summing dead and missing migrants.[14] I obtain the total number of arrivals in a given week, a_t, by summing over rescue operations in Frontex (2017). I measure survival frequency, $\bar{\pi}_t$, for migrants leaving the Libyan coast in a given week by dividing the number of arrivals by the sum of arrivals and deaths.

[14] The procedure agrees with IOM methodology registering migrants as 'dead' only if a body is found and 'missing' when a shipwreck happens and a body is not found.

To measure policy, I construct $\bar{\mu}_t$, representing the average observed distance from Libyan territorial waters for rescues occurring in a week, weighted by the number of migrants in the rescue. In math notation,

$$\bar{\mu}_t = \sum_{i \in I_t} \frac{dist_{i,t} * a_{i,t}}{a_t} - b, \tag{1.1}$$

where I_t represents the set of rescue interceptions in the week t, i indexes a given rescue interception, and $dist_{i,t}$ is the rescue distance. The constant b is the limit of territorial waters, 12 Nautical Miles $\approx 22.224KM$ from the coast, and $a_{i,t}$ the number of migrant arrivals for interception i in the week t. SAR activities by international assets cannot occur within Libyan territorial waters.[15] In this section, the formulation in KM from territorial waters sets 0 KM to the boundary that policy faces. It does not impact estimations, except for the magnitude of intercepts. In the model section below, I will interpret the mean distance of rescue operations as the inverse arrival rate of rescue for migrants. By subtracting the limit of territorial waters, I impose that rescue can occur from this boundary onwards.

The variable $\bar{\mu}_t$ represents a biased estimate of the mean distance set by policymakers, given that it does not take into account distances for dead and missing migrants in a week. I consider this fact when estimating the structural model of policy choice below. For the moment, let us abstract from the issue and consider rescue distance given rescue as the variable set by policy. This is without loss of generality since, as I show below, there is a one-to-one mapping between setting rescue distance and setting rescue distance conditional on rescue.

I am interested into how observed distance $\bar{\mu}_t$ affects survival frequency $\bar{\pi}_t$. I first investigate the issue with OLS, controlling for weather conditions (swell) w_t, year FEs, and quarter-of-the-year or week-of-the-year FEs; FEs capture changes in policy or smuggling practices, possibly correlated with interception distances and seasonality not captured by weather. I use HAC standard errors, allowing for arbitrary heteroskedasticity and

[15] There have been very few exceptions to this principle during the sample period. Indeed, I find only 2.4% of observations below the territorial waters limit. For this reason, only one of the 117 weekly observations in the dataset with a rescue has a negative value. This value is exceptional and is problematic for two reasons. First, when estimating the model, and for reasons that will be clear below, mean rescue distance will be the empirical counterpart of the inverse of an arrival rate of interception from the limit of international waters; both have to be positive. Second, I suppose and empirically assess that smugglers and migrants make departures decisions based on persistence, an idea that I exploit in the model. In that case, migrants should partly disregard the informative content of this observation. For this reason, I *winsorize* observations at the 1^{st} percentile, effectively replacing the value of the only negative observation with the second-to-lowest.

autocorrelation up to lag 3.

OLS is prone to some endogeneity concerns. The most pressing issue is that the policymaker might have information unknown to the econometrician about the risk features of crossings within a particular week. Knowing that migrants face particularly risky conditions in a given week, the policymaker might adjust distance downwards to avoid tragedies, inducing a bias towards zero in the negative coefficient on distance. Then, I resort to IV estimation relying on ship crossings of the Suez Canal.

The rationale for Suez Canal ship crossings' relevance is that authorities may take trade into account and 'protect' commercial ships from rescue duties when commercial traffic is high North of the rescue area. We would expect that authorities react to higher Suez crossings by intercepting migrants closer to Libyan coasts to ensure they do not reach commercial vessels' transit areas. Higher maritime traffic would then translate into reduced rescue distance and the probability of interceptions by commercial ships overall.

To construct my instrument, I first have to match monthly data on the instrument to weekly information on distance and rescue frequency because some of the weeks in my sample span over two different months. Then, I first transform the monthly number of Suez crossings to a daily average by dividing monthly quantities by the number of days in a month. Second, I assign daily averages to weeks averaging over the value of their days. In this way, I construct variable $suez_t^{nb}$, representing the average daily number of ships crossing at Suez South to North in a given week. Finally, I create my instrument as the sum of the past values of $suez_t^{nb}$ for a given time window of T periods:

$$suez_{t,T}^{nb} = \sum_{i=1}^{T} suez_{t-i}^{nb}. \tag{1.2}$$

Constructed in this way, the instrument allows for policy inertia and lag to adjust to new traffic conditions. When using $suez_{t,T}^{nb}$ as an instrumental variable, I rely on 2SLS, with a first stage of the following form:

$$\bar{\mu}_t = \beta + \beta_S suez_{t,T}^{nb} + \beta_Y Y_t' + \beta_Q Q_t' + \nu_t. \tag{1.3}$$

I estimate this specification using HAC standard errors, robust to arbitrary heteroskedasticity and autocorrelation up to the $T+1$ lag, as my transformation could introduce autocorrelation concerns; I set $T = 8$, in order to allow sufficient time for policy to adjust in response to traffic.

Before turning to results, I discuss three possible violations of the exclusion restriction and how I address them in my estimation strategy. First, shipping companies might consider migrant flows when conducting business. Using North-bound Suez crossings reduces this source of worry. A fraction of 87% to 88% of the cargo volume crossing Suez North-Bound comes from outside the Red Sea (SCA, 2017), with traveling distances going from 4,000 to over 10,000 KM before reaching the rescue area. The source countries for North-bound commercial flows are in South East Asia and the Arabian Gulf mostly, much farther from the rescue area than European countries, from which South-Bound traffic originates (ALEXBANK, 2018). Also, using lagged crossings strengthens the instrument's credibility because it reduces the concern that maritime traffic reacts to contemporaneous traveling conditions of migrants. Further, obtaining timely information about migrants' safety in a given week is certainly not easy for external observers. Still, departures might be easier to forecast given media coverage of migration, and they correlate with crossings' safety. A second possible threat to the exclusion restriction comes from migrants taking into account the opportunity to be saved by commercial ships. If this is the case, migrants and smugglers could exploit maritime traffic by increasing departures, inducing more crowded and possibly dangerous crossings. I check that both of the previous concerns do not affect my results by showing that controlling for departures does not change results. A third threat comes from the spurious correlation between trade and migrants' safety through weather, season, and long-term shifts in policy. I account for such confounders by controlling for weather, year fixed-effects, and quarter-of-the-year or week-of-the-year fixed effects.

1.4.2 Results

Table A.2 reports OLS estimations in the first four columns and 2SLS estimations in the last four. Couples of rows alternate the presence of year FEs and quarter-of-the-year FEs with the presence of year FEs and week-of-the-year FEs. Within each couple, the first row does not control for swell, while the second does. The table suggests that rescue distance reduces crossings' safety; however, the result is not significant for the OLS specification when not controlling for week-of-the-year FEs. Higher observed average distance of interceptions results in higher death risk for migrants. Also, the impact of weather is somewhat non-robust. In the OLS regression including year and week fixed effects, a 10 KM increase in observed distance corresponds to a rise in death probability by 1 percentage point, a sizeable impact if compared to an average death frequency of 4% over the period analyzed.

The Kleinbergen-Paap F-Stat for the instrument is larger than 10 both for specifications, including week-of-the-year FEs. I report the results of the first stage in Table A.3, in a specification with year and quarter-of-the-year FEs, and one including week-of-the-year instead of quarter-of-the-year FEs, in the first two columns. Higher North-bound Suez crossings reduce distances of interceptions. In the second two columns, I run a placebo test and check that future Suez crossings do not predict rescue distance when I control for past ones. The last two columns display the instrument's impact on the proportion of migrants intercepted by commercial ships. Higher maritime traffic reduces the proportion of migrants intercepted by commercial ships. This finding supports the idea that authorities wish to avoid disruptions to the maritime route passing North of the interception area.

As for the IV estimates, distance becomes significant across specifications. In my preferred specification, with quarter-of-the-year FEs, an increase in observed distance by 10 KM increases death probability of 2.2 percentage points. The results are very similar in other specifications. The 2SLS estimate is more than twice the OLS one, supporting the idea that the policymaker has information unknown to the econometrician about the risk of specific crossings and decreases distance in response to unsafe conditions. In Section 1.8, I show how one can cast this result in terms of actual policy by correcting the 'observability' bias explained above. Taking this bias into account, I show that increasing the actual mean distance of interception by 10 KM increases death probability by 2 percentage points.

As I pointed out above, shipping companies might be able to forecast departures; this might threaten my identification strategy if departures are correlated with safety, e.g., because crossings with more people per boat are riskier. As I show in Table A.4, controlling for log departures, my results remain unaffected.

1.5 Present Rescue Distance and Future Departures

1.5.1 Methodology

In order to investigate the relationship between present distance set by policy and future departures, I test whether lower rescue distance invites higher future migration. I regress the log of one plus departures on contemporaneous and lagged distances.[16] To measure departures (ℓ_t), the total number of attempted crossings, I sum arrivals, deaths, and missing migrants in a given week. I control for significant wave height w_t. I use standard errors robust to arbitrary heteroskedasticity and autocorrelation up to the 3^{rd} lag. I expect past distance to matter if migrants and smugglers forecast future policy based

[16] I choose to work with log-departures to be consistent with the framework of my model. Then, I add 1 to arrivals to take care of weeks with 0 arrivals–6% of observations in the sample.

on the present. Higher expected departures might lead the policymaker to move rescue interceptions nearer to the Libyan coast to avoid shipwrecks, biasing the coefficient on contemporaneous distance negatively–away from 0. Finding only lags to be significant would make exogeneity more credible in this context. Also, to make the assumption hold more plausibly, I show results in a specification, including quarter by year fixed effects; notice that including several lags reduces the number of the observations I can employ. In the baseline specification, I include present distance and four lags; to assess robustness, I experiment with other sets of lags and quarter-by-year FEs. The estimates below do not suffer from detection bias, as studied by Hanson and Spilimbergo (1999) for land borders. Such a bias would arise if lower distances increased the likelihood of detecting attempted crossings. According to policy sources, all migrants arriving in Italy from Libya over the sample period were rescued at sea, as documented in the previous section.

1.5.2 Results

Table A.5 confirms that past policy has an impact on future departures. In the first four columns, I estimate the impact of contemporaneous and lagged distance on log-departures by progressively including controls. Only the first lag matters across specifications, suggesting that smugglers and migrants forecast future policy based on the present one and that higher forecasted distances lower departures. The fact that present distances do not have a statistically significant effect reduces worries of potential reverse causality–policy adjusting in response to expectations in departures.[17] Further, this should solve any remaining worry about distances reducing detection: such an effect, if present, would negatively bias the coefficient on same-time distance. In the last four columns, I only include the first lag of distance. A 1-KM increase of observed distance corresponds to a reduction in departures by 2 percent. Weather conditions have a significant and large effect in all specifications: a 1-sd deviation increase in swell results in a 130% decrease in migration–though this approximation is imprecise. As I show in Table A.6, this result is not limited to the $T = 4$; the statistical significance of the first lags of distance and weather holds across specifications. Even though the estimate becomes noisier for $T = 1$, it retains a p-value below 10%.

It is not surprising that smuggling practices quickly adjust to rescue policy. According to Porsia (2015) and Micallef (2017), smugglers can use web-based trackers of the Automatic Identification System (AIS) of rescue vessels to collect information about the

[17]The coefficient on μ_t remains insignificant across all specifications also if I drop all lags; results available upon request.

location of rescues. Further, Sengupta (2015) and other accounts report that smugglers equip migrants' boats with GPS technology, which can also be used by smugglers to manage crossings (Jacquemet, 2020).

1.6 Public Attention and Rescue Distance

In this section, I test that an increase in public attention to migration reduces rescue distance. To do so, I exploit a baseline OLS specification and then show that results are robust to instrumenting attention to migration with newsworthy events uncorrelated to policy and outcomes. I further explore the attention-policy link by assessing if this effect is driven by one particular type of attention, using a time series of sentiment-classified news articles. Then, I turn to explore the role of NGOs in moderating the effect of attention on distances.

1.6.1 Methodology

I first use OLS to observe whether a relation exists between distance and attention. I regress observed mean distance $\bar{\mu}_t$ on lags and leads of attention g_t, representing weekly average Google-searches about migration, logged. I estimate one specification for each lag or lead separately to assess each lag's composite effect. I allow for arbitrary heteroskedasticity and autocorrelation up to lag 3. Then, I graphically inspect results by looking at a bar plot of coefficients, plotted with their confidence bans, and correcting for multiple-hypothesis testing à la Bonferroni.

I estimate the same specification using an instrumental variable for public attention to migration, for a selection of lags, still allowing for autocorrelation in the errors. Using an instrument addresses two potential concerns: omitted variables and measurement error in attention. The latter is particularly relevant if the policymaker cares about other types of attention–e.g., social media–for which Google data is just a noisy proxy.

I employ *noteworthy matches* in *Serie A* soccer matches as an instrumental variable. The rationale for relevance is that attention to sports might crowd out attention to migration as in Eisensee and Strömberg (2007). The effect of matches on migration searches can be direct if unexpected matches decrease the time people devote to acquire information about migration. The effect can also be indirect if sports events crowd out news about migration in newspapers, due to limited space, or reduce the salience of migration content in social media.

I define a match to be *noteworthy* if it respects the following two criteria: (a) the two teams participating in it are among the most popular and (b) its result is unexpected. As for (a), I restrict to matches played between the three teams ranking highest in Google searches during the twelve months until the start of the sample of interceptions (October 2013 to October 2014). As for (b), I define unlikely victories as those displaying the probability of occurred events–implied by odds–lower than the 50^{th} percentile. To retrieve probabilities implied by odds, I use a simple and usual model of the behavior of a betting agency, as explained in Section A.5.2 of the appendix.

The first stage will be:

$$\log g_t = \kappa + \kappa_n noteworthy_{t-1} + \kappa_y' Y_t + \kappa_w' W_t + \chi_t, \tag{1.4}$$

where $noteworthy_t$ is a dummy variable taking value 1 if an unexpected victory occurred in *Serie A* in week t. The exclusion restriction requires newsworthy matches with unexpected results not to be correlated with migration policy in the short run, except through the attention channel. A potential challenge is that *Serie A* matches do not happen during the summer, a period of higher departures. Another related concern is that unexpected results might occur during a particular period of the year, with an unusually low or high number of operations. To address these potential concerns, I include a full set of week-of-the-year fixed effects. I discuss relevance below when commenting on results.

To further explore the attention-policy link, I wish to assess whether slanted coverage drives the impact of attention on policy. To do it, I add a consistent measure of slant in my analysis. We have seen that news articles and Google searches are well correlated; for this reason, I consider them to be two consistent measurements of public attention to migration. Then, I use the sentiment classification explained above to construct weekly counts of objective, positive-sentiment, and negative-sentiment news articles.[18] In doing so, I reproduce the OLS estimation strategy used to investigate the impact of attention on distance; however, I now employ the weekly number of sentiment-classified articles as the independent variable. I include all three types of classified articles counts in regressions, objective obj_t, positive-sentiment pos_t, and negative-sentiment neg_t, as they are strongly correlated. Again, I estimate one specification for every lag and lead separately in order to look to the composite effect of each lag, allowing for arbitrary heteroskedasticity and autocorrelation up to lag 3.

[18]Alternatively, I could build three dictionaries of positive-, negative-charged positive, and neutral words to be looked up on Google Trends. However, this strategy would pose two methodological challenges. First, it would give me strong freedom in selecting words. Second, it would arguably end up selecting words with more zeros in Google search volume over time, which I have explained to be problematic above.

After visualizing the relationship between articles and distance, I show estimates for such a relation for given lags. I also estimate specifications where I weigh articles in the dependent variable by the diffusion of their source. I assign each source a weight equal to the share of source diffusion before the sample period–in October 2014. I do so for print and online media separately, in the absence of a clear concept on how to weigh online diffusion against print diffusion. I also show results adding the two together. Since I test my hypotheses for different lags and different definitions of the dependent variable–unweighted count, weighted print count, weighted online count–I show the significance for both baseline p-values and Bonferroni-adjusted ones. The number of hypotheses is given by lag tested times weighing type.

To investigate whether institutional or non-institutional players drive the effect of attention on distance, I explore how NGO presence moderates the impact of public attention. I regress distance on attention at different lags in separate estimations, interacting attention with mig_t^{ngo}, a variable measuring the percentage of migrants intercepted by NGOs in a given week. Again, I allow for arbitrary heteroskedasticity and autocorrelation up to lag 3. Then, I turn to an auxiliary analysis of NGO rescues to clarify their interaction with institutions.

1.6.2 Results

Figure A.11 reports the impact of attention on distance for attention at lags and leads between -10 and 10. Past attention has a negative effect from the first lag, increasing in magnitude and becoming significant at the 10% significance level on the 5^{th} lag, peaking at the 6^{th}, and then fading away. Leads have no effect whatsoever. Results support the idea that public attention makes policy more concerned with present objectives and more inclined to accept future arrivals to reduce deaths at sea. Visual inspection suggests the presence of persistence and amplification; I will explain these characteristics in the model section, referring to policy lag and feedback of the attention shock through policy outcomes. An increase in attention by about 10% on the 6^{th} lag decreases observed average distances by 1 KM.

Turning to the IV strategy, I report the first stage in Table A.7. The first three columns report the impact of *noteworthy* matches at different lags and leads, with different sets of controls, showing that only the first lag has a statistically significant effect; the latter is negative, implying crowding out of attention. The fourth column shows the specification with only one lag, as in the first stage of the 2SLS estimation. A week following one with a *noteworthy* match sees 65% less attention about migration. The last two columns show the impact of the presence in a week of a match respecting only criterion (a), namely that playing teams are among the three most popular in Italy. Effects point in the same direction, but they are more imprecise and lower in magnitude. Results suggest that migration and sports are competing issues in terms of attention. When matches are less newsworthy, they arguably circulate less in social media and newspapers, taking less space from migration as an issue. Choosing matches respecting both (a) and (b) as an instrument ensures relevance. I show the result of the 2SLS estimation for different lags, separately, in Table A.8, together with KP F statistics. F-stats are all above the 10 threshold, consistent with the effects found above, so relevance is not a concern. Consistent with the results in Figure, I find a negative and significant effect only from lag 4 to lag 6. Effects are somewhat larger than OLS estimates for the 5^{th} lag: an increase in attention by 10% decreases distance by 2 KM, more than double the OLS estimate–although the confidence intervals overlap. Coefficients on the 4^{th} and 6^{th} are still larger than OLS estimates but far closer in magnitude. The increase in the magnitude of the IV coefficients might indicate that OLS estimates are biased towards zero. The policymaker might be interested in migration coverage in newspapers and social media, for which Google searches might be a noisy proxy. In such a context, the noisy nature of our measure would introduce attenuation bias.[19] Figure A.12 also shows, reassuringly, that the IV estimation gives no significant coefficients for leads.

Figures A.13, A.14, and A.15 illustrate the impact of news articles for different lags, for objective, negative, and positive coverage, respectively. Results suggest that objective coverage, more than slanted coverage, is at the heart of the results. Slanted coverage does not have an apparent effect, while the objective one replicates the picture found with Google searches, although in a somewhat noisier setting. Coefficients for leads are not significant; coefficients for lags are generally negative between the 2^{nd} and 7^{th}, and peak in magnitude around the 5^{th}, significant at the 10% level–for Bonferroni-corrected p-values and 21 tests. Table A.9 helps visualizing results and contrasting them with diffusion-weighted measures. The table displays the impact of the 4^{th}, 5^{th}, and 6^{th} lag of news articles on distance, for different types of measure: count, diffusion-weighted for print, and diffusion-weighted for online media. I use the Inverse Hyperbolic Sign instead of the logarithm in this table because it can deal with one zero observation in the weighted-print objective attention. Stars on coefficients report levels of significance according to baseline tests, and stars on standard errors report significance according to Bonferroni-adjusted p-values, accounting for the nine hypotheses tested. In keeping with what we found above,

[19] Inspection of Weekly Media Reports used by Frontex Management, obtained under an FOIA request, shows that Frontex analyzes both newspapers and social media.

we observe that the effect of objective coverage is always negative and significant for 5^{th} and 6^{th} lags for the baseline test. Coefficients are larger when using weighted measures. However, the effect seems to be more concentrated on print media; indeed, coefficients on online media are 80% to 50% of those on print media, and insignificant according to Bonferroni p-values. Positive coverage is nowhere significant, and signs flip across specifications. Negative coverage signs are not consistent across specifications, but we observe a significant and positive effect for the baseline and online weighted measure. However, the effect is not significant when we turn to corrected p-values. Overall, objective coverage is the only one to show a robust effect, magnified when we take into consideration diffusion-weighted print media. Also, the effect of negative coverage on distance is positive, suggesting that policy responds to disadvantageous migration policy coverage by increasing risk for migrants, if it responds at all. Even if an effect of negative coverage is present, the objective coverage effect arguably prevails, as shown when considering the composite impact of attention on distance above.

Table A.10 shows how NGO presence affects the impact of attention on distance. When controlling for NGO presence and interacting it with attention, the effects of attention become somewhat larger, compared to the baseline specification. An increase in attention by 10% decreases distance by 1.4 KM on the 5^{th} lag. NGO presence, too, diminishes distances. An increase in NGO presence by 10 percentage points decreases interception distance by 3 to 13 KM. NGO presence also decreases the influence on attention on policy. To further shed light on the relative stance of NGOs and institutional rescues, we can look at Figure A.17, which compares the evolution of institutional (solid line) and NGO rescues (dashed line). There, we observe that NGOs consistently keep a lower distance–the mean for NGOs is 44.9KM versus 60KM for institutions. Their position varies less over time, too–the standard deviation for NGOs is 13.6 versus 23.8 for institutions. We observe some correlation between NGOs and institutional rescues, becoming less apparent as time passes and NGO presence in the rescue area becomes stronger. Two factors can partially explain this correlation. First, some long-term covariance arguably comes from long-term policy changes and seasonal variation affecting interception distance over time. Second, short-term correlation can partially be due to coordination, and, in particular, the fact that interceptions often involve different actors. Table A.11 shows the result of regressing NGO rescue distance on the institutional one, while progressively introducing year and quarter-of-the-year fixed effects (columns one to three). In the specification with no controls, we observe a positive and significant relation between NGO and institutional rescue distance, with a one-KM increase in institutional distance increasing NGO distance by 0.37. However, introducing year and quarter-of-the-year fixed effects more than halves the coefficient and makes it only significant at a 10% level. Then, policy changes and season seem to explain a good part of the relation between the two distances. The remaining correlation does not come from the role of attention; indeed, searches, added in the last specification, (5^{th} lag) are insignificant, and the coefficient on institutional distance displays little change. This result is not specific to the chosen lag in attention. Figure A.16 shows the impact of different lags and leads of attention on rescue distance for NGO rescues, finding no evidence of a relationship between attention and distance for NGO actors. Overall, this is coherent with the idea that NGOs take a humanitarian stance and do not pursue deterrence as an objective. Thus, they do not react to attention in the way that institutional rescues do.

I have shown evidence that policy influences migration outcomes and that attention influences policy. Now, I move to explore a mechanism for this to happen by proposing and estimating a dynamic model of policy choice.

1.7 Model

Time is infinite and discrete. Smugglers and migrants trade on the market for crossings, forecasting future policy based on the present one. An impatient policymaker sets migrants' safety, taking their forecast as given; she cares more about outcomes in periods of higher attention. Attention evolves in response to policy outcomes and shows persistence.

Let us spell out the timeline for one period t (week):

i. The PM observes $t-1$ arrivals, deaths, and attention and uses them to form an expectation for future attention.

i. A measure of migrants and smugglers observe $t-1$ distance and uses it to forecast t.

ii. Given $t-1$ distance, t weather, t expected attention, a law of motion for expected attention, and the forecasting process for migrants, the policymaker chooses policy.

iv. Given smugglers' cost-structure heterogeneity, and migrants' and smugglers' forecast for distance, a measure of migrants leaves the Libyan coast and travels on a segment at a constant speed, encountering shipwreck according to a Poisson process, with arrival rate λ, and rescue with arrival rate $1/\mu_t$ chosen by policymakers.

v. Time t arrivals, deaths, and attention realize.

Let us turn to a more precise definition of the model. I start by characterizing crossings. Then, I turn to the behavior of migrants and smugglers. Finally, I deal with the evolution of public attention and the problem of the policymaker.

1.7.1 Death probability and rescue distance

A smuggler can offer a crossing to a migrant, who travels on a line connecting Africa and Europe. Deadly incidents arrive over distance according to a Poisson process with arrival rate λ. Rescue happens according to a Poisson process, too. It can only occur from the end of Libyan territorial waters, b, onwards. The policymaker sets the arrival rate of rescue, or the inverse of mean rescue distance μ_t, for the migrant. Further, the arrival rate of shipwreck within territorial waters is λ_b, possibly different from λ. As shown in section A.5.3 of the appendix, the probability of rescue π_t as a function of μ_t is given by:

$$\pi_t = \frac{\exp(-\lambda_b b)}{\lambda \mu_t + 1}. \tag{1.5}$$

The probability of survival is decreasing in the arrival rate of shipwreck λ, and in the extension of the no-rescue area b. Also, it is decreasing in the mean rescue-interception distance, μ_t. Taking the model to the data will require expressing survival probability in terms of the observed distance for the rescued, $\bar{\mu}_t$. Observed distance will be lower than mean distance, as interceptions 'assigned' higher distances are more likely to result in a shipwreck and not being observed. In equation 1.18, I derive the following:

$$\mu_t = \frac{1}{\bar{\mu}_t^{-1} - \lambda}. \tag{1.6}$$

Since there is a one-to-one correspondence between $\bar{\mu}_t$ and μ_t, I can define the former to be the planner's policy, with no loss of generality. Given Equations 1.5 and 1.6, and allowing for a random component, we can write:

$$\pi_t \approx \exp(-\lambda_b b) - \exp(-\lambda_b b)\lambda\bar{\mu}_t + \varepsilon_{d,t}. \tag{1.7}$$

This relates survival probability and policy.

1.7.2 Departures and past distance

Consider a crossing smuggling market, with homogenous migrants having a higher marginal utility of consumption in Europe and smugglers with a heterogeneous cost structure. In particular, assume that smugglers pay a fixed cost for offering a crossing. Also, suppose that migrants and smugglers approximate policy at time t by:

$$\bar{\mu}_t = \kappa_0 + \kappa_1 \hat{\bar{\mu}}_{t-1}, \tag{1.8}$$

where $\hat{\bar{\mu}}_t$ is the average observed distance from rescues occurring in the week t:

$$\hat{\bar{\mu}}_t = \frac{1}{N_s}\sum_{i=1}^{N_s} dist_i. \tag{1.9}$$

Later, I discuss why past policy enters the approximation. I make the simplifying assumption that N_s does not vary by week–we fix it to its average level. Then, $\hat{\bar{\mu}}$ is Gamma-distributed with shape N_s and scale $\bar{\mu}_t$. In addition, I assume that crossing costs are increased by a positive constant in days of bad weather. In Section A.5.3 of the appendix, I show that under distributional assumptions on the fixed cost parameters for smugglers, departures at time t follow:

$$\log \ell_t = \omega_0 - \omega_1 \hat{\bar{\mu}}_{t-1} - \omega_2 w_t + \varepsilon_{\ell,t}, \tag{1.10}$$

where ℓ_t is the number of migrants leaving at time t, and w_t takes value one for bad weather, and ω_0, ω_1, and ω_2 are positive, and $\varepsilon_{\ell,t}$ is normally distributed with mean zero and variance σ_ℓ^2.

1.7.3 Public attention

Past policy outcomes should influence the level of present public attention. Also, I can envisage a certain degree of persistence of attention to migration in the public discourse, due to the inclusion of the issue in parties' platforms, or via the circulation of content on social media. I assume the following law of motion for attention:

$$g_t = \alpha_0 + \alpha_1 s_{t-1} + \alpha_2 d_t + \varepsilon_{g,t}, \tag{1.11}$$

where g_t stands for attention, d_t for deaths, and ε_t evolves according to $\varepsilon_{g,t+1} = \rho_g \varepsilon_{g,t} + \nu_{g,t}$. The variable s_{t-1} represents a stock of accumulated arrivals. I defer the discussion of its evolution to the next subsection. For the moment, I only stress that arrivals enter the evolution of attention with a week lag, while deaths affect contemporaneous attention. This formulation, other than being convenient for reducing the state space and simplifying the numerical implementation, agrees with the idea that arrivals affect attention with a week lag, as shown in Table A.12. A possible explanation is that the press covers arrivals on the day migrants are transferred to Italy from the rescue area, hours or days after the rescue operation. I work under the assumption that departures do not influence attention *per se*, but only through arrivals and deaths.[20]

[20]This is more than plausible over the sample period since refoulements were scarcely present in the news.

1.7.4 Policymaker

The policymaker faces a dynamic problem. She has to set policy μ_t by taking into account the current risk for migrants at sea and the impact on future departures. She faces the following flow loss for arrivals and deaths at sea:

$$L(a_t, d_t) = g_t^{\theta_3} \left(\theta_2 s_t^{\theta_4} + (1-\theta_2) d_t^{\theta_4} + \theta_5 n_t\right). \tag{1.12}$$

The first two addends in brackets are increasing and convex in deaths d_t and the stock of arrivals s_t, given by:

$$\forall t, \quad s_t = (1-\theta_1) s_{t-1} + a_t, \qquad \theta_1 \in [0,1]. \tag{1.13}$$

The depreciation parameter θ_1 is meant to capture at the same time time-decreasing costs of migrants' reception and memory depletion. The first term in the flow loss captures the complementarity between policy outcomes and attention. When attention, g_t, is higher, the flow loss from outcomes is higher. Finally, n_t is a dummy variable for high NGO presence. Intuitively, when NGO presence is high, policymakers can set their preferred policy with a cost. In particular, since NGOs follow humanitarian objectives, we could expect they impose a cost of increasing rescue distance so that *a priori* θ_4 should be positive. I assume that n follows a Markov process.

The policymaker takes her decision before the realization of g_{t+1}, but she can condition on past policy, stock of arrivals, weather, NGO presence, and shocks to attention. Then, I can describe the policymaker's problem as:

$$\begin{aligned}
V(s, \varepsilon_g, \hat{\bar{\mu}}, w, n) = \max_{\bar{\mu}'} & - \mathbb{E}_{w'|w} g_t^{\theta_3} \left(\theta_2 s'^{\theta_4} + (1-\theta_2) d'^{\theta_4} - n'\theta_5\right) + \beta \mathbb{E} V(s', \varepsilon_g', \hat{\bar{\mu}}', w', n' | \bar{\mu}) \\
\text{s.t. } & \log \ell' = \omega_0 + \omega_1 \bar{\mu} - \omega_2 w + \varepsilon_\ell, \\
& \hat{\bar{\mu}}' \sim \Gamma(N_s, \bar{\mu}^{-1}), \\
& \pi' = \exp(-\lambda b) - \exp(-\lambda b) \hat{\bar{\mu}}' + \varepsilon_d \\
& a' = \ell' \pi', \\
& d' = \ell'(1-\pi'), \\
& \hat{g}' = \alpha_0 + \alpha_1 s + \alpha_2 d' + \varepsilon_g', \\
& \varepsilon_g' = \rho_g \varepsilon_g + \nu_g \\
& s' = (1-\theta_1) s + a', \\
& w' \sim \text{Markov with transition matrix } \Pi_w, \\
& n' \sim \text{Markov with transition matrix } \Pi_n.
\end{aligned} \tag{1.14}$$

Now, assuming that migrants are not informed about attention, it is intuitive that $\bar{\mu}_{t-1}$ should enter the migrants' approximation for the evolution policy. Present attention correlates with past attention; for this reason, present policy will correlate with past policy. If migrants can observe the past distance, they can rely on its persistent structure to infer the policymaker's behavior.

In the next section, I summarize how I estimate the model.

1.8 Estimation strategy

1.8.1 IV for arrival rate of incident

Using death frequencies, $\bar{\pi}_t$, as an empirical counterpart to probabilities, I can estimate the relationship between distance and death risk. I should also instrument $\bar{\mu}_t$, for the reasons outlined above. Defining by $\bar{\pi}_t$ the observed proportion of migrants surviving at sea at time t, in a 2SLS framework, I can use the following specification:

$$\bar{\pi}_t = \beta_0 + \beta_1 \bar{\mu}_t + \beta_Y Y_t' + \beta_Q Q_t' + \nu_{d,t} \quad \bar{\mu}_t = \alpha_0 + \alpha_1 Z_t + \alpha_Y Y_t' + \alpha_Q Q_t' + \nu_{Z,t}. \tag{1.15}$$

The instrument Z_t is the sum of Suez entries over the past two months. Y_t and Q_t deal with potential endogeneity issues due to long-term changes in policy or seasonal variation. A comparison of 1.15 to 1.7 reveals that $\hat{\lambda}_b$ will be backed out from β_0, and $\hat{\lambda}$ will be given by β_1 over $\hat{\lambda}_b$.

1.8.2 OLS for departures

I estimate the relation 1.10 by OLS, as in Section 1.5.

1.8.3 Frequencies for Markov processes on weather and NGO presence

The estimations of Π_w and Π_n require evaluating the probability of a given transition. For a generic Markov process, define the sample as the set of transitions represented by couples of adjacent weeks. Define the variable $x_{ij,t}$ taking value 1 if a transition from i to j at time t. The probability of transition from i to j, π_{ij}, is given by:

$$\pi_{ij} = \frac{\sum_t x_{ij,t}}{\sum_{z \in \{i,j\}} \sum_t x_{iz,t}}. \tag{1.16}$$

We estimate both processes on NGO and weather transitions separately using this formula. I summarize both of these variables with a dummy counterpart, taking value 1 whenever the relative variable is higher or equal to its median value.

1.8.4 OLS and IV for public attention

I estimate the evolution of public attention in Equation 1.11 using GLS estimation. I use the residuals from the same estimation to estimate ρ_g with OLS.

1.8.5 MLE for optimization problem parameters

Define as follows the vector of states:

$$X_t = [\bar{\mu}, s, n_t, \varepsilon_g, w_t]. \tag{1.17}$$

Define by $\mu(x)$ the policy function for mean distance, and by R the event *rescue* for the observed unit (boat). The distribution of distances, given that I only observe rescued boats, and given states is:

$$\begin{aligned} f(dist|R, \mu(X_t)) &= \frac{\mathbb{P}(R|dist, \mu(X_t))f(dist)}{\mathbb{P}(R)} = \\ &= \frac{\exp(-\lambda b)\exp(-\lambda dist)\mu^{-1}\exp(-\mu^{-1}dist)}{\exp(-\lambda b)(\lambda\mu+1)^{-1}} = \\ &= \left(\lambda+\mu^{-1}\right)\exp\left(-\left(\lambda+\mu^{-1}\right)dist\right) \end{aligned} \tag{1.18}$$

Notice that the previous equation represents the density of an exponential random variable with a mean corresponding to our definition of $\bar{\mu}$, mean distance conditional on rescue, and such that:

$$\bar{\mu} = \frac{1}{\lambda+\mu^{-1}} \tag{1.19}$$

Also, with this we can write the following log-likelihood exploiting distance data:

$$\begin{aligned} ll(Y;\theta) &= \sum_{t:t\in T}\sum_{i:i\in I_t}\log f((dist_{i,t}-b)|\mu_t^*(X_t)) = \\ &= \sum_{t:t\in T}\sum_{i:i\in I_t}\log\left(\lambda+\mu^{-1}\right)-\left(\lambda+\mu^{-1}\right)(dist_{i,t}-b). \end{aligned} \tag{1.20}$$

1.8.6 Numerical Implementation

Since retrieving the likelihood value for a given vector of parameters requires first computing the policy function through Value Function Iteration (VFI), the model's estimation is computationally heavy. For this reason, I implement VFI by parallelizing over states on GPU. I also impose some simplification to shorten computation time and produce an error estimate. I estimate the model disregarding uncertainty over deaths, arrivals, and realized distances–focusing instead of mean distance set by policy. I use coarse grids on states (14 points for present distance, 7 for arrivals and attention). Further, I assume $\theta_1 > 0.25$ to exclude explosive dynamics on the arrivals stock variable, which I could not manage with my arrivals grid. This approach allows me to estimate the standard errors on utility parameters using bootstrap. In doing so, I account for the autocorrelation introduced by my instrument for policy. When estimating death probability; I use the Non-Overlapping Block Bootstrap scheme introduced by Carlstein et al. (1986).

1.8.7 Identification

I identify the parameter θ_1 by the cross-variation of arrivals at different time lags and policy, and the parameter θ_2 by the mean distance set by policy. I recover θ_3 by the cross-variation of distance and public attention. The estimation of θ_4 intuitively relies on the correlation between distances and attention at differing levels of past arrivals. Finally, I pin down θ_5 with the cross-variation of distance and NGO presence. I set β to 0.990; this is meant to capture patience, and the time-horizon of the main political actors involved. I assume that the discount rate in this domain coincide to that in consumption, estimated in the social time preference rate literature. In particular, I take the estimate of Evans and Sezer (2005) of a 4.7% annual discount rate. I model the time-horizon by a 0.009 probability that the government changes, and policymakers get a constant utility flow. In this way, I match the number of months before elections by the mean time before government change.

1.9 Results, fit, and counterfacturals

I introduce the estimation of the model and comment over counterfactuals.

1.9.1 Results

I start by estimating the evolution of attention given outcomes, as in Equation 1.11. Attention g_{t+1} is the weekly average of Google searches and deaths and arrivals, d_t and a_t, are sums. Below I report GLS estimated parameters with standard errors in parentheses:

$$\ln g_{t+1} = \underset{(0.125)}{2.517} + \underset{(0.196)}{0.028} s_{t-1} + \underset{(0.008)}{0.474} d_t + \varepsilon_{g,t} \tag{1.21}$$

Here, I express deaths and arrivals in thousands. As expected, outcomes and past attention have a positive effect on future attention. As for deaths, an increase by 1000 increases attention by 40%. Per the magnitude of the coefficient on arrivals, an increase in deaths at sea by 1000 increases attention by 3%.

Before estimating the AR1 process for the error term, I run an Augmented Dickey-Fuller test, and I reject the null of unit root, with a p-value lower than 1%. Then, I perform the estimation using OLS.

$$\varepsilon_{g,t+1} = 0.776\varepsilon_{g,t} + \nu_{g,t} \tag{1.22}$$

And $\sigma_g = 0.363$. I find the process of the error term to be very persistent.

As for departures, I estimate the equation as in Table A.5, allowing for autocorrelation in the error term up to the third lag. I find:

$$\log \ell_t = \underset{(0.327)}{8.60} - \underset{(0.00925)}{0.0188} \hat{\bar{\mu}}_t - \underset{(0.328)}{1.87} w_t + \iota_t \tag{1.23}$$

I control for weather by creating a dummy variable taking a value of one when average swell for a week is higher than the median.

I estimate the transition matrices for weather and NGO presence to be:

$$\Pi_w = \begin{bmatrix} 0.571 & 0.429 \\ 0.348 & 0.652 \end{bmatrix} \qquad \Pi_n = \begin{bmatrix} 0.642 & 0.358 \\ 0.291 & 0.709 \end{bmatrix} \tag{1.24}$$

It remains to estimate the equation 1.15. I find:[21]

$$\hat{\pi}_t = \underset{(0.040)}{1.1} - \underset{(0.000923)}{0.00222} \bar{\mu}_t + \beta_Y Y_t' + \beta_Q Q_t' + \varepsilon_{\pi,t} \tag{1.25}$$

Given that 1.1 is not statistically different from 1–and that it is actually estimated to be higher than 1–I estimate $\hat{\lambda}_b = 0$, and consequently I read $\hat{\lambda}$ off the coefficient on distance. Using $\hat{\lambda}_b$, $\hat{\lambda}$, and Equation 1.6, I can obtain an estimate of the increase in the probability of death coming from an increase in the mean distance of rescue from average values, μ_t,

[21] The number of observations is 103, and KP F-stat on excluded instrument is 5.84. Notice, however, that when I partial out long term and seasonal variation, by controlling for year fixed effects and quarter-of-the-year fixed effects, the KP F-stat becomes 12.8, and results remain almost unchanged.

instead of the observed one, $\bar{\mu}_t$. Increasing the mean distance of interception by 10 KM reduces survival probability by 2 percentage points, roughly 90% of the 2.2-percentage-points non-corrected estimate found in 1.4.

I can now turn to the Maximum Likelihood estimation for the policymaker's preferences parameters. Table A.13 reports estimated parameters. Results confirm that there is some persistence in how arrivals affect policymaker's utility since $\theta_1 < 1$; however, the planner is more interested in reducing the arrival flow than the stock since θ_1 is very close to 1. The fact that θ_3 is positive supports the explanation that periods of higher attention are more relevant to policy. Since θ_5 is positive, NGO presence increases the cost of setting a high distance.

1.9.2 Model fit

Figure A.26 shows actual mean distances (solid line) and model-predicted given actual state realizations (dashed line). The model's results fit well the time series of distances.

Table A.14 reports a list of moments from the model, compared to the same moments estimated through regressions on the actual data, with HAC robust confidence intervals. The model replicates the magnitudes and signs of the separate correlations between distances and past attention, past distances, and departures. The correlation between past deaths and distances has the same sign across data and model, but the model's one is lower. However, it falls within the confidence interval of the estimate in the data. The model also replicates well the relation between distances and past NGO presence, as well as with weather. Finally, I test how the model matches seasonal and long-term trends in the data by comparing across model and data time series the results of a regression of distances on year and quarter-of-the-year FEs. The model significantly under-predicts the decrease in average distances in 2016, possibly due to non-modeled long-term policy shifts; however, it replicates well seasonal variation.

1.9.3 Policies

The solid line in Figure A.18 depicts optimal future distance chosen by the policymaker as a function of present distance, holding attention, weather, NGO presence, and stock of arrivals fixed. I obtained the policy by VFI on a pre-specified grid; I plot it after fitting a 4-degree polynomial through each future-present distance policy. Optimal future distance is increasing in the present one because, for lower present distances, the policymaker expects more departures, which increases the stakes of ensuring safety for migrants. Also, the relationship is less steep than the 45-degree line, depicted as dashed, which suggests that, for given states, policy stabilizes at an interior point. Indeed, the simulated model quickly converges to a distance of 43 KM, on average, irrespective of the starting points used. Figure A.19 shows the future distance as a function of past distance again; however, each of the panels shows how such policy varies by other states: attention, past arrivals stock, weather, and NGO presence. The upper-LHS shows the past distance-policy relation by values of attention; warmer colors represent higher attention. Higher attention increases the incentive to save migrants at sea, compared to reducing future departures. For this reason, we see that as attention grows, policy shifts downwards. As we can see in the upper RHS panel, the role of previous arrivals, instead, is quite limited, consistent with the very high estimate of θ_1. Higher past arrivals (warmer colors) have two effects: on the one hand, they increase the marginal utility of decreasing arrivals, by convexity; on the other hand, they decrease the scope for decreasing the arrivals stock. The latter effect seems to prevail so that a higher arrival stock leads to a decrease in distance. In the lower-LHS panel, good weather is depicted in darker blue. Bad weather increases distances by decreasing the expectation over the number of migrants leaving, given past policy, reducing the incentive for rescue. This is consistent with the regularity in the data that distances increase in winter. Finally, in the lower-RHS panel, lighter blue represents a high NGO presence. As we can see, a higher NGO presence increases the cost of increasing distance, which then has to decrease.

1.9.4 Fixing distance

It is useful to compare historic and steady-state policy to the outcomes of a fixing distance to a level, depicted by distance level in Figure A.20. Upper panels represent the basic trade-off of the problem. As the LHS panel shows, departures decrease with distance; on the RHS panel, we observe that death probability decreases with distance. The composition of the two effects leads to a bell-shaped behavior of expected deaths with the fixed distance set by policy, shown in the lower LHS panel. Deaths are minimized for very low distance and low for high distances; they peak around 40 KM. Given that deaths and arrivals are lower when distance is high, it is then natural to ask why the policymaker distance stabilizes around 43KM, close to the historical average distance set by policy, as depicted by the blue vertical line. We may wonder whether this is a consequence of higher attention when policies are higher; however, according to the model, attention would be reduced by decreasing distance. Instead, the reason is that in the short term, since departures are given, reducing distance is sure to decrease deaths, while increasing distance is sure to increase departures in the future.

1.9.5 Externalization of border enforcement

We can use the model to think about a current policy undertaken by European authorities. In mid-2017, after my sample period, Italy started to progressively externalize border enforcement policy to Libyan authorities in exchange for financial support, after signing a Memorandum of Understanding with the Libyan Government of National Accord at the beginning of 2017. In the year following the start of the policy, arrivals decreased by 87% compared to the prior year, and deaths at sea decreased by 82% (Villa, 2015). Externalization can be thought of in different ways, depending on how they effectively reduced migrants' flows. One way is to think about it as unexpectedly reducing the magnitude of ω_1, the parameter regulating how past distance translates in future arrivals. A reduction of ω_1 causes a downward shift of departures as a function of past distance, keeping fixed the intercept. This means that for every distance value except 0, the amount of departures decreases; if the distance of rescues is zero, departures remain the same as before the policy change. In a sense, this captures well policies that increase interceptions and apprehensions by the Libyan Coast Guard at sea. We might imagine that such policies would reduce the profitability of smuggling activities for high distances more than for low ones, as a lower distance implies a lower probability of apprehension. Figure A.24 represents the shift in the rescue distance over time coming from a reduction in ω_1; this policy has the impact of increasing rescue distance. A decrease in ω_1 by 10% (5%) turns into an average distance increase in the steady-state distance of 3.5 KM (2 KM), taking effect in about one month. Indeed, decreasing ω_1 increases the marginal effect of distance on departures and increases incentives to set higher distance, reducing rescue probability by 0.4 (0.8) percentage points. Another way to think about the impact of such policies is to frame them as a reduction in ω_0. This corresponds to a reduction in departures by a fraction for any distance, including 0. This could then model an overall reduction in smuggling profitability due to policing activities on land or reduced support to smuggling networks. As we see in Figure A.25, this has the opposite effect on distance. Decreasing ω_0 by 10% (5%) decreases rescue distance by 9 KM (4 KM). Indeed, a decrease ω_0 reduces the marginal impact of departures of increasing distance. Reducing distance and increasing safety becomes more advantageous for policymakers, and survival probability goes up by 2 (1) percentage point(s). Overall, the effect of externalizing border policies depends on the relative decrease that it implies on ω_0 and ω_1. A higher reduction in the latter would result in increased distance, while the converse is true for a larger reduction in ω_0. In the next section, I show that the effect of externalizing border enforcement was consistent with a decrease in ω_1.

1.9.6 Deaths, arrivals, policymaker's welfare, and VSL

We can use the estimated parameters to analyze how the policymaker evaluates deaths and arrivals. Define $\Delta U^d(1;X)$ as the policymakers' welfare loss from one more migrants' death, for the realized vector of states and policy outcomes X, and $\Delta U^a(1;X)$, as the loss from one more arrival. I obtain an estimate of the relative loss from deaths and arrivals as:

$$\mathbb{E}\left(\frac{\Delta U^d(1;X)}{\Delta U^a(1;X)}\right) \simeq 9.662, \tag{1.26}$$

with X evaluated at steady-state expected values, and the expectation taken over weather and attention. At the steady-state, the policymaker is willing to accept roughly 1 death for a reduction of 10 arrivals. This squares both with a steady-state survival probability of around 90% and with the average survival probability at the end of my sample, computed to be around 89%.

Since we can back out the welfare loss of deaths within the model, it is natural to ask whether we can produce a Value of Statistical Life, summarizing how much policymakers value migrants' lives. To calculate this figure, we have to estimate the policymaker's willingness-to-pay for welfare. A possible way to get such an estimate is to compare the welfare increase produced by the agreement with Libya outlined in the previous section to the financial support provided to Libyan institutions. We can call the latter the price of the deal, P_{deal}, and, assuming that Libyans had all the bargaining power, we could view this as the entire willingness-to-pay for the agreement by Italian authorities. As I noted above, the agreement could have changed both ω_0 and ω_1, regulating how distance turns into future departures; define $\bar{\omega}_{deal} = [\omega_{0,deal}, \omega_{1,deal}]$. We can think about the deal as shifting the relation between distance and departures to:

$$\log \ell_{t+1} = \omega_{0,deal} + \omega_{1,deal}\bar{\mu}_t + \omega_2 w_{t+1}. \tag{1.27}$$

Then, we can then obtain the willingness-to-pay for welfare as:

$$WTP_{1U} = \frac{V(\bar{\omega}_{deal}) - V(\bar{\omega})}{P_{deal}}, \tag{1.28}$$

where $V(\bar{\omega})$ represents the welfare in a steady-state with $\bar{\omega}$. To find an estimate for the numerator in the RHS of Equation 1.28, we have to estimate the new vector of parameters $\bar{\omega}_{deal}$. Ideally, such an estimate could be obtained by regressing departures on distance under the new policy. Unfortunately, there are no time-series of distances after the policy entered into effect. To obtain an estimate, nonetheless, I can use aggregate data on departures and death probability after the deal, together with my model, in the following way. First, I express $\omega_{0,deal}$ as a function of new log average departures and $\omega_{1,deal}$, using Equation 1.27. Second, I define $\mu_{ss}(\omega_{1,deal})$ as the steady-state distance as a function of the new parameters. Third, I back out the new average distance by using the death probability observed after the deal, together with the OLS-estimated relation between death probability and distance, and call it μ_{deal}. Finally, I solve $\mu_{ss}(\omega_{1,deal}) = \mu_{deal}$ for the new $\omega_{1,deal}$, and use the latter to get $\omega_{0,deal}$. I obtain two solutions, $\omega_{1,deal} = 0.0399$ and $\omega_{1,deal} = 0.257$, but I discard the latter since it would result in implausibly high departures for zero-distance–roughly 13 million people per week, more than 30 times the migrant flow in the whole sample period. Consequently, I back out $\omega_{1,deal} = 1.890$. This is consistent with the policy having increased ω_1 while leaving ω_0 unchanged. As for the denominator, is not easy to determine how much financial support Italian institutions provided to Libyans; however, based on a recent journalistic investigation (Montalto Monella, 2019), we can set P_{deal} to about €475 million, provided by Italy and the EU jointly.[22] Using these results, I compute the average willingness-to-pay of the policymaker for saving one migrants' life from a shipwreck in involving D deaths, at steady-state expected outcomes, averaging over weather and attention. Setting D to the standard deviation of deaths, 128, I get an average willingness to pay of €78 000; given convexity of the policymaker's preferences, this estimate goes up to €146 000 for D equal to two times the standard deviation of deaths, and €250 000 for three times the standard deviation. It is insightful to compare these figures to the estimate in Ashenfelter and Greenstone (2004) that the US government is willing to pay at most \$ 1.54 million to prevent one citizen's death. We cannot be sure that the same estimate applies for European authorities; however, we can expect the Value of Statistical Life for natives in Europe will be close to its American counterpart. Then, we observe a much lower evaluation of migrants' lives compared to native ones.

1.9.7 Effects of attention

Figure A.21 shows the impact of a shock to attention. To construct it, I first simulate the model for 100 periods starting from average states, good weather, and no NGO presence. Then, I shock attention in the 100^{th} period by one and two times the attention noise standard deviation, register its evolution for 15 periods, and compute the difference with baseline evolution without the shock for every period. I simulate the model 10,000 times and plot the evolution of median differences. The upper LHS panel shows the effect of a

[22] The article I refer to is available at https://bit.ly/2HHgKfn in Italian, but I can provide an English summary if asked to.

shock in attention on distances. This is negative and persistent, reverting to zero in about 9 periods in the 2-sd case. Comparing to the OLS results in Figure A.11, we find the sign and strong persistence to agree with what we find in the data. The intuition on the sign is the same given above. A shock to attention will depreciate, eventually, and because policy outcomes are complementary to contemporaneous attention, the policymaker will be willing to take more future arrivals to decrease deaths today. Persistence can be explained by two factors. First, the attention shock itself is persistent. Second, by decreasing distance in reaction to an attention shock, the policymaker induces higher future departures–as shown in the lower LHS panel–and a higher benefit of setting a safer policy. This effect also induces amplification over time, and it leads to a lagged peak in attention's effect on policy, reached around the second or third week. Since the policymaker's loss is convex in arrivals, she will find it optimal to start decreasing distance gradually, which will eventually converge to the previous level. Considering the magnitude of the effect at the peak and the fact that we used a 0.363 shock to log-attention, a one-unit increase in log-attention in the model leads to a 5.2 KM median decrease in the distance of rescues. Mean effects are a bit larger; as shown in Figure A.22, the mean effect at the peak for a one-unit increase in log-attention is 5.8 KM. The overall effect on deaths is given by the composition of the effect on departures and of the effect on rescue probability–as shown in the upper RHS panel. Going back to Figure A.11, both effects closely track policy, increasing in response to a lower rescue distance. A one-unit increase in log-attention increases departures by about 17 persons at median at the peak and rescue probability by 0.5 percentage points. However, the effect on departures is lagged. Then, the first period sees a net decrease in deaths, due to a decrease in distances not matched by an increase in departures; then the effect reverts to positive in the third week. However, at that point, distances are already increasing, thereby pushing down departures, so any positive impact on deaths fades away. Hence, the net effect on deaths is negative.

The effects of attention are lower than what we find in the data as the 2SLS-estimated impact. This might be due to heterogeneity in the effect of attention due to the varying persistence of attention shocks. The estimated structural model helps us investigate this issue, which could be difficult to grasp in a reduced-form setting. Figure A.23 shows the impact of a 2-sd shock to attention as described above, but when the policymaker expects a higher persistence. This is done by re-evaluating policies for attention persistence $\rho_g = 0.9$, and $\rho_g = 0.999$, other than the baseline $\rho_g = 0.776$. Increasing persistence has two effects: on the one hand, it increases the informativeness of the present attention shock on next-period distance (when rescues take place), which should make for a comparatively stronger effect of attention shocks. On the other hand, it increases the expectations of $t + 2$ attention, increasing the incentive to limit departures. The second effect prevails: an increase in persistence reduces the impact of attention on policy, so much so that for persistence $\rho_g = 0.999$, attention shocks have virtually no effect on distance. We might think of the reduced form effects as averaging over shocks perceived to be more or less persistent, given the policymaker's information. This might explain why IV effects are larger than model ones; even if the policymakers do not observe the direct cause of such shocks, they might have information about their persistence. If this is thought to be low, it might magnify the impact of attention shocks on distance.

1.10 Conclusion

Border enforcement in the Mediterranean Sea involves a trade-off between deterrence and safety conditions for migrants' crossings. Given that border enforcement influences future migration pressure, this trade-off is dynamic. I construct a dynamic problem of border enforcement for the context of the Central Mediterranean route of migration, and I estimate it using high-frequency geo-referenced data of rescue operations in the Mediterranean. The policymaker sets the distance of rescues from the Libyan coast, and she faces a trade-off between risk for migrants at sea today and future arrivals. I use the estimated parameters to show that policymakers are willing to accept 1 death in exchange for 10 fewer arrivals, at steady-state. I also show that European policy between 2014 and 2017 was suboptimal in minimizing migrants' deaths at sea.

Irregular migration and border enforcement are central to the current political debate in Europe. The estimated model takes into account the effects of public scrutiny on the decisions of the policymaker, as measured by Google-searches volume about migration. Higher public attention in a given period increases the relevance of the policy outcomes for that period. Then, the policymaker accepts higher arrivals at later dates in exchange for a reduction of present risk for migrants. Such an effect depends on the persistence of attention shocks. If shocks to attention are more persistent, they are comparatively less effective at making present objectives more relevant for policy because they shift the value of policy outcomes both at present and in the future. These effects of attention generalize to all policy contexts in which the policymaker faces an intertemporal trade-off and public attention to policy outcomes changes over time.

Chapter 2

Informing Risky Migration: Experimental Evidence from Guinea

With Lucia Corno and Eliana La Ferrara

2.1 Introduction

Information about the benefits and costs of migration is not always available to potential migrants. This might lead to false perceptions among them, resulting in ex-post suboptimal decisions. If this is the case, this problem might be reduced by information interventions targeting potential migrants. Even in the presence of misinformation, the behavioral consequences of such interventions depend on the type of information migrants have.

In this paper, we design a randomized experiment in 160 secondary schools in Guinea, a Western African country that has been a major source of emigration to Europe over the last years, to reduce risky and irregular migration. In particular, we address the following questions: (i) can the provision of information about earnings in the destination countries and the risks of the journey to Europe update potential migrants' beliefs about them? (ii) Does updating influence their choice to migrate or not their migration route?

We divided the schools in our sample into four groups: the first group received information about risks and costs of the journey, the second received information about migrants' economic outcomes (e.g., wages, employment probability, etc.), the third received both types of information, and fourth, the control group, received no information. The first follow-up results suggest that information about risks and economic outcomes affects subjects' beliefs and leads to changes in stated migration intentions. Preliminary analyses on data collected during a second follow up, which we finished preparing for analysis in June, shows that effects on beliefs and migration attitudes are only partially persistent. Also, they show considerable heterogeneity in the effect of treatments on migration choices by wealth status. Non-wealthy students are the only ones to have diminished migration as a result of the treatment.

Our work builds and contributes to four strands of literature: (i) the literature on expectations of the benefits of migrating, (ii) the literature on the expected risks of migrating, (iii) the experimental literature on information intervention among potential migrants, and (iv) the literature on the effect of media interventions.

The literature investigating migration decisions by studying migrants' earnings expectations is relatively recent, but it already contains useful insights–although somewhat contradicting. McKenzie et al. (2013) exploit a lottery providing some Tongans work visas for New Zealand. Authors survey beliefs about earnings and employment probability for 102 refused applicants. Expectations are compared to the realized distribution of earnings abroad of 120 applicants who won the lottery. Authors find that migrants underestimate employment (55% against 90.5%) and income (mean and median 339 and 290 against 558 and 500). This finding is in contrast with other papers in literature. Shrestha (2017) surveys beliefs of 3319 prospective Nepali migrants about wages they will find in Gulf countries finding evidence that they overestimate their wage potential. Hoxhaj (2015) finds similar results comparing (point) wage expectations for roughly 555 illegal migrants to Italy from the Survey on Illegal Migration to Italy (SIMI) of 2003 to wages of legal migrants to the same country. The author constructs predicted wages for illegal migrants (building the counterfactual with a sample of regular migrants) based on Italian Statistics on Income and Living Conditions (IT-SILC). He finds that 84% of migrants overestimate their potential wages, which is a lower bound since counterfactuals are biased upwards by legal status. The sample investigated is very selected–illegal migrants from non-OECD countries–but nearer to our case than other works in literature. This result is also consistent with other, more indirect findings in the literature, based on behavioral outcomes. Farré and Fasani (2013) assess the impact of the TV sector's liberalization on internal migration in Indonesia. Exploiting time variation due to policy, joint with geographical variation in channels' penetration, they find a negative effect of TV exposure on internal migration. Their analysis is robust to instrumenting TV exposure with variation due to topography. They interpret their results as showing that TV exposure–information–decreased the expectations about income to be earned elsewhere in Indonesia. In sum, studies about earnings' beliefs agree on the fact that misinformation is widely present among migrants. However, authors come to different conclusions about the direction of such misinformation depending on the context. Our work adds knowledge of the phenomenon in a context that is particularly relevant to the current migration debate.

Second, work on migrants' perceptions of risks is much more scarce, but it points again to an information gap. The study by Shrestha (2017) offers some insights relating to the issue. In much the same way as he did with earnings, the author surveys Nepali migrants' beliefs about the probability of dying on the job in Gulf countries. He finds that migrants overestimate the risk of dying on the job abroad, and that an information treatment reduces perceived risk and increases migration. Bah et al. (2018) provides similar evidence in a context very closer to ours. They conduct a lab-in-the-field experiment involving 584 adults in the Gambia, investigating how information affects intentions to migrate illegally. They find that individuals overestimate the probability of obtaining a residence permit and risk. However, their design cannot directly look to the impact on migration decisions, which we consider in our work.

Third, the paper contributes to the recent literature on information interventions to target migrants' lack of information. Shrestha (2017) pioneered the field, informing Nepali migrants about earning potential and the risk of dying on the job abroad. Consistently with the results that potential migrants overestimate risk and earnings, he finds risk information to increase migration and earnings information to decrease it. Bah et al. (2018) find a similar result using hypothetical choices. They find that giving information about migration risks increases the willingness to migrate while giving information about the probability of obtaining legal status reduces it.

Finally, this paper contributes to a growing literature on the effect of media, videos, and short documentaries on behavioral change–see DellaVigna and La Ferrara (2015) and La Ferrara (2016) for a review. Part of this literature exploits non-experimental variation to study the effects of commercially-oriented TV programs, e.g. Jensen and Oster (2009), La Ferrara et al. (2012), Kearney and Levine (2015), and Kearney and Levine (2019). These evaluations typically use the expansion of access to television over time as the main source of variation. Recently. RCTs have been put in place to study 'edutainment' on socio-economic outcomes. Banerjee et al. (2015), Ravallion et al. (2015), Coville et al. (2014), Berg and Zia (2017), Banerjee et al. (2019) evaluate interventions to promote, respectively, the consumption of iron-fortified salt, knowledge about a public-work program, financial literacy, HIV reduction, and safer sexual behavior. Compared to these studies, our goal is to assess the impact of information on a different outcome that is the choice of migrating through irregular and dangerous routes.

The remainder of the paper is organized as follows. Section 2 describes the background and the study setting. Section 3 presents the experimental design and data, and section 4 the empirical strategy. In sections 5 and 6, we present our main results, and section 7 concludes.

2.2 Background

2.2.1 Study setting

Guinea is a small low-income country located on the West Coast of Africa with a GDP per capita equal to 825US$ and a total estimated population of 12 million people (WB, 2019), 2 of which live in the capital, Conakry (INS, 2014).

Despite being so small, Guinea ranked first as a country of origin for migrants arriving in Europe through the Mediterranean in 2018, with an estimated 14,400 arrivals (UNHCR, 2019). Figure B.1 shows the fraction of migrants crossing the Mediterranean by month and nationality in the last 3 years, divided by the total number of crossings. The graph focuses on the first 5 countries for the number of migrants' crossings. Guineans have represented a large fraction of migrants undertaking this perilous route throughout the period, averagely counting around 8% of total migrants, with peaks between 15 and 20%. Also, Western Africans face a particularly high risk of trafficking and violence on their migration to Europe (IOM, 2018b), which makes them an important target for an information intervention focusing on the issue.

2.2.2 Migration routes

In the last years, the main route of irregular migration to Europe from West African countries connected them to North Africa through the Sahara desert. From there, migrants usually cross the Mediterranean Sea and transit to Italy upon rescue. Migrants have been mostly leaving from Libya since the collapse of its institutions following civil war has provided a fertile ground for smuggling operations. Aside from the drowning risk, those who travel through this route have to endure life-threatening conditions when crossing the desert–see, e.g., MMC (2018) and MMC (2019)–and then enter war-thorn Libya, where human trafficking has flourished. For example, a recent survey of irregular migrants in Italy mainly contacted in reception facilities and meant to be representative of the illegal migrant population in terms of nationalities, sex, and age structures, 76% percent of male migrants and 67% of female migrants have reported having experienced trafficking (IOM, 2018b). Western African migrants have recently started to take up another route (MMC, 2018), in which they leave by boat to Spain from Algeria or Morocco. Comparing the two routes' risks and costs is by no means an easy task, given the scarcity of timely information. However, there is some evidence that Mediterranean crossings are safer on the Spanish route IOM (2019b) and that migrants going to Spain face less risk of trafficking–for example, comparing IOM (2019a) and IOM (2018b). Migrants interviewed in Spain by IOM report a longer time spent in transit. A lesser proportion of migrants report they do not know the cost of the last leg of the journey–boat through the Mediterranean Sea–an indication that they were subjected to trafficking. With all the caveats of the case, these data suggest that a trade-off exists in choosing between routes. For this reason, we elicit beliefs about both the Italian route and the Spanish route.

2.3 Experimental design and data

2.3.1 Sample and Intervention

This study is a parallel-group randomized trial. We randomly selected 160 out of 300 high schools in Conakry and divided them into four separate arms with equal allocation probabilities: one treatment arm received an information intervention about economic outcomes abroad (T1); one arm received information about risks of migration (T2); one received both types of information (T3), and one was the control group. The geographic location of the schools across treatment groups is reported in figure B.3.

Within each school, we randomly selected 50 individuals per school among the list of students attending the third to fifth (and last) year and present at school at the baseline survey date, for a total of 7,387 individuals in our sample. The random selection of students in the project was conducted *in loco* after collecting students' registers for each class. To get a sense of how this is representative of Conakry's youth, roughly 52% of individuals in the 15-24 age bracket attend school in the city (INS, 2014). The focus on third to fifth grades students is motivated by the fact that migration rates seem to be particularly high in this age bracket. Available survey data on migrants registered at transition hubs in Italy report an average (median) age of 20 (19) years among Guineans (IOM, 2018a).

The intervention was designed in collaboration with *Un Sole per Tutti*, an NGO based in Italy and implemented by a local NGO called Aguidie (*Association Guineenne pour le Développement Integral de l'Enfant et du Jeune*). It consisted of a one-day session per treated school where students were gathered by Aguidie's moderators in a common room.

The overall structure of the T1 and T2 intervention was very similar. In both treatments, we provided information using: i) video material, ii) slides where we represented the probability of a given outcome by depicting ten stylized silhouettes of humans shading a given number in a different color, and iii) distribution of a flyer that students could bring home. Video material included around 15 minutes of testimonies and 5 minutes of a public information film. Testimonies were given by migrants and recorded at a reception center for asylum seekers (SPRAR) in Brescia, Italy, in 2017. Migrants interviewed were from West Africa, and they participated voluntarily. Treatment T1 and T2 lasted about 30 minutes, and treatment T3 lasted about one hour. SMS reminders with the day/time of the intervention were sent to participants on the day before.

T1 (Risk Treatment). Treatment T1 was administered in 40 schools and focused on providing messages on the risk and the cost of traveling from West Africa towards Europe. In this treatment arm, the video-testimonies were characterized by the recounts of the tough conditions of every stage of the journey, with a particular focus on the hardships experienced in the Sahara Desert, the time in Libya, and the journey by boat across the Mediterranean Sea. According to the testimonies, crossing the desert involves traveling in cars or jeeps packed with migrants well over their capacity, with the risk of dying choked by sand or perishing in a car accident. They reported direct or indirect experience of violent extortion by authorities during travel in Mali and Burkina Faso, imprisonment and torture for the same aim in Libya, and human sales occurring along the journey. Interviewed migrants depicted boat trips as extremely unsafe due to the overcrowding of small boats unfit for travel. The ability to swim does not represent a solution, according to one migrant, because of the large distance between the Libyan and the Italian coasts. Migrants communicate a general feeling of lack of dignity and dehumanization by smugglers. Overall, they report an extremely high risk of dying over the journey and several testimonies of travelers' death due to accidents in the desert, violence, starving, and drowning.

The example story film included the story of a migrant leaving for Europe from a city in Africa, crossing the desert in hardships and finally drowning in the Mediterranean Sea.

The slides included real data on the length of the journey, assembling statistics from IOM (2018b), and on the probability of exploitation and the probability of suffering violence using data from UNHCR (2017). The upper panel of Figure B.4 reports an example of a slide where we show that 7 migrants out of 10 have experienced physical violence during their journey across the Mediterranean.

Before closing the session, students discussed what they had seen and heard. At the end of the treatment, a a flyer was distributed with information on the risks connected to the journey recounted through a short story.

T2 (Economic Treatment). The second treatment focused on providing information on economic conditions in the destination countries. In the video about economic outcomes abroad, migrants' stories revolve around the lack of jobs and irregular migrants' position in Italy. They compare their expectations before leaving to what they found once arrived. In some cases, expectations were simply finding "a job and documents"; in other cases, subjects claim they had high hopes in terms of their financial situation once they arrived. Some reported that they hoped to obtain a house and a car with their work. In some cases, they wished to obtain education to be able to send money home. All migrants report not to have met their expectations. They tell about their inability to obtain legal status in Italy and to find a job. In general, individuals communicate a lack of financial independence. One of them refers to the gap between expectations and the reality they found in Italy and invites not to trust information in social media.

Example stories depict a migrant texting a friend with pictures of a nice house, while sleeping at the railway station, and a migrant texting the picture of a nice car while begging in front of a supermarket.

Finally, we provide 'hard' information, through slides, about economic outcomes referred to France, Italy, and Spain, the three most frequent destination countries. They include the probability of working, the probability of studying, and the probability of getting asylum when requesting it. We retrieved the first two from the EU Labor Force Survey and the third from Eurostat.

The lower panel of Figure B.4 reports a slide we showed to the students. Before closing the session, students discussed what they have seen and heard. Again, at the end of the treatment, a flyer was distributed with information about economic outcomes of irregular migration, recounted through an example story.

T3 (Double Treatment). In treatment T3 we provide the information in T1 and T2.

2.3.2 Data

We conduct three rounds of data collection. Baseline data collection started in November 2018, at the beginning of the academic year, and lasted until January 2019. The intervention started in February and ended in mid-April 2019. The 1^{st} follow-up survey took place from April to June 2019, at the end of the academic year. The survey was rolled out so that each school was surveyed approximately one month after the intervention. A 2^{nd} follow-up survey has taken place from mid-January 2020 to mid-April, roughly one year after the treatment.

Participation in the surveys was voluntary, but we did not record refusals to participate by students present at school and available (not involved in exams). However, for all students who chose to participate, we did incentivize the completion of the survey by drawing three tablets among all participants who completed the questionnaire, with a value of around \$200—this was a relatively high incentive considering a GDP per capita of around \$824. Surveys were self-administered in class using tablets.

The main outcomes we elicited during the baseline and the follow-up surveys were migration attitudes, perceptions about risk, and perceptions about economic outcomes. During the 2^{nd} follow-up survey, we also collected migration outcomes.

Regarding questions about migration attitudes, we took inspiration from the Gallup World Survey: a series of three questions asking (i) whether the subject would migrate to another country if this were possible, (ii) whether she was planning to move to another country, (iii) and whether she was preparing for the move. For positive answers to (i) and (ii) we also asked which countries they wanted to migrate to, separately.

We elicited perceptions of risk as probabilities of trafficking and other risky events occurring along the journey. We also asked about the expected duration and the expected cost of the journey. We posed all risk questions about the sea route through Italy and Spain separately. To elicit probabilistic beliefs, we first asked the individual to imagine 100 people exactly like her undertaking a migration through a given route, and then we asked how many of those 100 individuals were going to see a particular event realizing. For example, *"Among those 100 people, how many of them will be beaten or physically abused during the travel?"*

As for economic outcomes abroad, we first asked the subject the intended destination in Europe for an individual like him/her. Then, we asked questions on the probabilities of both positive and negative economic outcomes referring to the country mentioned: finding a job. We posed these questions in the same way as before, by referring to 100 hypothetical individuals similar to the subject. We also asked a question about expected wage[1] abroad, and about the cost of living in the following way: *"Consider one person living alone in Conakry. This person spends 1 000 000 Guinean Francs per month to cover all his/her expenses (rent, food, transport, etc.). How much should this person spend to live in the same way in CHOSEN_COUNTRY in Guinean Francs? Suppose that his/her consumption (rent, food, transport, etc.) remain the same."*

[1]Our analysis of monetary outcomes has to deal with a possible complication. Due to recent high inflation, Guineans find it practical to refer to high quantities of GNF by disregarding millions, or, in some cases, thousands. For example, in some cases, people refer to 5,000,000 GNF as 5 GNF. To reduce the possibility of mistakes, our question had an automatic follow-up check question. For example, if an individual with 5 GNF as an imputed wage answer, we would ask: *"Did you mean 5 million GNF?"* If the answer was negative, the first question was re-asked. In cases of uncertainty, we use the "corrected answer".

During the baseline survey, we also collected data on the subject household's wealth. In particular, we are proxying this with two measures. First, we employ a measure of fees (with inscription/reinscription payments) at the school that the student attends at baseline. In particular, we take an average of the prices for grades composing *Lycée*–the three grades involved in the project. These do not vary by student, but only at the school level. To use this variable in heterogeneity analysis, we summarize it with a dummy taking value one if the student's school's fees are above the median for schools in the sample. Second, we construct an index summarizing durables ownership by the student household at baseline. We construct such index with a PCA aggregator—using the 1^{st} factor–from dummies for ownership of radio, television, mobile, watch, car, bike, refrigerator, fan, air conditioning, and motorbike. We summarize this information by constructing a dummy taking value one if the PCA aggregator is above the median for students in the sample.

We collect migration information at the 2^{nd} follow up from various sources, aggregated hierarchically, using the following order. First, we consider the presence at school at the date of the tablet survey. Second, we conduct phone surveys with subjects, based on phone numbers collected during previous surveys. Third, we completed phone surveys with one of two contacts, again using numbers given by the subject at previous surveys. The phone surveys in the previous two points were shorter than school surveys on tablet, and only collected information about the migration, school, and employment status of the individual, together with migration attitudes. We tried to reach the student for four days on the phone and the contact for 3. We stopped at the end of the time limit or when we were able to reach the student. Fourth, we conducted short school surveys on the day of the school survey. During these surveys, we asked classmates and schoolmates about the migration and school status of those absent. If they did not have any information, we asked at the school administration. Fifth, when the first day of calls was not successful in getting in touch with the student, we asked for migration information about the student to students contacted by the phone survey in the same school. Sixth, we kept track of the phone status of students during surveys. We check whether the phone was never on as a further indication of migration status. Using this surveys, we construct the variable 'Out of Guinea', a dummy taking value one if the subject has been outside Guinea since at least 30 days before the survey, and 'Out of Conakry', registering if the student is out of the city where surveys and interventions were conducted. The rationale for collecting the latter variable is that Conakry is not close to any of the borders, as suggested from the map in Figure B.2. Most importantly, it is far from the border with Mali, a key transit country for migration to North Africa and then Europe. For this reason, we might expect that anyone wanting to leave by land means of transportations will have to leave the city first. This could be even more important if migrants finance next steps of their migration by working at transit locations.

2.4 Empirical Strategy

To test the effect of our intervention on migration attitudes, risk perceptions, and perceptions about economic outcomes at follow-up t we estimate the following equation:

$$y_{ti} = \alpha + \beta_1 T_{1,i} + \beta_2 T_{2,i} + \beta_3 T_{3,i} + \rho y_{0i} + \sum \gamma_j S_{j,i} + \varepsilon_i \tag{2.1}$$

Where y is our outcome of interest at the follow-up t, and time 0 is the baseline, T_1 stands for risk treatment, T_2 for economic, T_3 for double, i indexes the individual and $S_{j,i}$ is a dummy taking value 1 if individual i was in the stratification partition j. We only stratified over school's students' number, and splitting schools in two categories–above the median and below the median. We cluster ε_i at the school level as the treatment was randomized at that level.

The outcome at baseline is meant to correct possible challenges to identification posed by attrition, and it is not included when analyzing migration outcomes for two reasons. First, because migration outcomes are not defined at baseline. Second, because as it will be clear in what follows, attrition for this variable is extremely low.

Outcomes are divided into four groups. Migration choice, migration attitudes, perceptions about the risk of the journey, and perceptions about economic outcomes abroad.

As far as migration choice is concerned, we construct a migration variable, and test robustness by varying the information used in determining migration status. The first measure (subject) only includes information obtained from the subject itself, from tablet surveys in school or the phone survey. The second measure (contact) contains information above and information gathered from contacts given by subjects, through phone surveys. The third variable, short school survey (SSS), added to the previous information also the results of the short survey conducted in school with schoolmates of absent students and the administration. The fourth measure adds information about phone status, considering 'migrated' those who have never had their phone on.

As for migration attitudes, the first variable, "Wishing to Migrate" took value 1 if the subject answered "Yes" to the question outlined above asking whether he was willing to migrate. As for "Planning to Migrate" was constructed in the same way, except that for those saying they would not migrate to another country ("Wish" = 0), the question was not asked and a "No" was imputed. "Preparing to Migrate" was constructed in the same way starting from "Planning".

Risk perceptions included probability questions with responses on a scale 0-100, referring to the following outcomes: being beaten or physically abused during the journey, working without pay, held against their will during the journey[2], dying before the trip by boat, dying during the trip by boat, having been sent back to Guinea one year after arrival. Questions about expected duration and the expected cost of the journey were asked in months and Guinean Francs (GNF), respectively; in the analysis, we winsorize them at the $5^{th}/95^{th}$, to deal with outliers, and we take the inverse hyperbolic sine of the variable to deal with skewness. We conduct separate analyses by the route.

As for economic outcomes abroad, probability questions (0-100) included: finding a job, continuing studies abroad, becoming citizens of the country, receiving money from the government, getting asylum, percentage of population in favor of migration in receiving countries, going back to Guinea in 5 years after arrival. Questions about wage and cost of living were asked in GNF, but we also asked them in currencies of the countries they referred to during the follow-up for a robustness check. Again, we winsorize them at the $5^{th}/95^{th}$, to deal with outliers, and we take the inverse hyperbolic sine of the variable.

We conduct analyses on the treatment impact on single variables and on indexes aggregating variables of a given category: this partially solves statistical problems connected to testing multiple hypotheses, and it augments the power of our tests by reducing random variation in the single variables. We construct these indexes in two ways. First, we aggregate our perceptions variable in two aggregate indexes using PCA, one for expectations about economic outcomes, *PCA Econ perceptions* index, and the other for expectations about risk outcomes, *PCA Risk perceptions* index. The indexes are constructed by running a principal component analysis on the Economic perceptions variable and the Risk perceptions variable, and extracting their first principal component. Second, we aggregate the same variables using the procedure described in Kling et al. (2007): we average the z-scores for all variables in a category and sum them with a sign agreeing with the message of the treatment. We construct *Kling Risk perceptions* index and *Kling Econ perceptions* index, by imposing a sing of (+) to all of the risk variables, and (-) to all of the economic, except probability of being sent back, entering with a positive sign. As a robustness check, we construct a further index where *Kling Risk perceptions* index where journey cost enters positively. Also, in order to deal with multiple-test hypotheses without

[2]The latter two are the working definition of trafficking experiences in (IOM), together with offers of arranged marriages, but these are infrequent in the Central Mediterranean route according to IOM (2017), and so they were not asked.

resorting to aggregation, we adjust p-values according to the free step-down resampling method Westfall et al. (1993), controlling the family-wise error rate (FWER).

2.5 Data and Descriptive Statistics

2.5.1 Balance and Attrition

Balance checks on main migration attitudes, perceptions, and controls are reported in Table B.1. The first column reports the mean and the standard deviation in the control group. The second, third, and fourth column report differences in means with their standard errors for the Risk Treatment arm, the Economic Treatment arm, and the Double Treatment arm. The only variable to display some imbalance is the expected length of the journey on the Italian route, with a positive difference compared to control in the double-treatment arm, the significant difference at a 10% level. However, since we performed tests for 30 variables, this might well be due to chance.

Table B.2 shows participation by treatment arm and round. We registered an attrition rate of 39% at the 1^{st} follow-up, where we only conducted tablet surveys. Attrition is slightly higher in the treatment arms than in the control arms. Still, the difference is only marginally significant for the Risk Treatment when controlling for baseline outcomes, as reported in Table B.3. As we show in Table B.3, attrition at the first follow-up is positively correlated with age. Also, attrition is positively correlated with migration intentions and negatively correlated with perceptions of the risk of migration, particularly with the cost of the journey, probability of being beaten, and the probability of death during the trip by boat. This is in line with the explanation that some of the attrited students are less likely to be at school precisely because they have decided to migrate; they might have migrated already or invest less in schooling because they do not consider it complementary to migration. In the second part of the table, we report the fraction of interviewed at the second follow-up, by progressively including data sources. We managed to conduct tablet surveys with 32% of the baseline students. As shown in Table B.4, we keep finding a higher rate of attrition in the risk group; however, the difference is significant only when controlling for outcomes at baseline. A fraction of 97% completed either a school table survey or a phone survey at follow-up. As reported in Table B.5, we do not find evidence of unbalanced attrition when considering the two data sources together. The same is true for the 97.6% having at least a survey with a contact, as reported in Table B.6, and for the 99.4% having at least a Short School Survey (SSS). We see close to no attrition for those having at least some information about phone status.

Summing up, we observe attrition to be potentially correlated with treatment when measuring beliefs and migration attitudes at the first follow-up, and beliefs at the second follow-up. Then, we control for outcomes at baseline when analyzing the impact of the information session on beliefs and migration attitudes.

2.6 Results

2.6.1 Main Analysis

In what follows, we show the effect of our three treatments on migration outcomes, migration attitudes, perceptions about risk, and perceptions about economic outcomes abroad. The reported effect is an Intention-To-Treat–because 12.6% of the students surveyed in the baseline did not attend the information session. As we will see, we find no impact overall on migration, and effects on attitudes and beliefs to be present at the first follow-up, but not to persist to the second. However, in the next session, we document strong heterogeneity in migration outcomes by wealth, with negative effects on migration variables concentrated among the poor.

Table B.8 and B.9 report treatment effects on the migration variables. Each column introduces one more source of data. The first column only reports measurements coming from interviewing the subject at school or on the phone. The second adds information collected on the phone from contacts given by the same students. The third adds information obtained from schoolmates and the administration. The fourth adds information about phone status. We find no effect on migration out of Guinea, which occurs for between 0.6% and 1.8% depending on the type of data used. We document only a timid effect on migration out of Conakry. This is negative and significant at the 10% for the treatment about economic information, and only present when considering surveys with subjects, exclusively. There, T2 reduces migration by 1.4 percentage points, compared to 5.2%-6.2% migration rates out of the city. Effects become insignificant when including other data sources, but they remain negative and very close in magnitude.

Table B.10 reports the impact of the treatment on migration intentions at the first follow up. The table reports treatment coefficients with and standard errors obtained from three separate regressions for outcomes: 'Wishing to migrate', 'Planning to migrate', and 'Preparing to migrate'. The coefficients are all positive across outcomes. The effect on 'Wishing to migrate' is significantly different from 0 for all treatments, and around 5 percentage points. This compares with 25.6% wishing to migrate in the control group at follow-up. As for 'Planning to migrate' only Risk (T1) and Double Treatment (T3) are significant; when they are, the impact is around 3 percentage points, against 16% planning to migrate in the control group at follow-up. The level of significance of coefficients decreases from 'Wishing' to 'Prepare', with outcomes becoming increasingly rare at the same time–4.2% say they prepare to migrate at baseline. Table B.11 displays the impact of our treatments on migration intentions at the second follow up. The students' sample in this table include tablet surveys with students present in school, and phone surveys with students themselves–no indirect information is employed here. Only the negative impact of the economic treatment (T2) on 'Wishing to Migrate', remains significantly different from 0, at a 5%. Such effect amounts to 10% of the proportion expressing a wish to migrate in the control group at the second Follow-Up–53.1 %. Table B.11 includes a much larger portion of the baseline students compared to Table B.10, since it also features phone surveys, which we did not conduct at the first follow-up. However, different results do not seem to depend on the different selection of students interviewed. Indeed, when we replicate the analysis restricting to students who were interviewed in school during the first follow-up, in Table B.12, results remain virtually unchanged.

Tables B.13 and B.15 report the impact of treatments on risk perceptions about the Italian and Spanish routes, respectively, at the first follow up. The former table shows the impact on perceptions for the Italian route, while the latter shows the effects on the Spanish route's perceptions. All treatments have a positive and significant effect on all risk outcomes. Impacts are very similar for the outcomes of the Italian route and of the Spanish one. Effects range between around 5 percentage points and 12 percentage points, comparing to probabilities at baseline between 38 and 57 percent. Accounting for FWER p-values does not affect significance.

Results are suggestive of two types of spillovers. First, we find that the economic treatment affects risk perceptions. This is possibly due to the fact that the treatment might have pushed students to look for information after the treatment. Second, we find a spillover across routes, hinting towards a strong perceived correlation between the two main routes to reach Europe.

The effect is positive and significant both for variables relating to hard information given during the treatment–'Kidnapped', 'Forced to work', and 'Beaten'–and for others. Some of them–e.g., probability of death, both by boat and not–was a minor theme in the testimonies. For others–e.g. probability of being sent back–students might have revised their expectations due to perceived correlation with other outcomes.

Now let us turn to the other two outcomes relating to the costs and risks of the journey–duration and cost– at the first follow up reported in Tables B.13 and B.15 for Italy and Spain, respectively. Risk treatment (T1) and Double Treatment (T3) have a positive and significant effect on the perceived duration, between 14% and 24%. In contrast, the economic treatment's impact is closer to zero and non-significant, differently from other outcomes. A possible explanation is that this is a less salient outcome than others, and then students end up acquiring less information about it than for other outcomes after the treatment. As for the cost outcome, there is almost no significant impact, which is consistent with this variable not being part of the information given to students. The only significant impact is that for the double treatment for the route through Italy. However, this effect is negative, with a magnitude of about 50%. A negative and similar effect, but not significant, on both of the other treatments suggests that it is not only one type of information that drives the result. Again, using FWER p-values does not change statistical significance. This might be due to a number of mechanisms involving both treatments. First, students might be revising the price of the journey downwards after having revised downwards perceptions about the journey's amenities, namely having increased the probability assigned to bad outcomes. Second, students might understand migrants' stories as implying that exploitation could substitute for a financial payment. Third, given outcomes abroad, students might be perceiving individuals who traveled, and their testimonies, as liquidity-constrained.

Overall, we find a positive effect of treatment on risk perceptions on the expectation of journey duration and a zero or negative impact on cost perceptions. We also check that the effect on the *PCA Risk perceptions* index and the *Kling Risk perceptions* index in Table B.19 described above–capturing undesirability of the journey outcomes–is positive and significant. Let us now turn to the effect on beliefs about economic outcomes abroad.

Table B.14 and B.16 report the treatment impact on risk perceptions at the second follow-up. As for the Italian route, the Double Treatment (T3) has a positive and (FWER) significant effect on the believed probability of being beaten, kidnapped, or dying in the boat trip, with effects ranging between 10 and 20% of control mean at the second follow up, and roughly half of effects in the previous follow up. Effects on the probability of being forced to work and death before boat are significant while somewhat smaller than those at the previous follow up, but not robust to FWER p-values. Also, the effect on PCA is positive and significant. The economic treatment seems to have a negative effect on expected journey duration and violence, but none of them are robust to FWER p-values. Switching back to Table B.19, we observe the same pattern when we look at Kling (2007) aggregates of our variables. These effects are less robust when we look to the impact of the treatment on risk beliefs for the Moroccan-Spanish route of migration. There, T3 has a FWER-robust impact on violence beliefs and an effect on the PCA aggregate. It also displays an effect on the probability of being forced to work or kidnapped, but this is not

FWER-robust. Also, T2 keeps having a negative impact on expected journey duration, which is now robust to FWER. The effect on Kling (2007) aggregates in Table B.19 is only significant when the journey cost enters negatively. In sum, we see little evidence of spillovers between information types at follow up and a persistent but limited effect of T2 and especially T3.

Table B.17 shows treatment on beliefs about economic outcomes at the first follow up, only focusing on probabilistic outcomes–leaving out expected wage and cost of living abroad.

All of the treatments pushed students to negatively update their beliefs about chances abroad: the effect on the probability of outcomes is negative. However, the size of coefficients and significance levels vary with the treatment type.

The risk treatment has the weakest effect. Using FWER p-values, it is only significant for the belief over the probability of finding a job and the probability of becoming a citizen. These two effects are not negligible in magnitude, decreasing the probability of good outcomes by around 5 percentage points, compared to averages at baseline between 26 and 28 %. Spillovers of the risk treatment on perceptions about economic outcomes might be understood, again, through students increasing information acquisition about migration in general, after the treatment. The economic treatment is also significant for the probability of the government giving financial help, the probability of having returned five years after arrival, the probability of obtaining asylum, and the probability of continuing studies at the destination country, with impacts now ranging between -9 and -3 percentage points. The strongest effect is on the perceived probability of finding a job, which was included in the treatment hard information section, alongside the probability of obtaining asylum, and education. The impact of the double treatment is higher for the previous variables, and ranges between minus 10 and minus 6. Also, the treatment has a negative effect of around 4 percentage points on the beliefs on the percentage of people in favor of migration at the destination country. Again, results are consistent with the idea that students see those outcomes as correlated, and update both on the variables stressed during the information session and those who are not. Once more, we check that the effect at the first follow-up on the *PCA Econ perceptions* index and on the *Kling Econ perceptions* index in Table B.19–that should capture a positive view about outcomes abroad–is negative and significant.

We report impacts on economic beliefs at the second follow-up in Table B.18. As we observe, T2 had a negative and significant effect on employment, education, and financial help beliefs, which are robust to FWER p-values, and about 15% of mean in control at the 2^{nd} Follow-Up. The effect on the probability of becoming a citizen and getting asylum is similar but not robust to FWER. The effect on the perceived living cost is reverse. Also, we find a negative effect on the PCA aggregator. The risk treatment (T1) has a negative impact on education and citizenship beliefs, comparable in magnitude to the previous, but these are not robust to FWER. The same is true for the double treatment (T3) in the case of education beliefs and beliefs about financial help from the government. Overall, we find that T2 is the only one to have a robust persistent effect on economic beliefs. The same point can be made by looking at the impact on a Kling (2007) aggregate of the economic variables, where negative outcomes have a positive sign. Such analysis is reported in Table B.20 and displays a positive and significant effect of T2. These results are unsurprising when thinking about T1 because this did not deliver information about economic outcomes; however, T3 did, together with risk information. Its effect might have been muted by the sheer amount of information delivered to students during the information session.

2.7 Heterogenous effects: Wealth

In this section, we explore heterogeneous effects of treatments by wealth. When looking at the effect on migration and migration attitudes, we employ the two measures of wealth listed above, one recording whether school fees at the subject's school are above the median, and the other telling whether the subject's household owns more durables than the median. Then, we focus on the fees variables when analyzing the effect on beliefs, to streamline the exposition.

Before proceeding to the results, let us look at the balance within each wealth category, by variable employed. Table B.21 reports the balance table for students at expensive schools. We find some imbalance in the expected duration of the journey to Italy–but not to Spain–, which is slightly higher for T3. Also, students in T2 expect a lower probability of asylum. The balance for inexpensive schools is reported in Table B.22. There, we find students in T1 to be less willing to migrate on average but this is not true for migration plans or migration preparation. The same group expects a somehow shorter journey, on average. In passing, we notice that such effects point in opposite directions in terms of pessimism, compared to the control group. Subjects in T2 expect a slightly higher expected living cost at the destination. Those in T3 have slightly more father's schooling, but not mother's one, and perceive a higher probability of having returned after five years of migration. In short, we do find some imbalance in the two tables. However, this is very limited if compared to the over 37 potential variables tested, and it relates to isolated variables as opposed to groups relating to beliefs, attitudes, or demographics.

Turning to the balance by categories of durables ownership, we report results for students with durables above the median in B.23. Students in T2 have more contacts abroad and perceive a lower probability of finding a job abroad. Statistics for students with low durables are reported in B.24. Students in T2 expect a lower cost for the journey to Italy, but not to Spain. Also, they expect a lower probability of being held against their will in the route through Spain, but not through Italy. Students in T3 attach a somehow larger probability to dying in a shipwreck and to the event of suffering from violence while taking the Moroccan-Spanish route. Students in T4 attach less probability to suffering violence when passing from the Libyan-Italian route. Again, overall we observe some imbalance, limited to few items.

As for results on migration outcomes, we first show treatment effects on migration from Guinea interacted with the high fees dummy in Table B.25. We report the standard error for the sum of the base coefficient and the interaction in square brackets, with relative significance stars, under the interaction coefficient and its standard error. The base coefficients represent effects at inexpensive schools. There, we find negative coefficients for all treatments. These become significant for the economic treatment T2 for the survey with the subject, for short school surveys, and for the sources up to phone status, with significance levels 5, 10, and 5%, respectively. In terms of magnitude, these effects range between -0.4 percentage points and -1 percentage point. The interaction, too, is significant, but the sum of the base coefficient and interaction is not significantly different from zero. We document a similar pattern for migration from Conakry in Table B.26. T2 is significant for all data categories, with 10, 10, 5, and 5% significance levels, respectively. The coefficient ranges from -1.8 to -2.3 percentage points. The sign on T3 is negative, too. However, the sign on T1 is positive. No interaction or sum of interaction and base is significantly different from 0.

We find additional effects on migration from Guinea when looking at the interaction with the dummy reporting a durables index above the median in Table B.27. However, effects are now concentrated on the T1. The effects are significant at the 1% level or all data sources when looking to students with durables ownership below the median, ranging in magnitude from -0.8 to -1.8 percentage point. All other base coefficients are negative. Interaction coefficients are positive, and also significant in the case of T1 and T2. The sum of base and interaction is positive and significant for T2 when for sources up to the short school survey and up to the phone status. Then, there is some evidence that migration has increased by 0.4-0.5 percentage points in response to the T2 among the wealthy. As for effects on migration from Conakry, these are reported in Table B.28. Here, all the base treatment coefficients are negative. However, only the economic treatment coefficients are significant at the 10, 10, 5, and 5% level. Magnitude is comparable to the case of the fees interaction, ranging between -1.9 to -2.4 percentage points. Also, we see that the sum of base and interactions is positive for T1, suggesting that this treatment increased migration out of Conakry for the wealthy.

Results on migration are mirrored somehow in the results about migration intentions, with minor discrepancies. Table B.29 shows the treatment results on migration attitudes when interacting treatment with the dummy for high fees. We see a negative effect of T2 on the students of inexpensive schools, and significantly different from 0 for wishing, planning, and preparing to migrate, at the 5, 5, and 10% significance level, respectively. We also document a negative and significant effect of T2 for students at expensive schools, but only in the variable 'Wishing to Migrate'. Table B.30 reports the same analysis, but performed using the dummy for high ownership of durables. We find a significant and negative effect of T2 on the least wealthy for 'Wishing to Migrate' and 'Preparing to Migrate'. Coefficients on T1 are also negative and significant in the case of 'Preparing to Migrate'. We also find such an effect for wealthy students for T1, for 'Wishing to Migrate'. Finally, we document a positive impact on 'Wishing to Migrate' of T1, for the wealthy.

Using data on beliefs, we try to determine whether heterogeneous effects could be due to differential changes in beliefs across expensive and inexpensive schools. In particular, we estimate effects on beliefs separately for expensive and inexpensive schools. This analysis should be taken with a grain of salt for the relatively low fraction of students who completed a survey in school at the second follow up–however, they do not seem to support this channel. Tables B.32 and B.31 look at the effect on risk beliefs about the Italian route for inexpensive and expensive schools, respectively. If there is a differential effect, this seems to be that the double treatment had a larger impact on beliefs in wealthy schools. The same applies to the route through Spain, as reported in B.34 and B.33. Looking at the effects on economic beliefs, splitting the sample, we find no result robust to FWER p-values in Tables B.36 and B.35, although we find that T2 had slightly more pronounced effects on the least wealthy. In sum, we do not see overwhelming evidence that beliefs drove the differential effects.

2.8 Conclusion

Potential migrants might sometimes miss valuable information regarding their choice to leave. In the case of irregular migration from West Africa to Europe, this information can relate to the dangers of migrants' journeys and scarce integration in the European labor market. We assess the impact of an information intervention, where students are informed using previous migrants' testimonies, together with hard data. Results show that this information successfully changes beliefs and changes intentions to migrate at the first follow-up. However, not all of these effects persisted in the second follow up. Migration choices at follow up are impacted negatively only among poor students. Depending on the measure of wealth used, the effect is localized on risk or economic treatment. These findings are very preliminary, but they seem to suggest that information changed the behavior of the category most at risk.

Chapter 3

Third Party Interest, Resource Value, and the Likelihood of Conflict

With Matteo Bizzarri and Riccardo Franceschin

3.1 Introduction

Armed conflict is often related to the ownership of a resource, such as an oil field, a stretch of land, or access to the sea. Incentives to engage in war depend on the value of resources that can be appropriated with it by any prospective participant. On the one hand, high resource value invites conflict by increasing incentives to predate. On the other hand, resource wealth induces stabilizing efforts by powerful third parties interested in safeguarding access to extraction or consumption. Since an increase in resource value induces higher predation but also higher deterrence by third parties, its effect on conflict occurrence is unclear *a priori*. This paper sheds light on the issue, formulating and testing a theory of resource war in the presence of third parties.

Our work makes a number of contributions to the understanding of resource curse in conflict. First, we set up a simple and flexible theoretical framework involving a resource-holder, a predator, and a powerful third party; in this setting, we establish a hump-shaped relation between resource value and conflict. Second, we specialize our model and show its mechanics for two main cases of interest: resource-buying and resource-selling third parties. Third, we show empirical support for our results, highlighting third parties' role in driving the relation between resource presence and conflict.

A deeper understanding of the mechanisms linking the value of natural resources to conflict contributes to the appreciation of the geographical determinants of conflict; further, it improves our comprehension of the challenges raised by today's rapid technological change. Technological progress can rapidly affect the importance of a resource as input for production. For instance, the surge in the use of battery-powered devices quickly raised the strategic importance of cobalt for our economies (USGS and USDI, 2012). Similarly, pollution and the threat of climate change prompted investments in the development of alternatives to fossil fuels, in turn affecting conflict incentives in oil-rich areas for local countries and third parties. Our results are a step toward a more thorough understanding of these issues.

We develop a model of resource war as a sequential game. First, a predator decides whether to attack the resource holder. Then, a powerful third party decides if to intervene and back the defendant to protect the resource. Both the third party and the predator want to maximize their payoff, which depends on the resource value. Heterogeneity in the cost of war induces a probability of conflict, which depends on value. Under general conditions, such probability is increasing in value if the value is low enough and decreasing if the value is high enough. Adding a bit more structure, we find that the probability of conflict is a single-peaked function of resource value. We also explore several extensions to our baseline model. Results are unchanged if we add private information on war costs. In other cases, such as transfer opportunities better modeling civil conflict, uncertainty in the third party's victory, and resource-value-dependent probability of conflict, we find them to be robust under some condition. For instance, results carry through in the context of civil wars with non-concentrated resources, as long as there is conflict. The latter occurs due to a mismatch between the predator's ability to exploit the resource and its military power, similar to Herrera et al. (2019). Also, how the likelihood of conflict is related to value depends on the specific characterization of resource value. For this reason, we analyze in depth two benchmark examples and make comparative statics on different notions of resource value.

In our framework, a third party is any entity commanding military power directly or indirectly. The former can be a state or ethnic group endowed with an army, interested in keeping access to the resource. One instance of the latter case is a multinational enterprise extracting the resource abroad, able to lobby its home country into conflict. Third parties are known to intervene in interstate and intrastate conflicts. Their role has been analyzed in the extended deterrence literature of political science: a classic reference is Huth (1989). Many works have added to this corpus analyzing in depth many policy-relevant cases where third parties side with one of the contestants. Chyzh and Labzina (2018) argue that, for deterrence concerns, third parties may support incumbent leaders even when they are likely to fail. Chang et al. (2007) study third party intervention in a context similar to ours, with third parties siding with an ally, but their focus is on the relation between the timing of intervention and the equilibrium outcome. Rosenberg (2020) studies a third-party intervention and rent extraction, focusing on cases where the third party uses war between resource-holder and defendant to extract a rent. Di Lonardo et al. (2019), instead, study how foreign threats influence the stability autocratic regimes, when they support the incumbent's. Levine and Modica (2016) study the outcomes of interventions of a third party interested in avoiding other players' hegemony in a region. Another group of papers studies 'neutral' interventions with humanitarian or welfare motivations, such as Meirowitz et al. (2019) and Kydd and Straus (2013). The distinction between neutral and biased intervention is empirically relevant. For instance, Regan (2002) documents that external intervention in civil wars often increases conflict length; however, biased interventions, backing one opponent, result in lower duration compared to neutral interventions. Our work connects the previous literature on the role of biased third parties to the key issue of the conflict resource curse. We consider the universe of situations in which the third party can only side with the resource-owner. Among others, this captures high transaction costs, or reputation costs from reneging on alliance commitments, which Gibler (2008) shows to be empirically relevant in understanding dispute behavior. Further, we abstract from the moral hazard problem induced by the third-party intervention on the incentives for the resource holder to declare war. We focus on the case in which it is the resource-poor country that can attack, but the resource-rich one has no interest in doing so. After providing a general formulation of biased third-party presence and its role, we specialize our framework to the cases of resource-buying and resource-selling third parties. We show that, under a reasonable way to model such cases, our main result of a hump-shaped relation between conflict and value holds in this context. We connect to work by Acemoglu et al. (2012) analyzing the interaction between the natural resources' market structure and the incentives of predatory countries to start a war; we include the role of deterrence in this context, abstracting from dynamic strategic incentives.

We find empirical support for our theory, verifying the prediction that the probability of conflict should be non-monotonic in resource value; in doing so, we draw on the accumulated evidence on the resource curse. A long-lasting stream of literature has explored the correlation of resource presence with negative outcomes in economics, politics, and international relations (see Van der Ploeg [2011] for a multidisciplinary survey). Seminal work by Collier and Hoeffler (2004) has found a statistically significant and hump-shaped relationship between the probability of civil conflict onset and resource dependence that they use a proxy for resource abundance. Their empirical strategy exploited Correlates of War (COW) data on civil conflict and primary exports over GDP to measure resource abundance. Fearon (2005) showed that the results were not robust to several small changes to the definition of the dependent variable, conflict onset, or in the specification used in OLS. Instead, he claims that the relation found in the data is increasing due to predation incentives. Brunnschweiler and Bulte (2009) conduct a similar analysis to Fearon (2005), measuring resource wealth with the net present value of rents from natural resources measured by the World Bank; they find little association between resource presence and conflict. Nonetheless, a recent wave of literature has revived the strength of the resource-conflict link. Caselli et al. (2014) study the case of oil, using the Militarized Interstate Disputes (MID) dataset to measure conflict; they highlight the role of resource distance from the border. Berman et al. (2017) show a positive impact of the price of minerals on conflict in Africa, using conflict microdata from the Armed Conflict Location & Event Data Project (ACLED). Also, Paine (2017) and Paine (2019) theorize that economic activities such as oil extraction can rationalize also civil war incentives. Indeed, Hunziker and Cederman (2017) have shown a positive association between resource presence and civil conflict in the case of oil resources, leveraging on exogenous variation in sedimentary basins presence in a given area, and using the UCDP/PRIO Armed Conflict Dataset, including civil wars and interstate disputes. Like many other works in the literature, authors use a linear model; if, however, strategic considerations lead to a hump-shaped relation, this may impair inference (Signorino and Yilmaz, 2003). In this work, after providing a new conceptual framework to think about the link between resource-presence and conflict, we test the proposed model using established measures of conflict and resource, together with the plausibly exogenous measurement of oil presence introduced by Hunziker and Cederman (2017). We couple such data with a theoretically driven functional form. Further, we add two innovative way to measure third party involvement, relying on measures of personnel of the US Department of Defense abroad and arms imports from the US. We find a hump-shaped relation between resource value and conflict, driven by countries exposed to third party presence.

We organize the rest of the paper as follows. In the next section, we explain our model, show our theoretical results, and comment. In Section 3.3, we show how our results apply to contexts of civil war. In section 3.4, we show how our results apply in the context of resource-selling and resource-buying third parties. In section 3.5, we empirically test our theory. Finally, we conclude.

3.2 Model and Main Result

The model is a sequential game played by three countries. At the beginning of the game, country R holds a scarce resource. Country P, the predator, can attack R and obtain control of the resource if he wins the confrontation. In this case, R loses control of the resource. Country T is a powerful third party that suffers damage if resource ownership shifts to P. T cannot be attacked and cannot attack first, for example, because of institutional and international constraints. However, it can intervene if P attacks R. If there is an attack and no third-party intervention, P wins with probability p_w. If there is a third-party intervention, R wins for sure.

The payoff of P from having possession of the resource is Π_P, while the payoff of T from exploiting the natural resource is Π_T. This can also be interpreted as the amount of payoff that is lost if P gains control. The payoffs from losing control of the resource are normalized to 0. We assume that these payoffs are functions of a common parameter, v, that we think of as an index of the value of the natural resource owned by player R. We assume that both payoffs Π_P and Π_T are increasing in v. We exploit this formulation to comparative statics about context-dependent variables of interest, such as the price or quantity of the resource. We explore these different interpretations in section 3.4. For now, to describe the mechanics of the model, we remain agnostic on the precise nature of v.

We introduce a stochastic additive cost of war, ε_i, with distribution F_i, paid by contestants if conflict occurs. These costs are common knowledge in the baseline model, but this assumption is relaxed later on in this section. The purpose of modeling this component is twofold. First, we aim to model war costs[1], including physical, financial, political costs. Second, we can think of them as analogous to a "measurement error" faced by the econometrician or external observer, that, as a consequence, perceives war as a stochastic outcome. We adopt the perspective of this external observer; so, our object of study will be the probability of conflict and how it varies with parameter v.

Consistently with this interpretation, we want to be as agnostic as possible on the characteristics of the distribution. So we impose minimal assumptions: we assume it has a density f_i, and $supp f_i \subseteq [m, M]$, where m is finite and smaller or equal to 0, while $M > 0$ can also be infinite. We allow for $m < 0$ to accommodate cases where a player might have "preferences for war". We assume that the errors are independent, $\varepsilon_P \perp \varepsilon_T$.

We normalize $\Pi_i(0) = 0$. This is without loss of generality because we allow the errors

[1] For simplicity, we initially assume that these costs are common knowledge of the players, and we later show that this assumption is not crucial.

ε_i to be negative and have different distributions, so the threshold 0 retains no special effect. To put it differently, $\Pi_i(v)$ is the difference in the payoff of i in the case where i has access to the resource compared to the case where he has no access.

3.2.1 Equilibrium

We look for the SPE of the game. If there is an attack and no third-party intervention, P wins with probability p_w. Then, if there is an attack, and given that $\Pi_T(0) = 0$, the payoffs for the third party are:

a) $(1 - p_w)\Pi_T(v)$ if there is no third party intervention;

b) $\Pi_T(v) - \varepsilon_T$ if there is intervention.

Then, the third party wants to attack if $p_w\Pi_T(v) > \varepsilon_T$.

There are four possible equilibria, depending on the parameters:

1. if $p_w\Pi_P(v) < \varepsilon_P$, P never wants to attack and there is no war;
2. if $p_w\Pi_T(v) > \varepsilon_T$ then T would intervene in case of conflict, hence P does not attack;
3. if $p_w\Pi_P(v) > \varepsilon_P$ and $p_w\Pi_T(v) < \varepsilon_T$ then there is no intervention and P attacks;
4. if $\varepsilon_P < 0$, P always attacks.

Given the equilibria listed above, we compute the ex-ante probability that the SPE of the game involves an attack, that is the probability before the ε_i are drawn. It is:

$$\mathbb{P}(war; v) = F_P(0) + \big(F_P(p_w\Pi_P(v) - F_P(0)\big)\left[1 - F_T\left(p_w\Pi_T(v)\right)\right] \tag{3.1}$$

The expression is the sum of the terms corresponding to equilibria 3 (the predator attacks no matter the possibility of intervention) and 4 (the predator attacks if the cost of war for the third party is high enough to avoid intervention).

Now, we analyze how this probability behaves as a function of v, which is the focus of the next section.

3.2.2 Baseline result

Our main result answers the question of the effect of a variation in the resource value on the probability of conflict. The main assumptions we make are:

Aligned Interests - AI We assume that payoffs are differentiable, strictly increasing, and that they can become high enough to offset any cost of war, namely $\Pi_P(+\infty) = \Pi_T(+\infty) \geq M$ (e.g., if $M = +\infty$, this says that $\lim_{v\to\infty} \Pi_i(v) = \infty$).

In addition, we will need some conditions of a more technical nature:

Regularity conditions - RC Assume that the densities are positive in the interior of the support, that is $f_i(x) > 0$ for any $x \in (m, M)$. Assume also that Π'_P/Π'_T is bounded above and away from zero (that is there exist constants c and C such that $c < \Pi'_P/\Pi'_T < C$ for any v). Moreover, assume that the following holds:

1. if $\lim_{x\to M} f_T(x) = 0$ (as has to be if e.g. $M = \infty$), there is a left neighborhood of M such that $x^2 f_T(x)$ is strictly decreasing and $\lim_{x\to M} x f_P = 0$
2. if $m = 0$ and $\lim_{x\to m} f_P(x) = 0$, there is a right neighborhood of m such that f_P is strictly increasing and $\lim_{x\to m} x f_T = 0$

Decreasing Ratio of Marginals - DRM Assume that $\frac{\Pi'_P(v)}{\Pi'_T(v)}$ is nonincreasing.

Another way to express the last condition is that the marginal value grows faster for the third party than the predator - or it decreases more slowly.

Conditions *RC* are general enough to be satisfied by many commonly used probability distributions on the positive reals, such as the gamma, the chi-squared, the lognormal, and any commonly used distribution on the whole real line restricted to $[m, M)$.

We will show later examples where the *DRM* is naturally satisfied.

Now we are ready to state our main result.

Proposition 3.2.1. *Assume Aligned interests and Regularity conditions. Then the probability of conflict is increasing for small v and decreasing for high v. If we further assume DRM and that densities f_i are log-concave, $\mathbb{P}(war; v)$ has only one maximum.*

The result's intuition is simple; an increase in the value results in a higher incentive to go to war only if the realization of the cost for the third party is sufficiently high to imply no intervention. This means that the predation effect dominates when the value is small, while the deterrence effect dominates when it is high.

This happens because if the value is small, the third party will not intervene almost surely. An increase in the value will incentivize the predator to attack for many realizations of the errors; so, the predation effect dominates the deterrence. On the contrary, if the value is high, the third party will intervene almost surely; so, an increase in the resource's value will increase the incentives to attack for very few realizations of ε_P, so the deterrence effect dominates.

The following shows that the main intuitions are robust to settings where players have private information on costs and if the relative military strength is affected by the resource value. To simplify the analysis and have lighter formulas, from now on, we work under a simplified model in which $supp f_i = [0, M]$, $M < \infty$. All the results can be extended to the general model.

3.2.3 Private information on costs

In this section, we explore the robustness of our baseline result if the costs ε_i are players' private information. For simplicity, now assume $\varepsilon_P > 0$. The game formally becomes a dynamic bayesian game. We look for the Perfect Bayesian Equilibrium; this is a simple task in this context because the cost of P does not affect the payoffs of T directly. Hence, the decision of T will depend only on the attack choice. Therefore, we can neglect beliefs of T about the cost–players do not need to do bayesian updating.

This said, we can closely mimic the analysis done for the baseline, and the results go through. The intuition is a close analog to the baseline, the difference being that now P takes into account the expected probability of an intervention rather than the intervention itself. As in the baseline, if the value is small, the third party almost surely will not intervene. Hence, an increase in the value will incentivize the predator to attack for many realizations of ε_P, so that the predation effect dominates the deterrence. If the value is high, the third party will intervene almost surely, so an increase in the value of the resource will increase the incentives to attack for very few realizations of ε_P, so the deterrence effect dominates.

Formally, we can state the following proposition (proof in the appendix).

Proposition 3.2.2. *In the model with asymmetric information, if we assume AI and RC, the probability of conflict is increasing for small v and decreasing for high v. If we assume further DRM and that densities f_i are log-concave, the probability of conflict is single-peaked.*

3.2.4 Resource-dependent military strengths

It is natural to think that richer countries have a higher probability of winning a war. It might be the case that as the resource value increases, the countries with access to the resource can allocate more funds to military investment and become stronger in case of a war. Consequently, in this section, we relax the assumption that the probability of the predator's victory, p_w, is a constant, and we let it vary with v. A common assumption in the literature is that the dependence of the probability of victory on relative investments follows a Tullock contest success function (Beviá and Corchón (2010), Jackson and Morelli (2007)):

$$p_w(v) = \frac{w_P^\gamma}{w_P^\gamma + (w_R + v)^\gamma}$$

were w_P and w_R represent the baseline financial strengths of P and R, to which R can add the funds obtained through the resource.

Generalizing this intuition, we are going to assume that p_w is decreasing in v, p'_w is bounded, $p_w(0) > 0$. These assumptions generalize the idea present in the example above that R has some amount of wealth to devote to war that does not depend on v.

The probability of war is still given by Equation 3.1, but now we have to take into account the variation in the probability of victory coming from changes in value. Hence, the FOC is:

$$f_P \left[p_w \Pi'_P + p'_w \Pi_P\right] (1 - F_T) > f_T \left[p_w \Pi'_T + p'_w \Pi_T\right] F_P$$

The behavior of the expression depends on the terms in brackets. If they are positive, we can replicate the proof of the main proposition with minimal changes, and we get the following.

Proposition 3.2.3. *Assume RC and AI. Define $\eta_T = \frac{\Pi'_T}{\Pi_T} v$, $\eta_P = \frac{\Pi'_P}{\Pi_P} v$, $\eta_{prob} = \frac{p'_w}{p_w} v$. If If $\eta_P > -\eta_{prob}$ and $\eta_T > -\eta_{prob}$ then the probability of conflict is increasing for small v and decreasing for high v.*

The conditions $\eta_P > -\eta_{prob}$ and $\eta_T > -\eta_{prob}$ are stating that an additional unit of the resource value affects the payoff, which is larger than the (negative) effect on the probability that the predator wins. For instance, this describes a setting in which just a fraction of the resource value is employed to increase military power. So the implied variation in the probability of victory is less than proportional.

In concrete example of the Tullock contest success function the elasticity would be:

$$\eta_p = v \frac{\gamma (w_R + v)^{\gamma - 1}}{w_P^\gamma + (w_R + v)^\gamma} = \frac{\gamma v}{w_P^\gamma (w_R + v)^{1-\gamma} + w_R + v}$$

We can see that $\frac{v}{w_P^\gamma (w_R+v)^{1-\gamma} + w_R + v} < 1$. Therefore, for $\gamma \in [0, 1]$ (the typical assumption, yielding concavity of the function, see Beviá and Corchón (2010)), $\eta_p < 1$. So, for example, in the setting described in Section 3.4.2 the conditions of the proposition above are always satisfied, because the payoff elasticities are always larger than 1.

3.3 Civil wars: bargaining and non-concentrated resources

In this section, we build two extensions of our model that are particularly relevant for civil war. First, since shared institutions likely increase the enforceability of conflict-avoiding contracts, we analyze the case of bargaining. Second, we look to the case of non-concentrated resources, in which resource-holder and predator partially share the resource. This is meant to model, for example, the case in which different groups control different areas of a country homogenous in terms of resource-presence.

3.3.1 Bargaining

If country R is resource-rich, it is natural to wonder if he could avoid war by buying off the predator, and what happens to the probability of conflict in this case. Given that war is clearly wasteful, the study of how and why bargaining might fail is a central and much-studied question in the conflict literature (Fearon (1995)), and a full exploration of the issue goes beyond the purposes of this paper. This section aims to show that even under a classical bargaining framework, similar to Fearon and Laitin (2003), under some conditions, conflict can arise. If it does, the probability of conflict follows the same non-monotonic pattern of the previous sections.

We assume that, before the game outlined in the previous section starts, the resource holder R has a chance to make a take-it-or-leave-it offer to the predator P, inducing her not to declare war. At the time of the offer, R does not know the war cost of P. If P accepts, there is no war; if he rejects, the game proceeds as before.

The possibility of bargaining allows for a new trade-off. On the one hand, the increase in the resource value v enlarges the total surplus to be split, thus facilitating successful bargaining; on the other hand, it makes the prize of war more attractive. Assuming that payoffs are normalized such that the distribution of errors is uniform on $[0, 1]$, we find a simple condition that allows us to understand which effect will prevail, detailed in the following proposition:

Proposition 3.3.1. *Assume conditions AI, AR, DRM hold. If $\Pi_P - \Pi_R$ is increasing, then the probability of conflict is hump-shaped in the resource value v.*

If $\Pi_P - \Pi_R$ is decreasing, there is no conflict.

Concretely, the condition states that, in contexts where bargaining can be expected, the relationship between the probability of conflict and resource value is hump-shaped when the value of the resource for the predator grows more than the value of the resource for the resource holder. This describes a context in which the predator has access to a similar technology for exploiting the resource but is poorer than the resource holder; so, a marginal increase in the resource value is more profitable for P than for R. Another example in which the condition would be satisfied is the framework described in Section 3.4.1, where the payoff comes from the profit raised from selling the resource to the third party. In this case, this condition is satisfied if, for example, the resource holder R has access to more extraction sites beyond the contested one that can be seized by P. If this is the case, simply by decreasing marginal returns, we find that $\Pi_P - \Pi_R$ is increasing; hence conflict can arise.

3.3.2 Non-concentrated resources

In a civil war, ownership of a natural resource is hard to enforce perfectly, especially if the resource is not very concentrated because it is spread across an area. In particular, natural resources can be a financing channel for rebels, as discussed, e.g., by Collier and Hoeffler (2004). Furthermore, natural resources are often non-concentrated, so it might be hard or impossible for one of the parties in conflict to control *all* of the, say, extraction sites. Rebels or armed groups can appropriate amounts of the resource or some extraction areas with relatively less effort compared to the context of interstate wars, in which the army must occupy an area of the adversary state to seize the control of the resource. If this is the case, rebels in a civil war might benefit from the natural resource as much as the central government (or adversary armed group). Hence, in this section, we relax the assumption that absent conflict, the natural resource benefits only player R, assuming that anyway P can secure a portion of the profits. We explore two contexts: the case in which the predator has access to a fraction η of the profits that can be secured, which applies for example to the case in which v represents the price of the resource; and the case in which v represents the quantity of resource available, and the predator has access to a fraction ηv of it.

Predator has access to a fraction of profits Here we assume that the predator has access to a constant fraction η of the profits that can be obtained from the resource. In particular, assume there is a function $\pi(v)$ representing such profits, and the payoffs to R and P are fractions of it: $\Pi_P(v) = \eta\pi(v)$ and $\Pi_R(v) = \eta\pi(v)$. If P wins the conflict, he can secure the full amount of profits: $\pi(v)$. The payoff of the third party, π_T, may now depend on η. For instance, the third party might earns a royalty τ out of the resource profit earned by the incumbent: Π_T would be given by $(1-\eta)\tau\pi(v)$. If the payoff of the third party derives instead from using the natural resource for production, η might enter the payoff in a more complex way. In any case we keep the assumption that $\Pi_T(v)$ is increasing in v: even if the third party has access to a fraction of the resource profits, the larger the value the larger the benefit for the third party deriving from the resource.

Given the payoffs specified, P will attack if $(p_w - \eta)\pi > \varepsilon_P$, and T will behave as in the baseline. The mechanism will be very similar to the baseline if the LHS is increasing in v, that is, if and only if $p_w > \eta$. This states that conflict can occur if the "military power" of P is greater than its "political power" η. In recent literature, this *mismatch* between political and military power has been proposed as one important driver of conflict (Esteban et al. (2020), Herrera et al. (2019)).

Predator has access to some quantity of resource If v represents the quantity of the contested resource, and this is non-concentrated, we can assume that the parties in conflict control a fraction of the quantity each. In particular, say that the predator controls a fraction ηv of the quantity. The relevant payoff for P then becomes: $p_w\Pi_P(v) - \Pi_P(\eta v)$. If this payoff increases in v, the situation is exactly analogous to the baseline, with the non-monotonic relation between v and the probability of conflict because the trade-off between desirability and deterrence realizes again. On the contrary, if the payoff decreases in the resource value, there is no trade-off, and the probability of conflict is decreasing with v.

The payoff of P is increasing if:

$$\frac{\Pi'_P(v)}{\Pi'_P(\eta v)} > \frac{\eta}{p_w}$$

that is, if the marginal payoff grows (decreases) at a rate higher (lower) than η/p_w. The ratio η/p_w has an interesting interpretation as the relative value of P's "economic" and "military" strengths; if it is high, it means that P can secure a high fraction of resources under the status quo, even if it would hardly win in a military confrontation; if it is low, the reverse happens: P has access to a very low fraction of resources even if its military strength is high. This difference does not immediately translate in war decisions, though, because the payoffs' shape must be factored in.

In other terms, if η is very high, meaning that a large fraction of the resource goes to the predator anyway, an increase in the value of the resource makes war less attractive (income effect). Conversely, if the resource value is very low, an increase in the value makes war more attractive.

The payoff of T is the same as in the previous sections, so the fact that Proposition 3.2.1 can be applied depends on the fact that the payoff of P is increasing, which gives us the Aligned Interests condition. If this is the case, we have a non-monotonic probability of conflict. If, instead, the payoff of P is decreasing, we get that the probability of conflict is monotonically decreasing.

We can identify the following clear-cut cases:

1. if Π_P is concave and $\eta > p_w$, then there is no conflict. The interpretation is that the "rebels" can extract enough rent under the status quo, and the marginal value of owning additional resource is decreasing, so, even as the value grows, P is never willing to attack;

2. if Π_P is convex and $\eta < p_w$, then the rebels can extract small rents in peace, but are military strong *and* additional units of the resource are more and more valuable; hence, as the value grows, the resource becomes more attractive, and the probability of war is initially increasing in v.

3.4 Resource-buying and resource-selling third parties

This section illustrates some of the model's many possible applications, choosing instances of the payoff functions and the value parameter. This will show that the framework is fit to be adapted to a wide range of instances.

3.4.1 Third party as a resource buyer

In the last decade, personal electronic devices, such as laptops, smartphones, and tablets, have been widely adopted both in developed and developing economies (see Pew [2016] for the case of smartphones). All these devices require technologically advanced batteries. To this moment, lithium-ion batteries are the ones typically used for these devices, such as Apple and Samsung smartphones. Commonly hand-held devices use lithium cobalt oxide $LiCoO_2$ as cathode for their battery. So, even though Sony commercialized the first one of this type in 1991 Sony (2017), its fortune is largely due to the mass adoption of electronic devices in our daily life in the last years. Lithium cobalt oxide requires cobalt as an input, whose production largely depends on cobalt ore. As of 2015, cobalt ore was mostly extracted and exported by the Democratic Republic of Congo (DRC), which exported a dramatic 89% of the world \$752 million trade volume. On the importers' side, China gets 58% of the total, followed by Zambia 31%, which converts it into cobalt and sells it in a \$2.86 billion international market in which, again, the main importer is China (28% of sales) and the main exporter is DRC (26% of sales) Simoes and Hidalgo (2011). China was already importing most cobalt ore and cobalt to meet the extraordinary demand for batteries for devices in 2004 USGS and USDI (2012).

Resource conflict in DRC is widespread. However, a relatively safe area can be found in the South of the country, where most of the cobalt is extracted. This is also the area in which China's involvement is most relevant, as documented in Hoslag (2010). This setting is an ideal real-world application for our model, in which China plays a third-party role, helping the stabilization of the resource-rich area.

To connect this example to our model, we need to consider a third party interested in a resource because it is a fundamental input in the economy's production chain. In our model, the country that owns the resource, e.g., the cobalt ore, is player R, while P is a rebel group or a neighbor country wanting to seize the resource. We can add a non-strategic player, which we call M, the "market", that is not active, but it provides an additional amount of resources.

Extraction operations and trade are negatively affected during a war. Then, conflict results in a higher price for the resource. We explicitly model the formation of resource-prices in equilibrium. Through this channel, the third party has a clear interest in maintaining peace since higher prices hurt its economy.

For simplicity, we assume that the third party T has no endowment of the resource, and its firms need to buy it on the market to produce consumption goods. Also, we assume that T is the only buyer of the resource to avoid useless algebraic complications. Players M and R are not active; they sell the resource to T. Our players could be seen as representative agents of economies where production and consumption decisions are taken by identical infinitesimal, hence price takers, individuals. The profits coming from the ownership of the resource for players P and R are:

$$\Pi_i = pR_i \tag{3.2}$$

while the third party behaves as a representative neoclassical firm and it maximizes the following profit function:

$$\Pi_T = \Omega_T g_T^{\alpha} - pg_T \tag{3.3}$$

where Ω denotes the resource-specific productivity, and g the amount of resource bought.

The timing of the model is: player P decides whether to attack or not, then player T decides if to intervene or not, then prices and payoffs are realized. If a war occurs, production drops by a fraction η. Hence, the third party stands to lose from the war in two ways: the quantity available is smaller, and the price will be higher due to the supply-side shock.

We define a market equilibrium of this model as a price-quantity vector $(p^*, g_T^*, g_R^*, g_M^*)$. Any player is choosing the resource amount g^* optimally given price p^* and such that the market-clearing condition $g_T = g_M + g_R$ is satisfied. We solve for the SPE and then show how this model can be thought of as an instance of our general formulation.

Proposition 3.4.1. *Assuming the program has an interior solution, the equilibrium has the following structure. There are two thresholds Π_T, and Π_P, functional of parameters, such that: Player T intervenes whenever P attacks and $\varepsilon_T < \Pi_T$, player P attacks whenever $\varepsilon_T > \Pi_T$ and $\varepsilon_P < \Pi_P$. The expressions of the thresholds are:*

$$\Pi_P = \frac{\alpha\Omega}{(R_M + \eta R_R)^{1-\alpha}} \eta R_R \tag{3.4}$$

$$\Pi_T = (1-\alpha)\Omega \left((R_M + R_R)^\alpha - (R_M + \eta R_R)^\alpha\right) \tag{3.5}$$

Hence, in this example, we can interpret the payoffs of the players as the thresholds Π_T, Π_P, and the value of the contended resource as $R_R = v$.

We can apply Proposition 3.2.1 to get the following corollary.

Corollary 1. *Condition AI is satisfied, so the probability of conflict is non-monotone. Also, if $R_M > (1-\alpha)\frac{\eta}{1-\eta} R_R$, then also DRM is satisfied, so that the probability of conflict is single-peaked if we assume log concavity in the density function of the distribution of the cost of war.*

The proof can be found in the Appendix.

There is another, symmetric way to parameterize the value of the resource in this setting. If, for example, we consider oil, a raise in the world supply R_M is a simple representation of the effect of the large increase in the oil supply following the breakthrough of the shale-oil technology, which has dramatically increased the supply of oil over the world. In the language of our main model, $v = 1/R_M$, representing relative scarcity of the resource owned by R. The effect of an increase in R_M is to decrease both Π_P and Π_T. Indeed, both derivatives of the payoffs with respect to R_M are negative, as shown in the Appendix. Then, we can again apply Proposition 3.2.1 and obtain this other corollary (proof again in the Appendix).

Corollary 2. *Assume that M, the maximum cost of war, is small enough compared to the profits from the resource: $M < \alpha\Omega(\eta R_R)^\alpha$ and $M < (1-\alpha)\Omega(1-\eta^\alpha)R_R^\alpha$ Then AI and RC are satisfied, so the probability of conflict is non-monotone.*

3.4.2 Third party as a seller of the resource

As another example of a third party, consider a multinational firm extracting the resource and selling it in the market. The firm earns a profit and pays royalties that could attract other players' attention, such as neighboring countries or rebel groups in the country.

Colombia makes for a good instance of this process. Oil extraction attracted many multinational corporations: British Petroleum, Occidental Petroleum Corp., and Texas Petroleum Company (Richani, 2005). This contributed to exacerbate civil conflict in the country among the government, left-wing *Guerrillas* and the paramilitary groups (see Richani [2005] and Dube and Vargas [2013]). Multinational firms did not have an army, but they commanded military power in two ways: lobbying activities prompting the intervention of a military power, the US, and subcontracting to security services and the Colombian Army (Richani, 2005).

Let us consider the following way to map this context to our model. The third party T is a multinational firm, player R is the Colombian municipality where royalties are paid, and P is a rebel group stealing the resource.

The multinational firm taking the international price p as given. This assumption is realistic in the Colombian case since Colombia is a minor oil-producer; according to EIA data, Colombia provided around 1% of world daily barrels in 2000. Figures are similar today. Also, profits are positive in the model because of entry barriers in the extraction sector. We abstract from the royalties that it is paying to the resource owner since this player is never active, so the results will not depend on these fees.

In this context, the measure for the value of the resource would be the market price p. In the language of our abstract model, $v = p$. We can write the third party's profit function Π^* as:

$$\Pi^*(p) = \max_{q_1, q_2, \ldots, q_n} \left(pF(q_1, q_2, ..., q_n) - \sum_i w_i q_i \right)$$

where the vector q indicates all the inputs that the firm needs to extract the resource, and w is the vector of input prices. We think of the input prices as fixed parameters.

The predator aims to appropriate part of the profits from the sale of the resource, so his possible gain is:

$$\Pi_P = \Pi^*(p)$$

There are various reasons why the third party might be concerned about conflict: because the predator could disrupt the resource's extraction or because he might impose higher royalties or appropriate the profits altogether. We capture these incentives by assuming that if P wins a fraction $1-\delta$ of the profit is lost[2], so that $\Pi_T = \delta\Pi^*(p)$.

In this case, we investigate the impact of changes in the market price of the resource. This is interesting, in this context, as the price is given exogenously. Price changes arise as a consequence of many different events. For example, a productivity shock of the type analyzed in the previous sector might drive the price up, while an increase in the competition would have the opposite effect.

Since the third party behaves as a competitive neoclassical firm, it is immediate to compute the marginal impact of a variation in the value-price of the resource. By Shepard Lemma, the marginal impact of a variation in the output price is equal to the output quantity:

$$\frac{\partial \Pi_P}{\partial p} = F(q)$$

$$\frac{\partial \Pi_T}{\partial p} = \delta F(q)$$

Taking the ratio of the two:

$$\frac{\Pi_P'}{\Pi_T'} = \frac{1}{\delta}$$

Therefore, if the share of profits lost in conflict is constant, the condition DRM is satisfied. So, also this case fits under our general framework.

Moreover, the payoff elasticities are:

$$\eta_T = \frac{\delta p F(q)}{\delta \Pi^*} = \frac{pF(q)}{\Pi^*} > 1$$
$$\eta_P = \frac{\tau p F(q)}{\tau \Pi^*} = \frac{pF(q)}{\Pi^*} > 1$$

so that Proposition 3.2.3 applies if the variable military strength follows the Tullock functional form described there.

3.5 Empirical Evidence

In this section, we construct a test of the theory formulated above. In particular, we test whether the probability of conflict is a non-monotonic function of resource value. We use data from the Peace Research Institute of Oslo (PRIO) and the Uppsala Conflict Data Program (UCDP). We produce tests based on a general measure of natural resource value provided by the World Bank; also, we apply an empirical strategy similar to the one used by Hunziker and Cederman (2017) to our case, proxying the presence of oil resources with sedimentary basins, to circumvent endogeneity concerns.

[2] It is equivalent to suppose that the production is not affected directly, but input prices are higher, as this is a reasonable consequence, especially for the labor force.

3.5.1 Data

Our main measure of resource value comes from the World Bank Wealth Accounts. This provides, among others, a measure of natural capital for a country in a given year, a very comprehensive measure of resource wealth, defined as the discounted value of energy, minerals, agricultural land, protected areas, and forests. This measure is calculated for every country roughly every 5 years starting from 1995. A full account of the methodology employed is available at WB (2018). There are, however, considerable endogeneity concerns when using these variables in our analysis. For instance, conflict onset can directly impact the value of resources in a given country. To diminish such concerns, we do not employ temporal variation in the value of resources. Instead, we only use the value determined for 2014 and focus on conflict up to 2000 in analyses to reduce reverse causality concerns.

Further, we adapt the novel methodology and data by Hunziker and Cederman (2017). In their work, they acknowledge that oil extraction is likely endogenous to several characteristics of a country that can correlate with conflict. Therefore, they instrument it with geographical variation in the presence of thick layers of sedimentary rock, a determinant of oil presence. They identify such regions using the CRUST 1.0 dataset by Laske et al. (2013), containing thickness information on a 1-decimal-degree-cell grid, for the planet Earth; they show thickness to be associated with oil and gas presence. The authors organize information from oil datasets in a country dataset. In our estimation, we use their thickness information as an alternative measure of natural resources, as we will explain in detail later.

As we briefly sketched above, we measure conflict incidence using UCDP/PRIO Armed Conflict Dataset, recording conflict onset episodes from 1946 to 2014. Its operational conflict definition requires the use of (i) armed force, (ii) at least one state or government contestant, (iii) at least 25 battle-related deaths. The data also includes an intensity variable reporting whether there the conflict caused at least 1,000 battle-related deaths. We use such variables to construct a 'High Conflict' indicator, which we use as an alternative measure to assess robustness. We employ the location variable and the year variable to reshape this into a country-year couples dataset, to be matched to the resource data.

We measure US military influence based on two sources. First, we collect the number of US Department of Defense (DoD) personnel deployed by country in 2014, collected from the Defense Manpower Data Center (DMDC). Coupling these data with the GeoDist database, we define our first measure of US involvement by creating a country dummy taking value 1 if the nation has 1,000 or more DoD employees or borders with one such country. Second, we use the Stockholm International Peace Research Institute (SIPRI)

Arms Trade Database to obtain information about US arms importers. We use this dataset to build a dummy taking value 1 if a country was a US arms importer in 2014. We chose the year to reduce endogeneity concerns and to be consistent with the resource measures.

Finally, we include in our data a battery of geographical controls used in Ashraf and Galor (2013).

Our sample consists of countries included in both the World Bank dataset and Hunziker and Cederman (2017) dataset, except for G8 countries and China. Hence, our sample excludes powerful nations, potentially acting as third parties. We are left with a panel of 119 countries from 1950 to 1999 included.

In the appendix, Figure C.1 and C.2 respectively show the distribution of the World Bank wealth measure of natural capital and the volume of sedimentary basins by CRUST 1.0. The two measures are strongly correlated and considerably spread across continents. Figure C.3, instead, depicts the distribution of conflict years occurrences in the sample period. Again, there is variation in the number of conflicts within and across continents. In the time interval considered, on average, the share of countries reporting at least one conflict in the year was 14.0%, while this share decreases to 3.9% for conflicts with at least 1,000 battle-related deaths. In Figure C.4, we report the countries hosting more than 1,000 US DoD personnel or their neighbors. It can be noted that their presence is concentrated in the Middle East and Europe. Finally, the distribution of arms importers is more widespread across the world, as shown in Figure C.5.

3.5.2 Empirical Strategy

We are interested in estimating the following equation:

$$W_{c,t} = \beta_0 + \beta_1 v_i + \beta_2 v_i^2 + \gamma' X_i + \delta_t + \varepsilon_{i,t} \tag{3.6}$$

Where $W_{c,t}$ is the chosen conflict outcome, v_i is resource value, δ_t is a year fixed effect, and X_i is a vector of geographical controls common in literature, including area, average elevation, dispersion in elevation, mean distance to the nearest waterway, temperature, and precipitations. We also control for absolute latitude and an index of the suitability of land for agriculture based on ecological indicators of climate suitability for cultivation taken from Ashraf and Galor (2013). With the latter, we aim to control for potentially confounding long-run determinants of institutions, settlement choices, and population density[3].

According to the number of casualties, conflict outcomes can be 'Conflict' and 'High Conflict', as previously described. In our main specification, we use the natural resource value measured by the natural capital collected by the World Bank. However, as already anticipated, we also tested our model using the volumes of sedimentary basins provided by Hunziker and Cederman (2017). Given its morphological determinants, this variable does not suffer from possible endogeneity concerns regarding the value of natural resources, possibly linked to previous conflict disruptions. Hunziker and Cederman (2017) uses this measure to instrument the amount of oil extraction in a country. Instead, we use this measure directly in an OLS regression. In this way, we can capture possible non-linearities through the squared term and avoid the use of multiple instruments. This choice is without loss of generality since the authors have already shown that the amount of sedimentary basins is robustly associated with oil extraction. Furthermore, given that the results of an OLS regression can be strongly affected by the presence of a few outliers, we winsorize the data for the resource value before moving to the model estimation. The left part of the distribution is naturally limited by the hard zero threshold, using winsorize the right end of the distribution at the 97.5 percentile.

As a test of our model, we first check that $\beta_1 > 0$ and $\beta_2 < 0$, and then we show that non-monotonicity is stronger in the proximity of US partners, as defined in two ways: (1) by the number of employees American Department of Defense, and (2) by whether they are US arms' importers. Regarding number (1), we run a separate analysis on the sample of countries where at least 1,000 US DoD employees are present or neighbors to such countries and on the sample of nations that do not belong in this set. For number (2), we perform two separate estimations on US arms importers and on the other countries. The rationale of such measures is that lower distance from a third party's ally reduces the cost for the third party to enter in conflict, thus making its threat more credible. The presence of many employees at the US Department of Defense is a proxy for a formal alliance with the USA or the US' ability to control the area. Choosing the USA as the relevant third party is consistent with the high military and geopolitical value of the actor in the second half of the last century and using sedimentary basins to measure value. Indeed, according to the authors' own elaboration of data by the U.S. Energy Information Administration, the USA was the largest importer of crude oil for 16 of the 20 years from 1980[4] to 1999–Japan was the first importer in the remaining years.

[3] Results are robust to excluding such controls from the analysis.

[4] This is the first year available in EIA data on oil imports by country.

3.5.3 Results

Results for the analysis on UCDP/PRIO data are shown in Table C.1. Outcomes in (1), (2), (5), and (6) are conflict dummies that take one if there were at least 25 battle-related deaths in the country in that specific year. Other columns have High-Intensity conflict episodes as an outcome, which means that there were at least 1,000 battle-related deaths in the year. The first four columns have natural capital as the main independent variable, while the last four have sedimentary basins. All columns include year and continent controls. Odd columns include geographical controls. Errors are clustered at the country level. Reported signs across value type and conflict measures agree with the non-monotonicity prediction, displaying a positive sign on the linear term and a negative term on the square. The linear term is always significantly different from zero, at least at the 10% confidence interval and at least at the 5% when geographical controls are present. The square term is always negative and significantly different from zero, at least at the 10% confidence interval.

Turning to the analysis of Table C.2 and C.3, we observe that non-monotonicity is mostly driven by countries near American troops. Indeed, in Table C.2, signs and significance agree with the previous analyses. To provide an easier interpretation of our results, we provide the estimated peak of the hump-shaped relation. For the WB measure, peaks range between 3.32 and 3.84 trillion dollars, well into the 0-6.88 winsorized range. As for sedimentary basins' volume, peaks are between 2.88 and 3.67 tens of cubic KM, compared to a 0-9.32 winsorized range. In Table C.3, reporting the effect for countries having less than 1,000 DoD personnel in their territory and in the territory of their neighbors, the squared term estimates become much more noisy, remaining significant only for three estimations out of eight, and they are never statistically different from zero in the specifications with the World Bank measure of natural capital. We get similar results when estimating the model separately for US arms importers. In Table C.4, reporting estimates for countries that are US arms importers, the squared term is negative and significant for seven out of eight specifications, and it is always significant when geographical controls are included. When we turn to the estimates for countries that are not US arms' importers, in Table C.5, none of them retains significance.

Overall, this provides evidence that the relationship between resource value and conflict is non-monotonic and that third parties' presence moderates the effect. A potential limitation of this empirical strategy is that other third parties could be present in some countries, e.g., the USSR. Since the latter countries are likely different from countries with US troops or US arms importers, this would likely produce a source of non-monotonicity in the ‘control’ group, going against our main hypothesis.

3.6 Conclusions

Predation incentives are not enough to make for an increasing relation between resource abundance and conflict. In fact, this relation can be decreasing if we introduce conflict-stabilizing third parties in the analysis. We have developed a simple sequential game that considers third-party involvement in describing the relationship between conflicts and resource value. The result is a non-monotonic relationship between the resource value and the probability of conflict holding in a number of realistic settings, under some conditions. The theory proposed is supported by an econometric analysis performed on UCDP/PRIO data, employing a measure of natural resource data from the World Bank and plausibly exogenous measures of sedimentary basins, proxying for oil presence. We document an empirical hump-shaped relation between resource value and conflict probability, driven by countries exposed to US military involvement.

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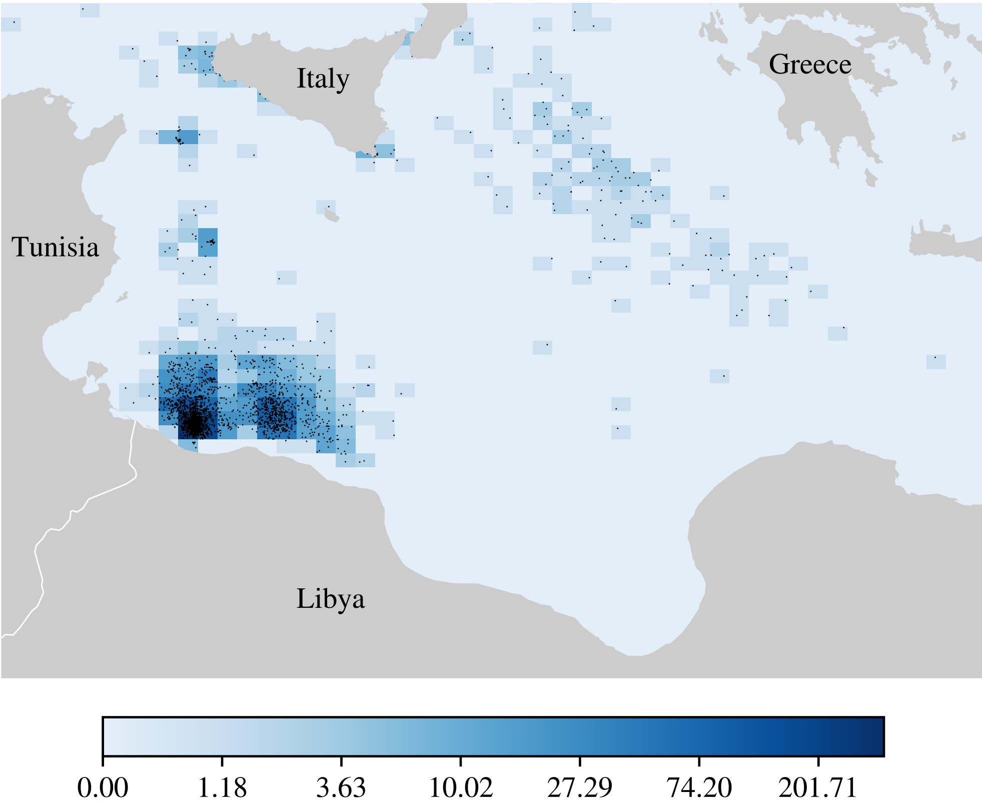
Appendix A

Appendix for Chapter 1 ‘Rescue on Stage: Border Enforcement and Public Attention in the Mediterranean’

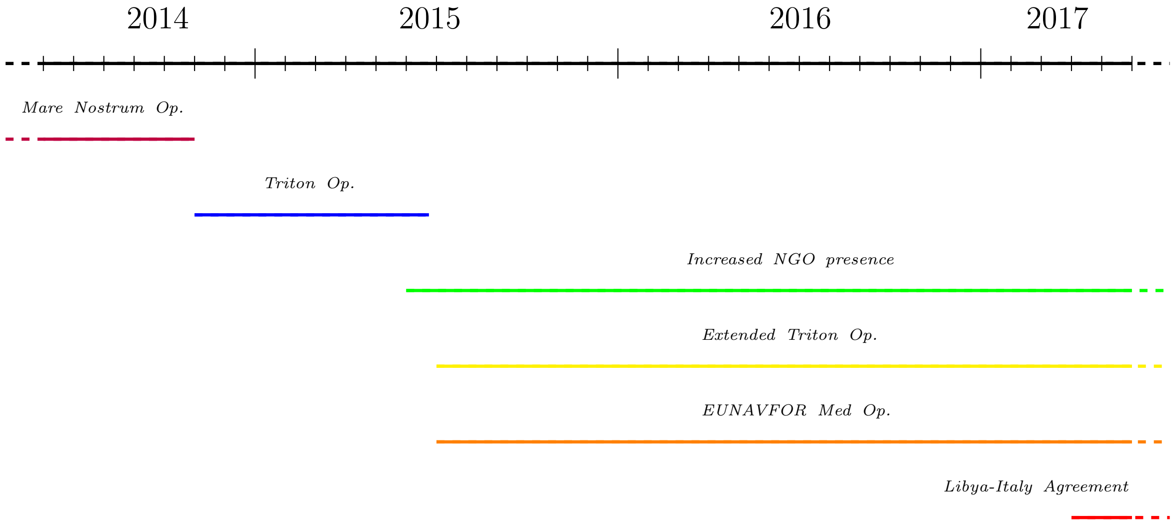
A.1 Figures

Figure A.1: Interception Locations overlaid on 2-d Histogram, Frequency in IHS Units



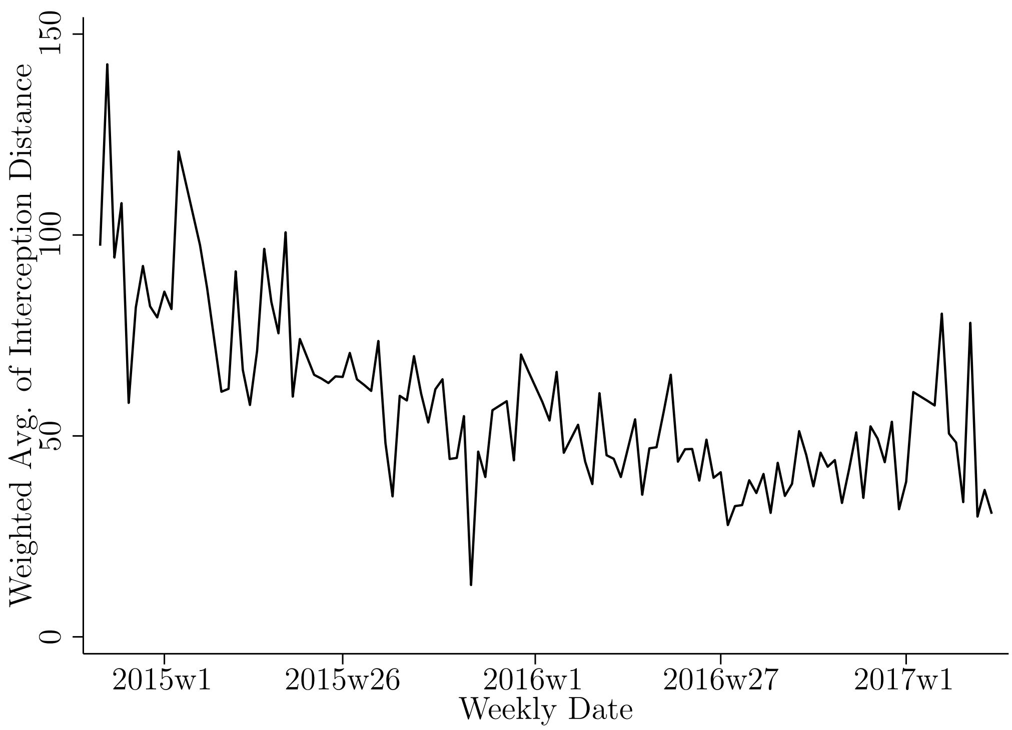
Scatter of interceptions' locations from November 1, 2014, to April 1, 2017, overlaid over 2-d histogram (50 bins on the *x-axis* and on the *y-axis*), with frequency expressed in Inverse Hyperbolic Sine units. Own elaboration of Frontex data. Referenced in Section 1.2.1 and A.3.1.

Figure A.2: Chronology of Operations and Main Events



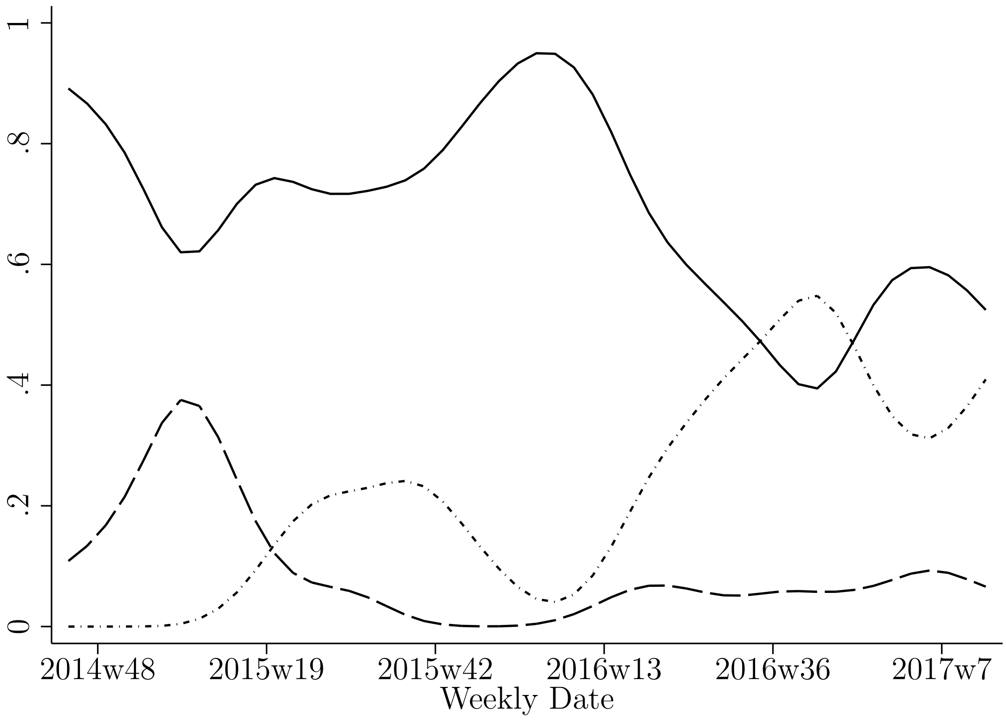
Source: own elaboration of EPSC (2017). Referenced in Section 1.2.1.

Figure A.3: Migrants-Weighted Mean of Interception Distances over Time



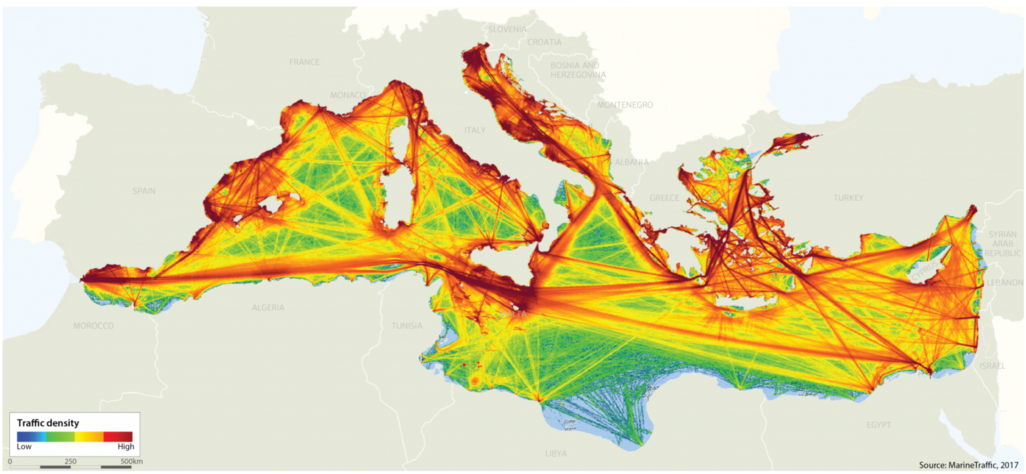
Average distance of interceptions, weighted by number of migrants in each interception of over time (KM). Referenced in Section 1.2.1.

Figure A.4: Migrants' Share Intercepted by Actor, over Time



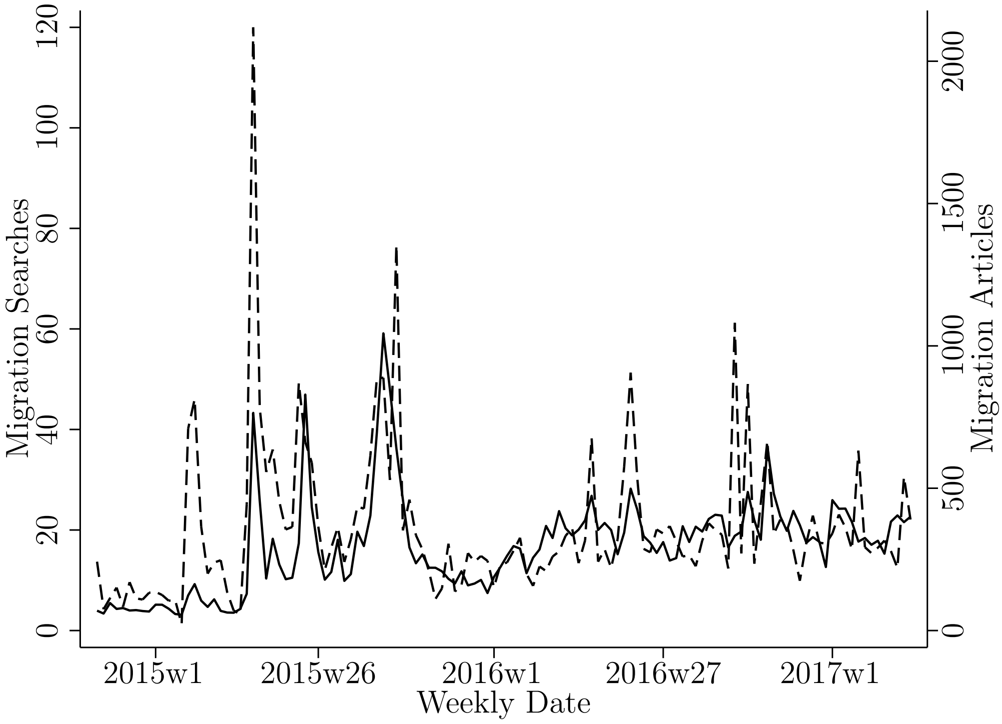
Proportion of migrants intercepted by different actors over time; kernel regression with Gaussian kernel. Polynomial used for smoothing has degree 3, bandwidth is 5 weeks. The dashed line represents commercial ships, the dashed-dotted line represents NGOs, and the solid line represents residual institutional interceptions. Referenced in Section 1.2.1 and Section 1.2.2.

Figure A.5: Maritime traffic density in the Mediterranean Sea



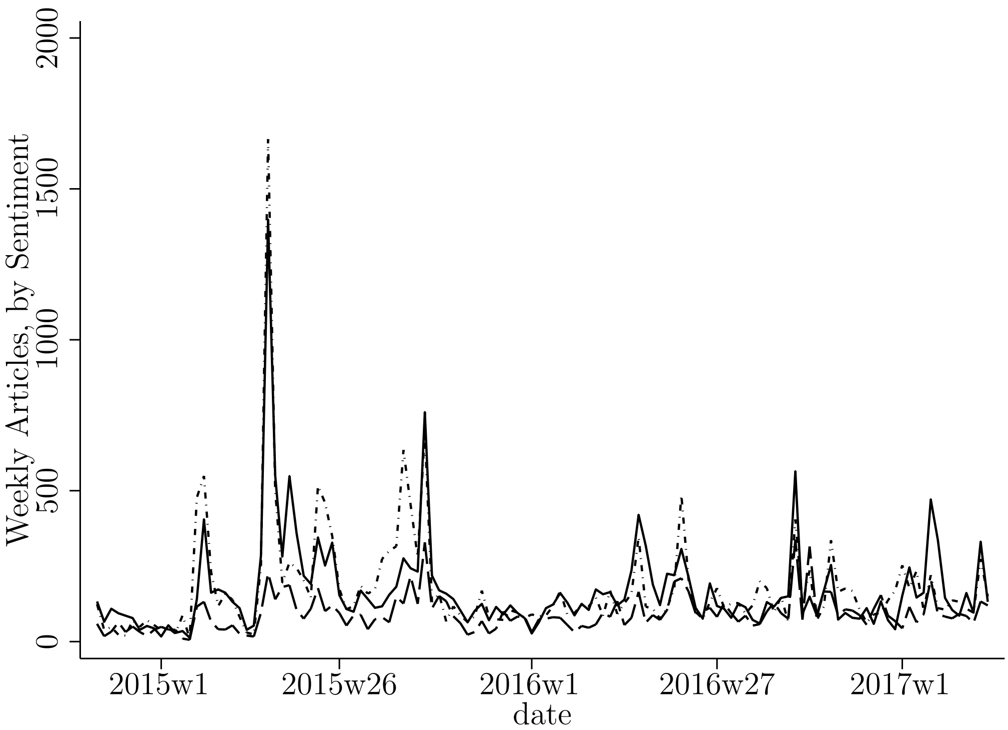
Source: MarineTraffic (2017) as in UNEP (2017). Referenced in Section 1.2.2.

Figure A.6: Migration Google Searches and News Articles over Time



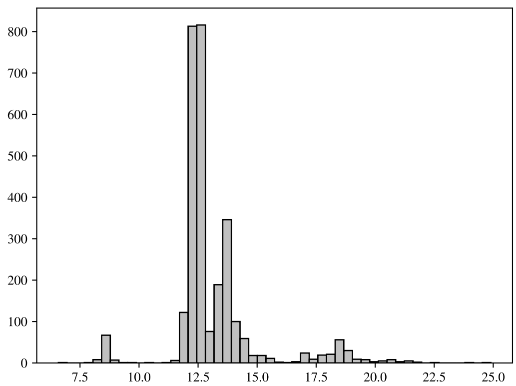
Solid line represents the weekly average of Google searches in Italy over time. The relative y-axis is on the LHS. Before averaging, the value is normalized, assigning 100 to the maximum. The dashed line represents weekly average articles about migration in the Italian press, retrieved by Factiva. Relative y-axis on the RHS. Referenced in Section 1.2.4.

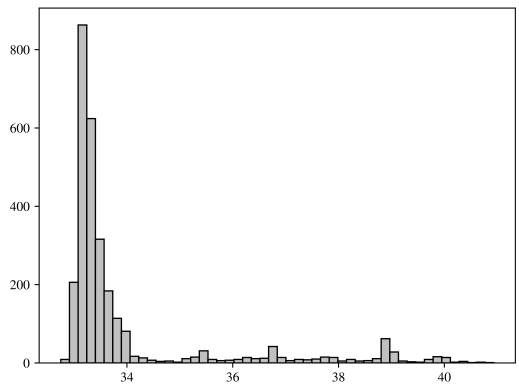
Figure A.7: Articles by Classification over Time



Number of online and print newspaper articles in Italy relating to migration, over time, by sentiment classification. The solid line represents objective articles; the dashed line shows positive-sentiment articles, and the dashed-dotted line depicts negative-sentiment articles. Referenced in Section 1.2.4.

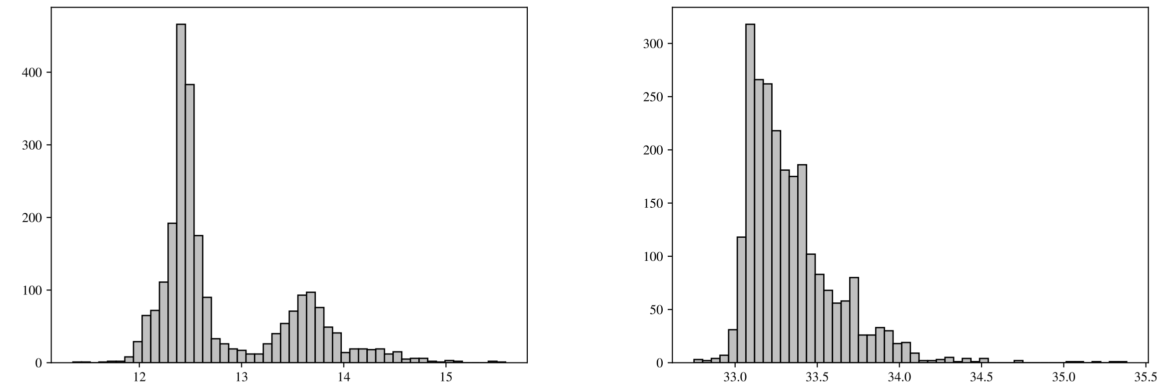
Figure A.8: Interception Longitudes and Latitudes Histograms





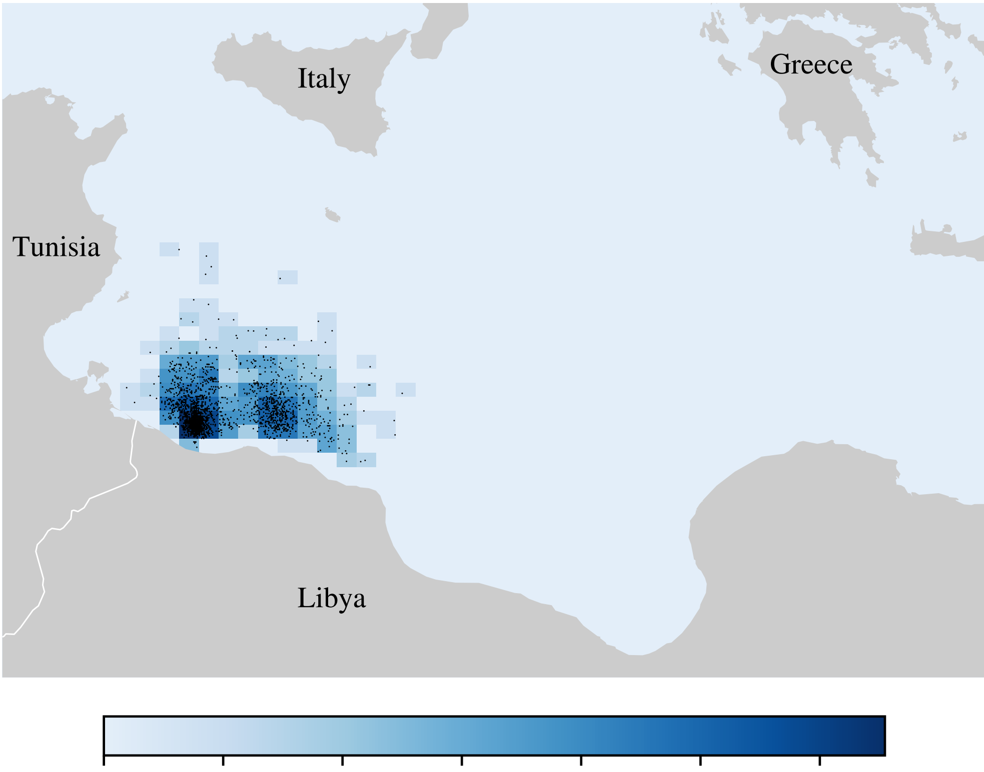
Histograms of interception longitudes (LHS) and latitudes (RHS) from November 1, 2014, to April 1, 2017. Own elaboration of Frontex data.

Figure A.9: Interception Longitudes and Latitudes Histograms for Final Sample



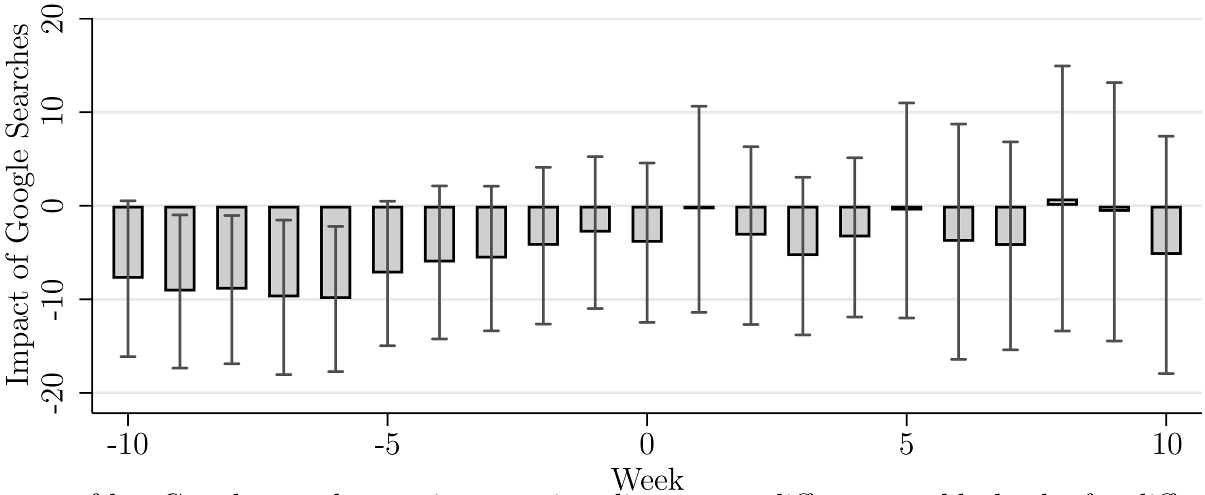
Histograms of interception longitudes (LHS) and latitudes (RHS) from November 1, 2014, to April 1, 2017, restricting to the final sample. Own elaboration of Frontex data.

Figure A.10: Interception Loc. of Final Sample overlaid on 2-d Histogram, Frequency in IHS Units



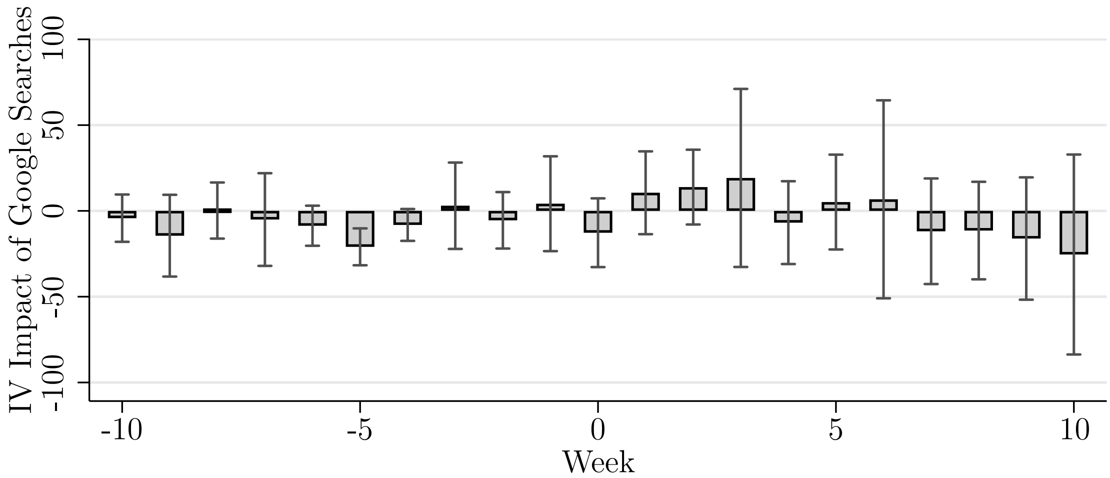
Scatter of interceptions' locations from November 1, 2014, to April 1, 2017, restricting to the final sample, overlaid over 2-d histogram (50 bins on the *x-axis* and on the *y-axis*), with frequency expressed in Inverse Hyperbolic Sine units. Own elaboration of Frontex data. Referenced in Section A.3.1.

Figure A.11: Impact of Different Leads of Searches on Distance



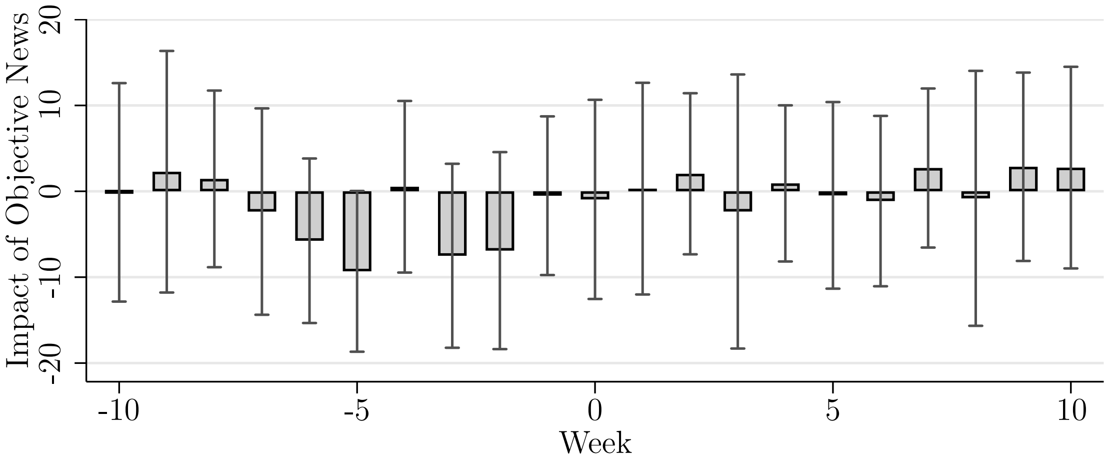
Impact of log Google searches on interception distance at different weekly leads, for different regressions. Controls include year and quarter-of-the-year fixed effects. Plot includes Bonferroni-corrected confidence intervals for $\alpha = 5\%$. HAC standard errors robust to arbitrary heteroskedasticity and autocorrelation up to lag 3. Referenced in Section 1.6.2.

Figure A.12: Impact of Different Lags of Searches on Distance (IV)



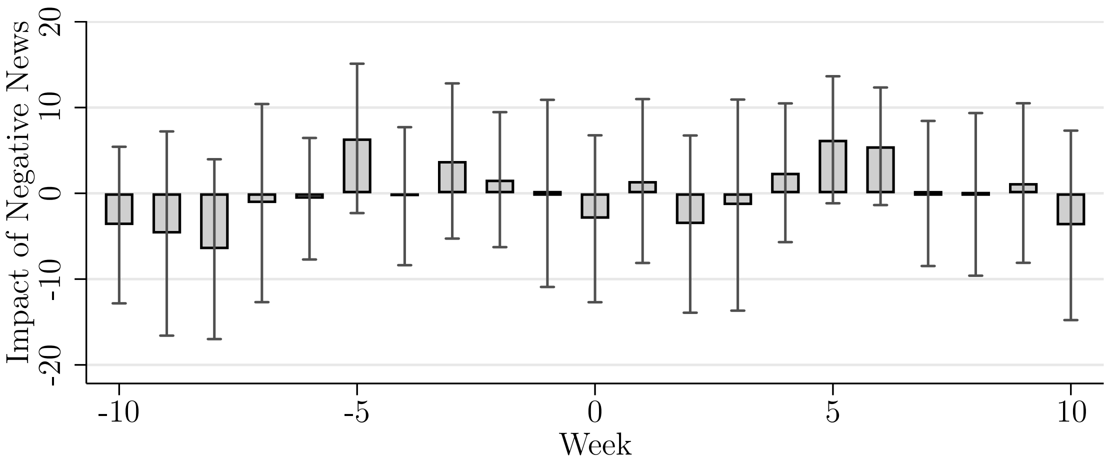
Instrumented impact of Google Searches at different weekly leads, for different regressions. The instrument is one lag of *noteworthy matches*. This is defined as a *Serie A* match respecting the following two criteria: (i) it was played between two of the three teams in Italy that were most searched on Google during the year starting on October 2013, and (ii) the ex-ante probability of its outcome, based on odds data from Bet365, is below the median of predicted probabilities. The table reports coefficient for separate specifications, each including only one lag for attention at different weekly. Controls include year and week-of-the-year fixed effects. Plot includes Bonferroni-corrected confidence intervals for $\alpha = 5\%$. HAC standard errors robust to arbitrary heteroskedasticity and autocorrelation up to lag 3. Kleibergen-Paap rk Wald F-statistic for regression on the 5^{th} lag of attention is 20.3. Referenced in Section 1.6.2.

Figure A.13: Impact of Different Leads of Objective News Articles on Distance



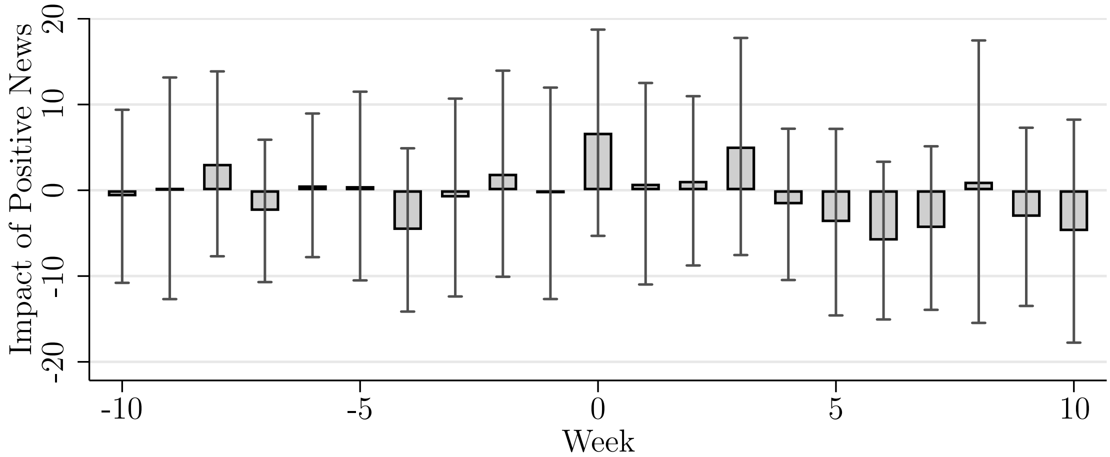
Impact of log number of objective news on interception distance at different weekly leads, for different regressions. Controls include logarithm of negative-sentiment and positive-sentiment articles, year and quarter-of-the-year fixed effects. Plot includes Bonferroni-corrected confidence intervals for $\alpha = 5\%$. HAC standard errors robust to arbitrary heteroskedasticity and autocorrelation up to lag 3. Referenced in Section 1.6.2.

Figure A.14: Impact of Different Leads of Negative-Sentiment News Articles on Distance



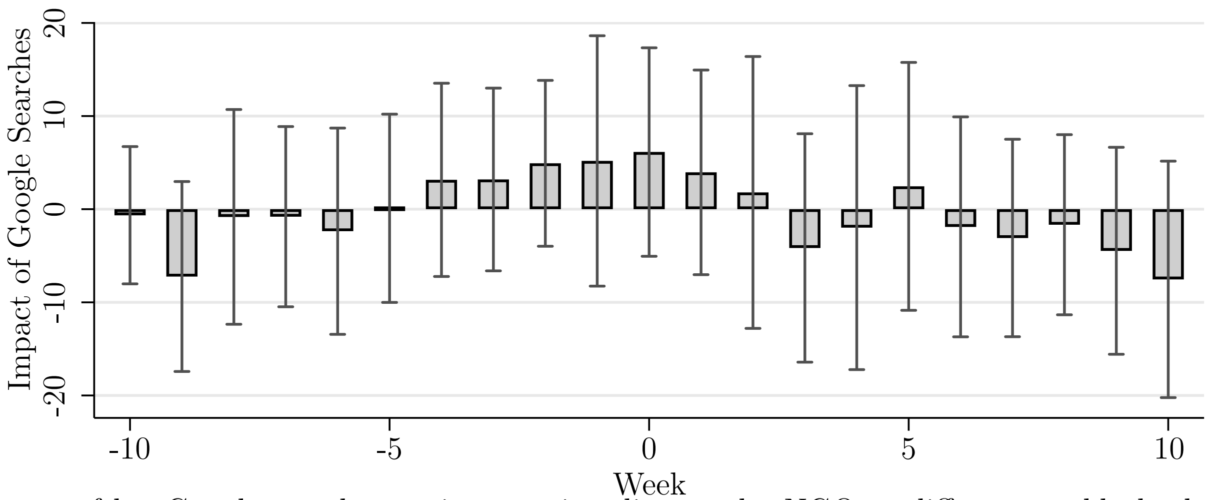
Impact of log number of negative-sentiment news articles on interception distance at different weekly leads, for different regressions. Controls include logarithm of positive-sentiment and objective articles, year and quarter-of-the-year fixed effects. Plot includes Bonferroni-corrected confidence intervals for $\alpha = 5\%$. HAC standard errors robust to arbitrary heteroskedasticity and autocorrelation up to lag 3. Referenced in Section 1.6.2.

Figure A.15: Impact of Different Leads of Positive-Sentiment News Articles on Distance



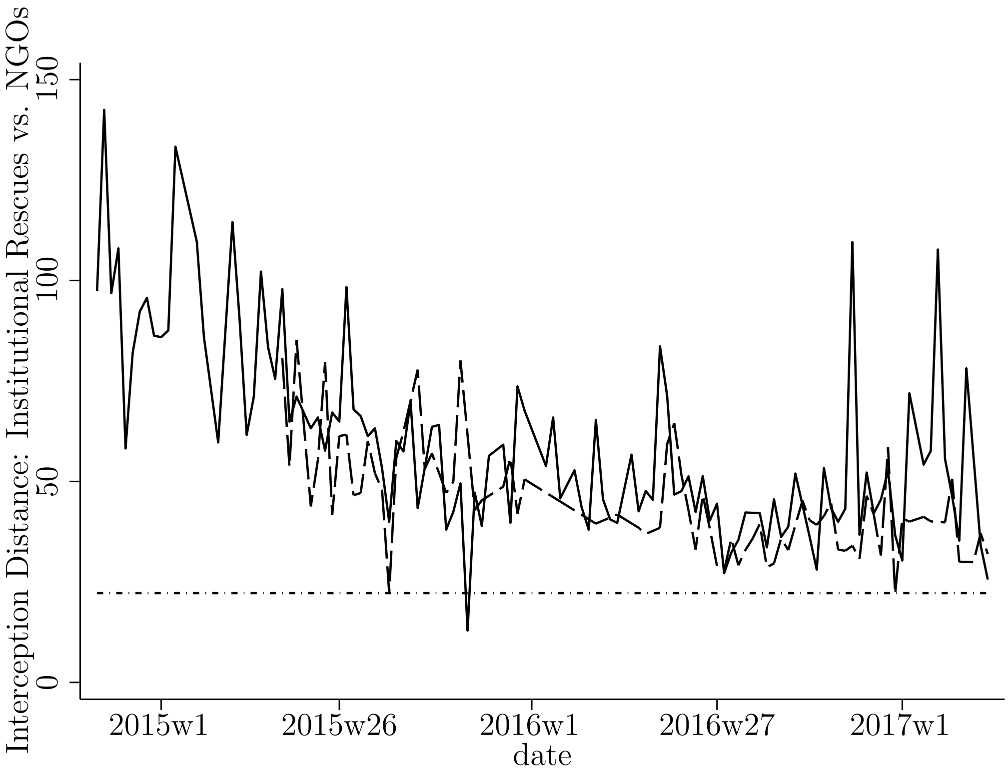
Impact of log number of positive-sentiment news articles on interception distance at different weekly leads, for different regressions. Controls include logarithm of negative-sentiment and objective articles, year and quarter-of-the-year fixed effects. Plot includes Bonferroni-corrected confidence intervals for $\alpha = 5\%$. HAC standard errors robust to arbitrary heteroskedasticity and autocorrelation up to lag 3. Referenced in Section 1.6.2.

Figure A.16: Impact of Different Leads of Searches on NGO Distance



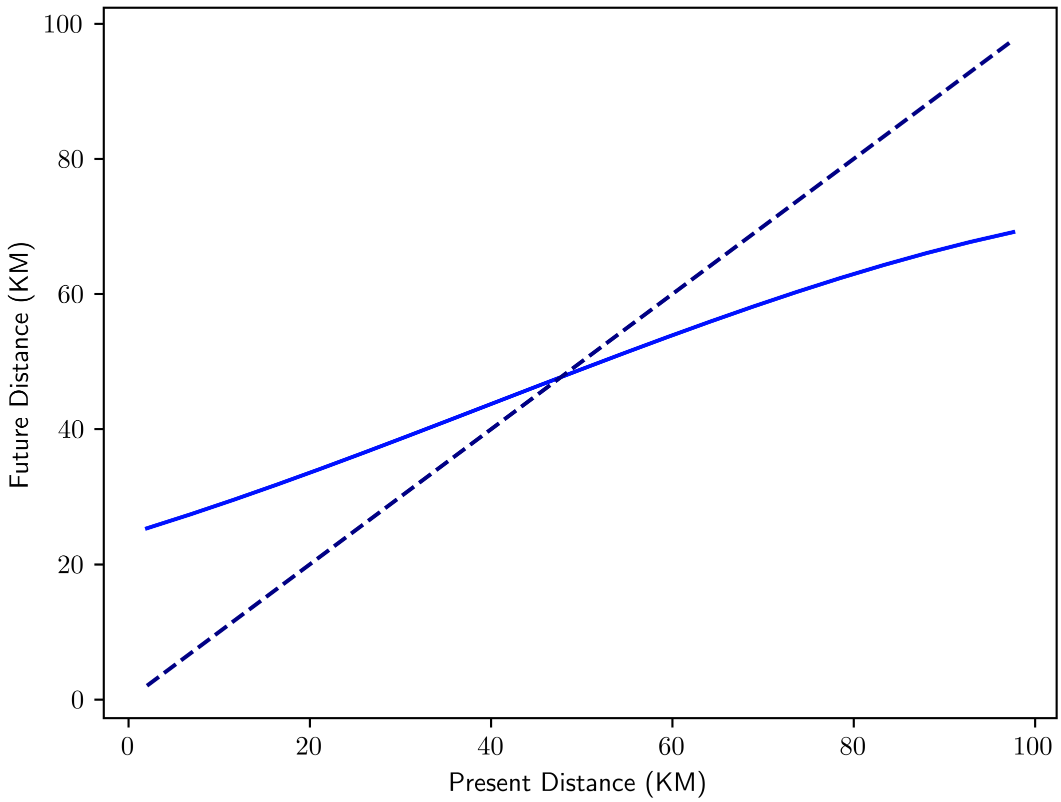
Impact of log Google searches on interception distance by NGO at different weekly leads, for different regressions. Controls include year and quarter-of-the-year fixed effects. Plot includes Bonferroni-corrected confidence intervals for $\alpha = 5\%$. HAC standard errors robust to arbitrary heteroskedasticity and autocorrelation up to lag 3. Referenced in Section 1.6.2.

Figure A.17: Average Rescue Distance by Actor over Time



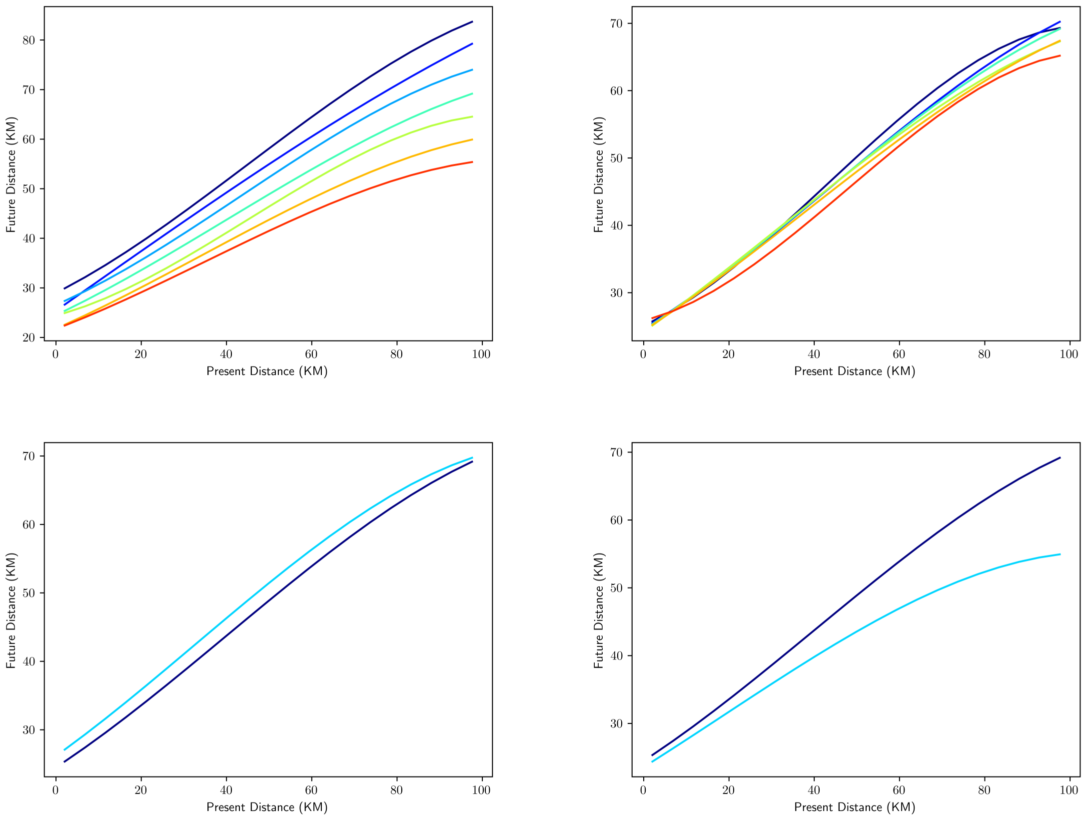
Average rescue distance by actor over time: the solid line represents institutional rescues; the dashed line represents NGOs. The dashed-dotted line defines the limit of territorial waters. Referenced in Section 1.6.2.

Figure A.18: Optimal future distance given present distance



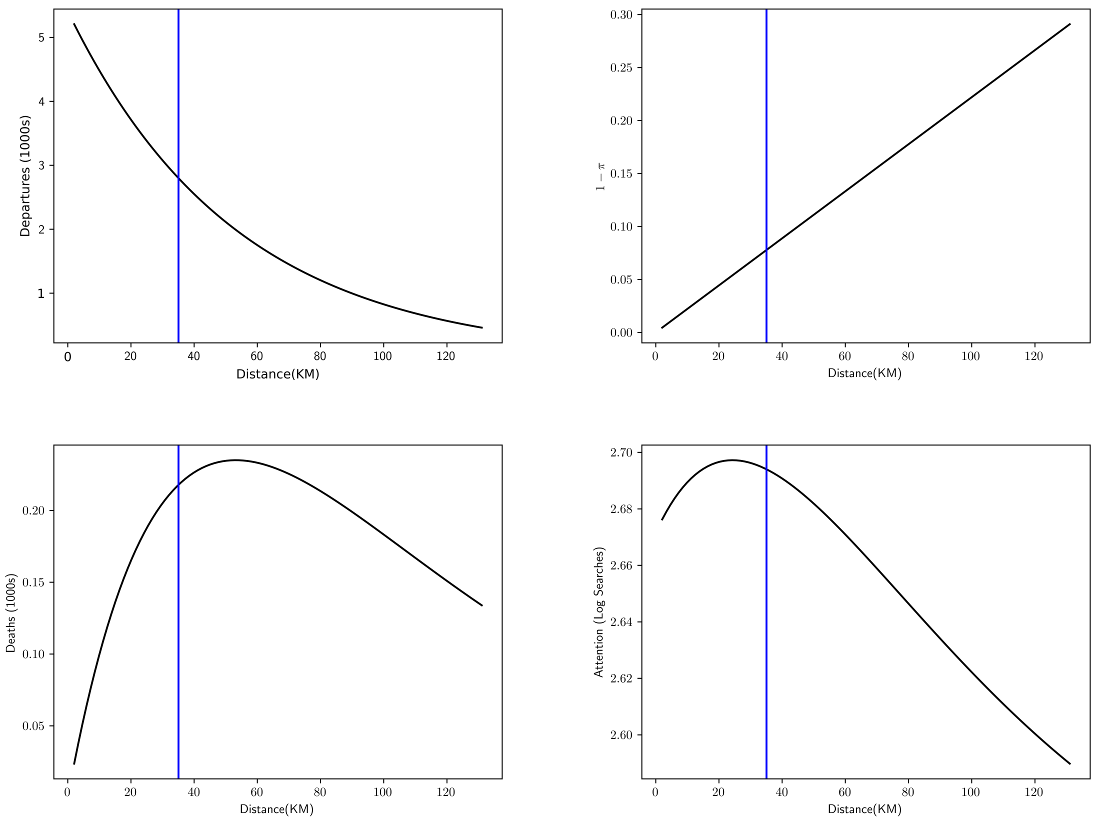
Optimal future distance (KM) given present distance (KM), solid line, with attention shock fixed to mean, good weather, low NGO presence, and past arrivals' stock fixed to 2,000. The dashed line is the 45-degree line. The policy is obtained by VFI using fixed grids, as explained above, and then a 4-degree polynomial is fit through grid points.

Figure A.19: Optimal future distance given present distance, by other states



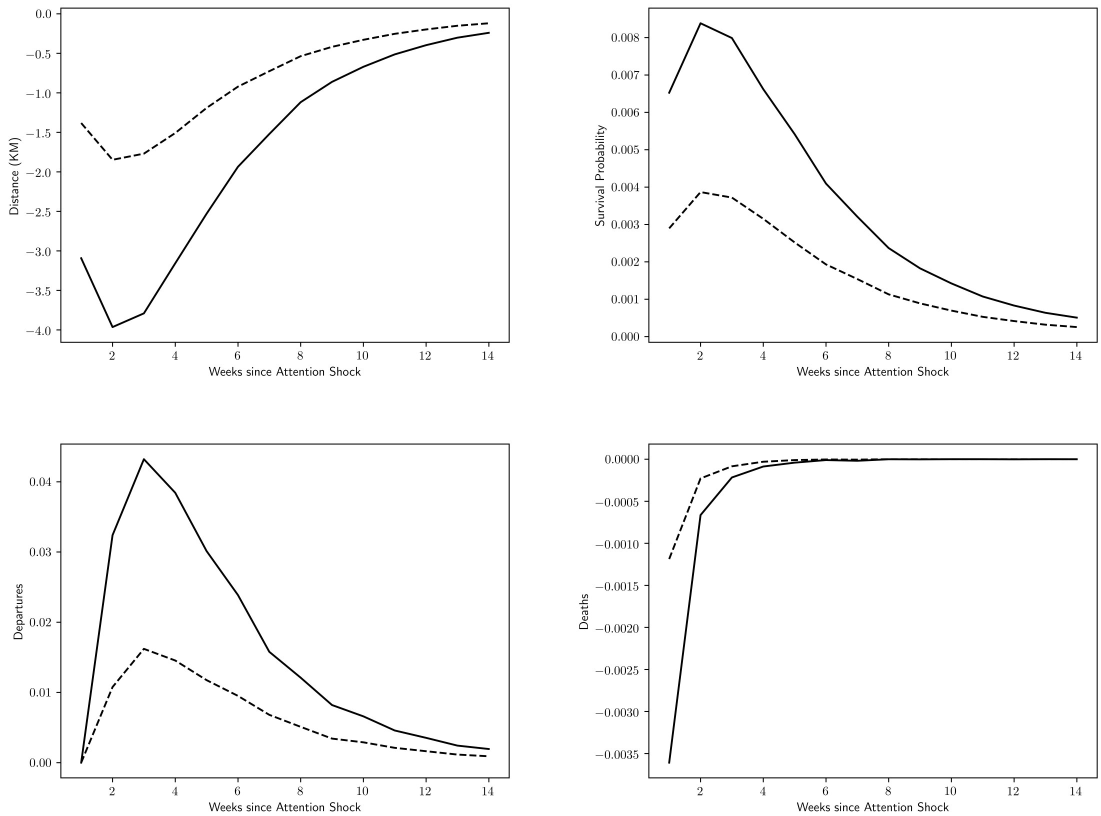
Optimal future distance (KM) given present distance (KM), by attention (upper-LHS panel, warmer color for higher attention), past arrivals stock (upper-RHS panel, warmer color for higher arrivals), weather (lower-LHS panel, darker color is good weather), NGO presence (lower-RHS panel, darker color is low NGO presence). Policies are obtained by VFI using fixed grids, as explained above, and then a 4-degree polynomial is fit through grid points.

Figure A.20: Fixed-distance Policy Impact on Arrivals, Death Probability, and Deaths



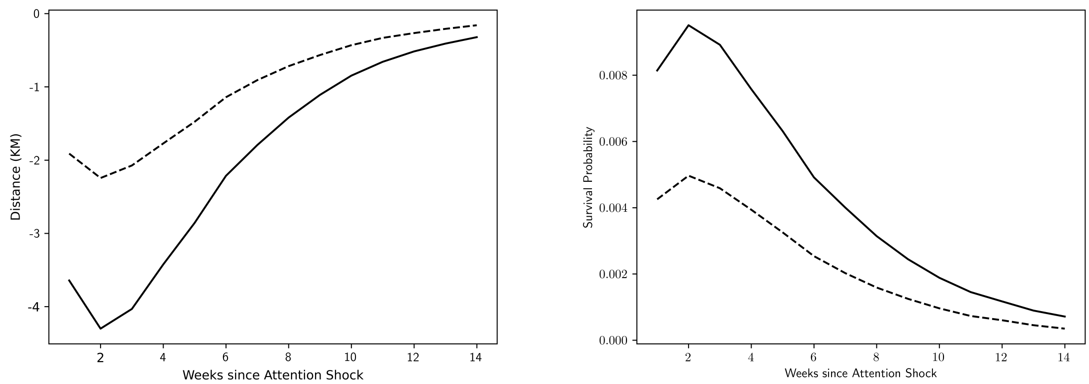
Outcomes of a fixed-distance policy on arrivals, in thousands, (upper-LHS panel), death probability (upper-RHS panel), deaths, in thousands, (lower-LHS panel), and attention (lower-LHS panel). Distance on the x-axis.

Figure A.21: Impact of a Shock to Attention over Time (Median)



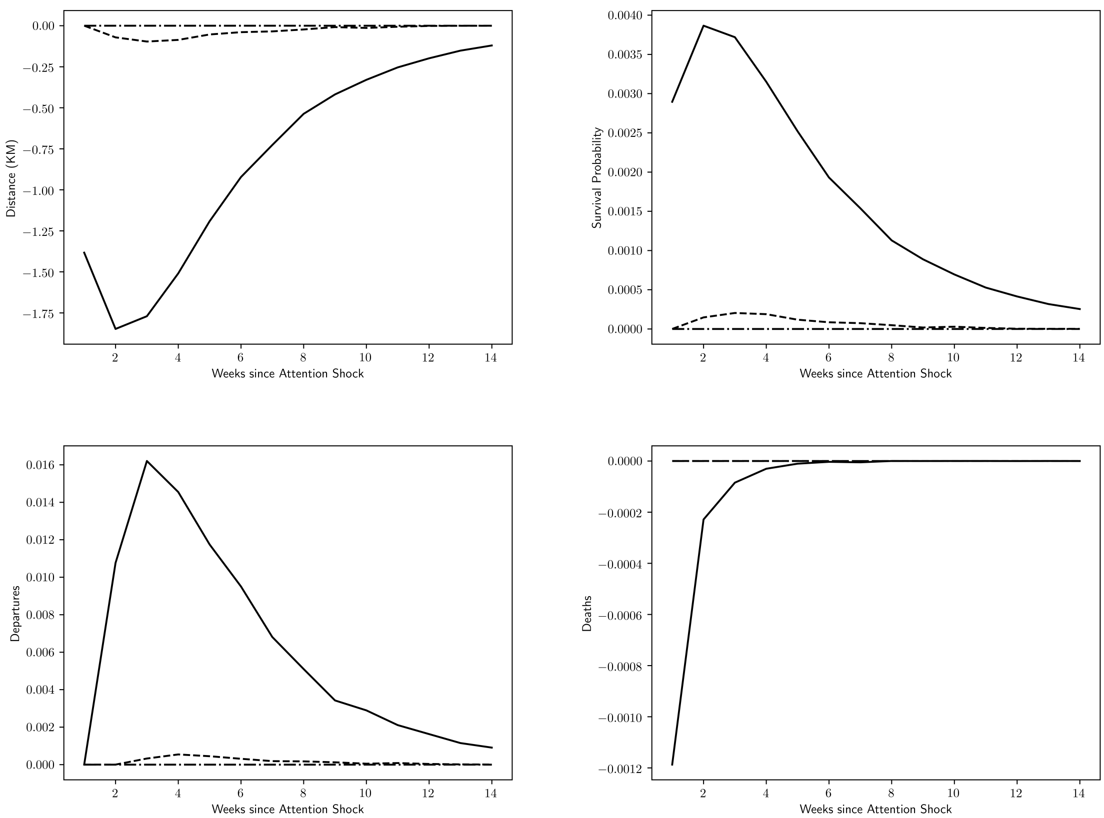
IRF of a positive log-attention shock of 2-sd (solid line) and 1-sd (dashed line) with $\rho_g = 0.776$, in differences with base case, after simulating the model for 100 weeks starting from average values, good weather, and no NGO presence. One standard deviation corresponds to 0.363 log-attention. Upper LHS is variation in median distance set by policy, upper RHS is variation in median probability of rescue, lower LHS is variation in median departures, in thousands, lower RHS is variation in median deaths, in thousands. Montecarlo simulation for 10,000 draws of random vectors of shocks and 15 weeks. The figure is obtained by differentiating the path of the variable in the un-shocked case from that in the shocked case. Figure referenced in Section 1.9.

Figure A.22: Impact of a Shock to Attention over Time (Mean)



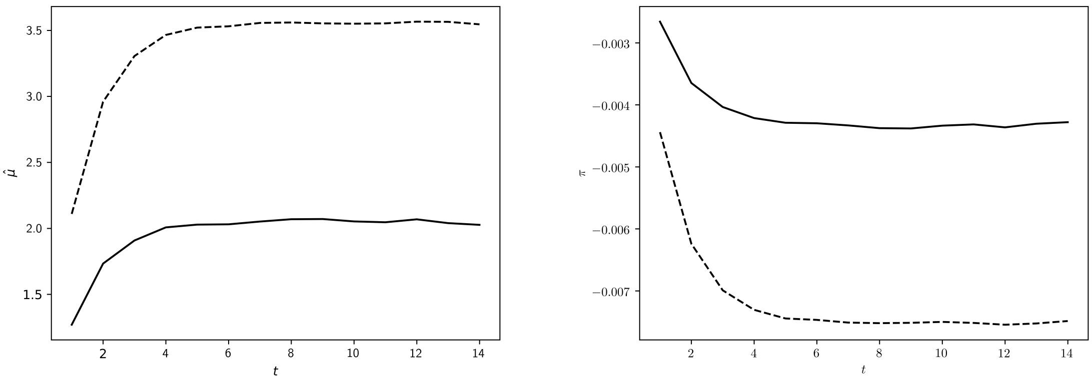
IRF of a positive log-attention shock of 2-sd (solid line) and 1-sd (dashed line) with $\rho_g = 0.776$, in differences with the base case, after simulating the model for 100 weeks starting from average values, good weather, and no NGO presence. One standard deviation corresponds to 0.363 log-attention. The LHS panel displays the variation in the median distance set by policymakers; the RHS panel shows the variation in the mean probability of rescue. Montecarlo simulation for 10,000 draws of random vectors of shocks and 15 weeks. The figure is obtained by differentiating the path of the variable in the un-shocked case from that in the shocked case. Figure referenced in Section 1.9.

Figure A.23: Impact of a 1-sd Shock to Attention over Time (Median), by Persistence



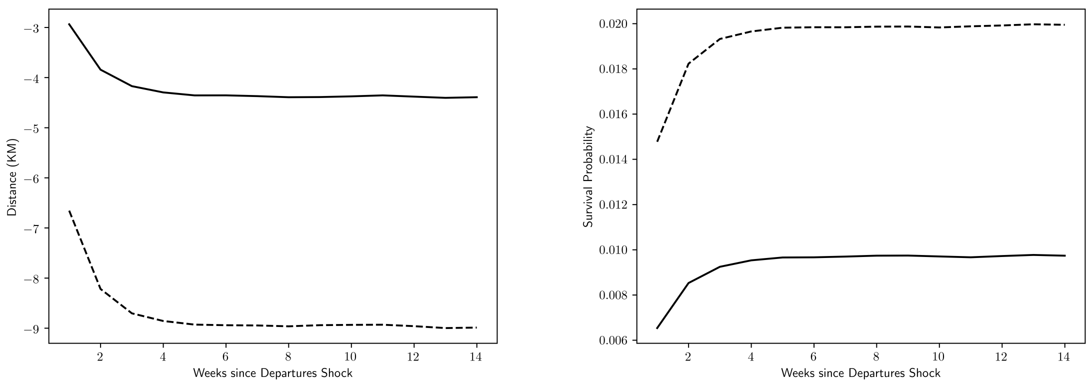
IRF of a positive log-attention shock of 2-sd with $\rho_g = 0.776$, differences with base case, after simulating the model for 100 weeks starting from average values, good weather, and no NGO presence. One standard deviation corresponds to 0.363 log-attention. Different styles represent different degrees of persistence of attention shocks: (1) solid line represents baseline persistence $\rho_g = 0.776$, dashed line represents (2) $\rho_g = 0.9$, and dashed-dotted line represents (3) $\rho_g = 0.999$. Upper LHS is variation in median distance set by policy, upper RHS is variation in median probability of rescue, lower LHS is variation in median departures, in thousands, lower RHS is variation in median deaths, in thousands. Montecarlo simulation for 10,000 draws of random vectors of shocks and 15 weeks. The figure is obtained by differentiating the path of the variable in the un-shocked case from that in the shocked case. Figure referenced in Section 1.9.

Figure A.24: Impact of an Unexpected Permanent Shock to ω_1 over Time (Mean)



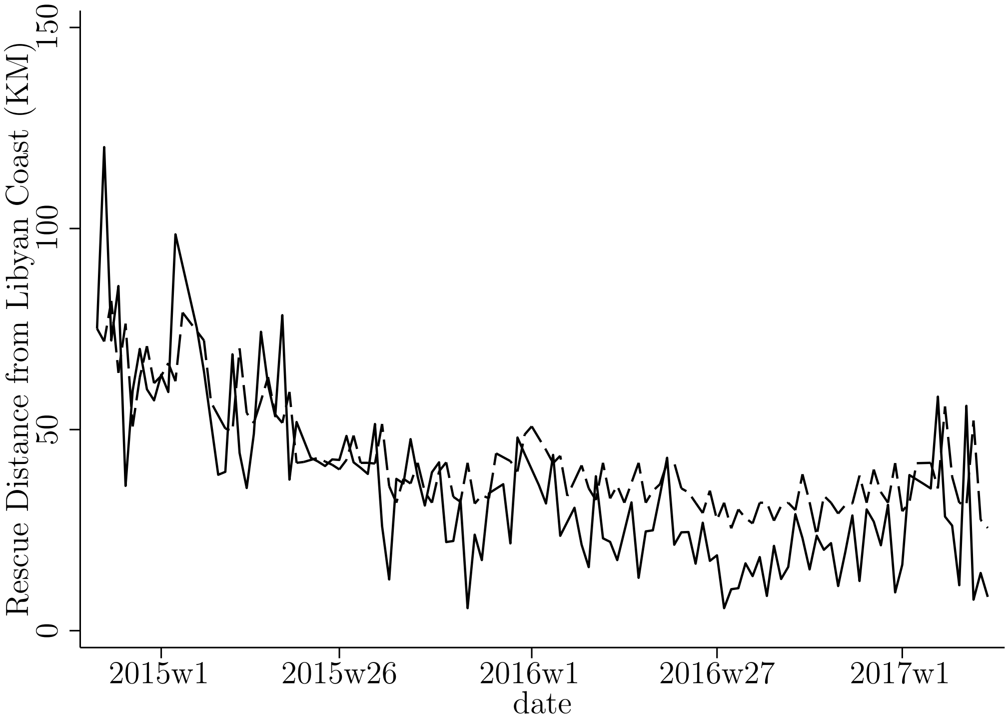
IRF of a permanent unexpected reduction of ω_1 by 5% (solid line), and 10% (dashed line) in differences with the base case, after simulating the model for 100 weeks starting from average values, good weather, and no NGO presence. The LHS panel displays the variation in the mean distance set by policymakers; the RHS panel shows the variation in the mean probability of rescue. Montecarlo simulation for 100,000 draws of random vectors of shocks and 15 weeks. The figure is obtained by differentiating the path of the variable in the un-shocked case from that in the shocked case. Figure referenced in Section 1.9.

Figure A.25: Impact of an Unexpected Permanent Shock to ω_0 over Time (Mean)



IRF of a permanent unexpected reduction of ω_0 by 5% (solid line), and 10% (dashed line) in differences with the base case, after simulating the model for 100 weeks starting from average values, good weather, and no NGO presence. The LHS panel displays the variation in the mean distance set by policymakers; the RHS panel shows the variation in the mean probability of rescue. Montecarlo simulation for 100,000 draws of random vectors of shocks and 15 weeks. The figure is obtained by differentiating the path of the variable in the un-shocked case from that in the shocked case. Figure referenced in Section 1.9.

Figure A.26: Evolution of Data and Model-Predicted Distances



Evolution of model-predicted distances (dashed line) and distances in the data (solid line). Referenced in Section 1.9.

Table A.1: Main Summary Stats from Data

	Mean	sd	Min	Median	Max	N
Arrivals	2584	2797	0	1705	15373	126
Deaths and Missing	55.4	128	0	5	825	126
Survival Frequency	.957	.143	0	.998	1	119
Distance from Ter. Waters.	35.1	20.6	5.6	31.6	120.3	117
Swell	.133	1.03	-1.32	-.265	3.0	126
Migration Searches	16.8	9.66	3.15	17.2	59.1	126
Obj. Articles	171	162	13	130	1398	126
Obj. Art. (Weighted Online)	.681	.6	.0581	.529	5.0	126
Obj. Art. (Weighted Print)	.307	.28	0	.222	1.5	126
Pos. Sent. Articles	93.2	59.1	6	83	338	126
Obj. Art. (Weighted Online)	.371	.238	.000552	.329	1.2	126
Obj. Art. (Weighted Print)	.251	.148	.00819	.239	0.8	126
Neg. Sent. Articles	177	185	10	125	1665	126
Obj. Art. (Weighted Online)	.626	.657	.0343	.438	5.6	126
Obj. Art. (Weighted Print)	.801	.719	.0221	.582	5.1	126
Number of Matches	.119	.325	0	0	1	126
Noteworthy Matches	.0635	.245	0	0	1	126
Avg. Ships by Suez (8 weeks)	185	7.72	174	184	210.8	109

Main summary stats about migration outcomes, weather, attention, searches, articles, and maritime traffic. All variables are weekly aggregates, except for trade variables, displaying monthly values for the 126 weeks in the sample. Arrivals represent all migrants arrived during rescue operations involving migrant boats leaving the North African coast from Libya, obtained from Frontex data. Survival frequency is the ratio of arrivals to departures–arrivals, deaths, and missing in the rescue area. Deaths and missing data are retrieved from Missing Migrants Project. The average distance of rescue operations from territorial waters is reported in KM, obtained from Frontex data. Swell is defined as 4 times the square root of the integral over all directions and all frequencies of the two-dimensional wave spectrum; the integration is performed over all frequencies up to infinity. Swell data was downloaded from the ECMWF database, and it refers to the sea at the crossing of territorial waters around Tripoli and a line connecting the center of Tripoli to the island of Lampedusa–the closest Italian territory. Migration searches on Google refer to Italy. In the same way, objective, positive-sentiment, and negative-sentiment articles about migration are counted among Italian newspapers. The two weighted measures of articles weigh them by a measure of the audience of the newspaper or newspapers' website, using data from *Audiweb* and *Accertamenti Diffusione Stampa*. Noteworthy match is a dummy taking value one if a noteworthy match occurred over a week. The latter is defined as a *Serie A* match respecting the following two criteria: (i) it was played between two of the three teams in Italy that were most searched on Google during the year starting on October 2013, and (ii) the ex-ante probability of its outcome, based on odds data from Bet365, is below the median probabilities. The number of ships crossing Suez North-bound, obtained by Suez Canal Authority, is summed over the 8 weeks prior to the observation.

Table A.2: Impact of Distance and Weather on Risk

				$\bar{\bar{\pi}}_t$				
	OLS	OLS	OLS	OLS	2SLS	2SLS	2SLS	2SLS
$\bar{\mu}_t$	-0.000953	-0.000939	-0.000733^{+}	-0.000890*	-0.00222*	-0.00208*	-0.00229***	-0.00232***
	(0.000622)	(0.000599)	(0.000394)	(0.000392)	(0.000923)	(0.000876)	(0.000571)	(0.000626)
w_t		-0.0180		-0.0192*		-0.00874		-0.0139^{+}
		(0.0122)		(0.00822)		(0.00686)		(0.00716)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-o-y FEs	Yes	Yes	No	No	Yes	Yes	No	No
Week-o-y FEs	No	No	Yes	Yes	No	No	Yes	Yes
N	117	117	117	117	103	103	103	103
$KP\ F$					5.844	5.732	12.784	11.243

All variables are weekly aggregates. The dependent variable is survival frequency, the ratio of arrivals to departures–arrivals, deaths, and missing in the rescue area. Arrivals represent all migrants arrived during rescue operations involving migrant boats leaving the North African coast from Libya, obtained from Frontex data. Deaths and missing data are retrieved from Missing Migrants Project. The main independent variable is the average distance of interceptions (KM), weighted by the proportion of migrants saved, obtained from Frontex data. The first four columns are estimated with OLS, the last four with 2SLS, using as an instrument an 8-week rolling sum over lags of North-bound Suez Crossings. A varying set of season and time controls is used in each specification (partialled out), together with weather and log of one plus departures, as reported in the table. Weather is defined as swell, 4 times the square root of the integral over all directions and all frequencies of the two-dimensional wave spectrum; the integration is performed over all frequencies up to infinity. Swell data was downloaded from the ECMWF database, and it refers to the sea at the crossing of territorial waters around Tripoli and a line connecting the center of Tripoli to the island of Lampedusa–the closest Italian territory. HAC standard errors (in parentheses), robust to arbitrary heteroskedasticity up to 3 lags in the first four columns, and up to 9 lags for the last two. Table referenced in Section 1.4. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.3: Distance, Interceptions by Com. Ships and Suez Crossings

	$\bar{\mu}_t$				mig_t^{com}	
$suez_{t,8}$	-0.553*	-0.730***	-0.495*	-0.718***	-0.00774**	-0.0121***
	(0.221)	(0.139)	(0.197)	(0.153)	(0.00272)	(0.00344)
$suez_{t+8,8}$			-0.184	0.00980		
			(0.168)	(0.111)		
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-o-y FEs	Yes	No	Yes	No	Yes	No
Week-o-y FEs	No	Yes	No	Yes	No	Yes
N	103	103	95	95	103	103

All variables are weekly aggregates. The dependent variable in columns in the first four columns is the average distance of interceptions (KM), weighted by the proportion of migrants saved, obtained from Frontex data. The first two columns have the daily average of Suez North-bound crossings, summed over the previous 8 weeks, as the main independent variable; partialled-out controls include Year and Quarter-of-the-Year FEs, and Year and Week-of-the-Year FEs. Estimations in the third and fourth columns add the main dependent variable forwarded by 8 weeks. In the last two columns, the dependent variable is the proportion of migrants rescued by commercial ships in a given week. The main independent variable is average Suez crossings summed over the previous 8 weeks; controls include Year and Quarter-of-the-Year FEs, and Year and Week-of-the-Year FEs. HAC standard errors (in parentheses), robust to both arbitrary heteroskedasticity and arbitrary autocorrelation up to 9 lags. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.4: Impact of Distance and Weather on Risk, Controlling for Log Departures

	$\bar{\pi}_t$			
	2SLS	2SLS	2SLS	2SLS
$\bar{\mu}_t$	-0.00225*	-0.00213*	-0.00226***	-0.00218***
	(0.000915)	(0.000927)	(0.000543)	(0.000595)
$log(1 + departures)$	0.00577	0.00315	-0.00193	-0.00971*
	(0.00381)	(0.00486)	(0.00438)	(0.00427)
w_t		-0.00656		-0.0198***
		(0.00847)		(0.00588)
Year FEs	Yes	Yes	Yes	Yes
Quarter-o-y FEs	Yes	Yes	No	No
Week-o-y FEs	No	No	Yes	Yes
N	103	103	103	103
$KP\ F$	5.715	5.629	14.336	11.454

All variables are weekly aggregates. The dependent variable is survival frequency, the ratio of arrivals to departures–arrivals, deaths, and missing in the rescue area. Arrivals represent all migrants arrived during rescue operations involving migrant boats leaving the North African coast from Libya, obtained from Frontex data. Deaths and missing data are retrieved from Missing Migrants Project. The main independent variable is the average distance of interceptions (KM), weighted by the proportion of migrants saved, obtained from Frontex data. All columns report 2SLS estimations, using as an instrument a 12-week rolling sum over lags of North-bound Suez Crossings. A varying set of season and time controls is used in each specification (partialled out), as reported in the table. Weather is defined as swell, 4 times the square root of the integral over all directions and all frequencies of the two-dimensional wave spectrum; the integration is performed over all frequencies up to infinity. Swell data was downloaded from the ECMWF database, and it refers to the sea at the crossing of territorial waters around Tripoli and a line connecting the center of Tripoli to the island of Lampedusa–the closest Italian territory. HAC standard errors (in parentheses), robust to arbitrary heteroskedasticity up to 3 lags in the first four columns, and up to 9 lags in the last two. Table referenced in Section 1.4. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.5: Impact of Distance and Weather on Departures

	$\log(1 + dep_t)$							
$\bar{\mu}_t$	0.00357	0.00527	0.00247	-0.00430				
	(0.00943)	(0.00893)	(0.00844)	(0.00881)				
$\bar{\mu}_{t-1}$	-0.0168*	-0.0133*	-0.0167*	-0.0249**	-0.0157*	-0.0198*	-0.0217*	-0.0329**
	(0.00682)	(0.00662)	(0.00743)	(0.00803)	(0.00733)	(0.00929)	(0.0100)	(0.0106)
$\bar{\mu}_{t-2}$	0.00304	0.00682	0.00401	-0.00308				
	(0.00681)	(0.00682)	(0.00732)	(0.00649)				
$\bar{\mu}_{t-3}$	-0.00639	-0.000733	-0.00294	-0.00762				
	(0.00849)	(0.00857)	(0.00869)	(0.00797)				
$\bar{\mu}_{t-4}$	0.00537	0.0136	0.0117	0.0119				
	(0.00810)	(0.0116)	(0.0114)	(0.0111)				
w_t	-0.708***	-0.721***	-0.732***	-0.738***	-1.292***	-1.340***	-1.339***	-1.403***
	(0.0845)	(0.0990)	(0.117)	(0.125)	(0.185)	(0.196)	(0.226)	(0.217)
Quarter-by-y FEs	No	No	No	Yes	No	No	No	Yes
Year FEs	No	Yes	Yes	No	No	Yes	Yes	No
Quarter-o-y FEs	No	No	Yes	No	No	No	Yes	No
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	83	83	83	83	116	116	116	116

All variables are weekly aggregates. The dependent variable is the logarithm of one plus departures, defined as the sum of arrivals, deaths, and missing in the rescue area. The main independent variable is the average distance of interceptions (KM), weighted by the proportion of migrants saved, obtained from Frontex data. The first three columns include weekly lags for distance, with a varying set of controls (No control, Year FEs, Year and Quarter-of-the-Year FEs). Specifications include a varying set of year and season controls, reported in the table. All regressions include weather as a control, defined as swell–4 times the square root of the integral over all directions and all frequencies of the two-dimensional wave spectrum; the integration is performed over all frequencies up to infinity. Swell data was downloaded from the ECMWF database, and it refers to the sea at the crossing of territorial waters around Tripoli and a line connecting the center of Tripoli to the island of Lampedusa–the closest Italian territory. HAC standard errors (in parentheses), robust to both arbitrary heteroskedasticity and arbitrary autocorrelation up to 3 lags. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.6: Impact of Distance and Weather on Departures, Other Lags

	log$(1 + dep_t)$				
$\bar{\mu}_t$	0.00111	0.000722	-0.00383	-0.00430	-0.00365
	(0.00661)	(0.00785)	(0.00833)	(0.00881)	(0.00943)
$\bar{\mu}_{t-1}$	-0.0125^{+}	-0.0144*	-0.0237***	-0.0249**	-0.0177*
	(0.00689)	(0.00703)	(0.00720)	(0.00803)	(0.00887)
$\bar{\mu}_{t-2}$		-0.000142	-0.00122	-0.00308	0.000248
		(0.00544)	(0.00529)	(0.00649)	(0.00789)
$\bar{\mu}_{t-3}$			-0.00774	-0.00762	0.00266
			(0.00849)	(0.00797)	(0.00586)
$\bar{\mu}_{t-4}$				0.0119	0.0126
				(0.0111)	(0.0114)
$\bar{\mu}_{t-5}$					-0.00191
					(0.00807)
w_t	-0.759***	-0.742***	-0.731***	-0.738***	-0.771***
	(0.0890)	(0.107)	(0.103)	(0.125)	(0.114)
Quarter-by-y FEs	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes
N	108	99	91	83	77

All variables are weekly aggregates. The dependent variable is the logarithm of one plus departures, defined as the sum of arrivals, deaths, and missing in the rescue area. Arrivals represent all migrants arrived during rescue operations involving migrant boats leaving the North African coast from Libya, obtained from Frontex data. Deaths and missing data are retrieved from Missing Migrants Project. The main independent variable is the average distance of interceptions (KM), weighted by the proportion of migrants saved, obtained from Frontex data. All regressions include year by quarter-of-the-year FEs and weather as a control, defined as swell–4 times the square root of the integral over all directions and all frequencies of the two-dimensional wave spectrum; the integration is performed over all frequencies up to infinity. Swell data was downloaded from the ECMWF database, and it refers to the sea at the crossing of territorial waters around Tripoli and a line connecting the center of Tripoli to the island of Lampedusa–the closest Italian territory. HAC standard errors (in parentheses), robust to both arbitrary heteroskedasticity and arbitrary autocorrelation up to 3 lags. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.7: Impact of Soccer Matches on Migration Searches

			g_t			
$noteworthy_{t+1}$	-0.363	-0.155	-0.105			
	(0.246)	(0.167)	(0.183)			
$noteworthy_t$	-0.131	-0.128	-0.222			
	(0.147)	(0.150)	(0.141)			
$noteworthy_{t-1}$	-0.467*	-0.395*	-0.614***	-0.651***		
	(0.212)	(0.179)	(0.0793)	(0.0760)		
$matches_{t+1}$					-0.0285	0.0663
					(0.130)	(0.0861)
$matches_t$					-0.0615	-0.0541
					(0.123)	(0.0849)
$matches_{t-1}$					-0.235^{+}	-0.260**
					(0.120)	(0.0816)
Year FEs	No	Yes	Yes	Yes	Yes	Yes
Week-o-y FEs	No	No	Yes	Yes	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
N	124	124	124	125	124	124

All variables are weekly aggregates. The dependent variable is log migration searches. Impact of *noteworthy matches* and *matches* dummies on attention. A *noteworthy* match as a *Serie A* match respecting the following two criteria: (a) it was played between two of the three teams in Italy that were most searched on Google during the year starting on October 2013, and (b) the ex-ante probability of its outcome, based on odds data from Bet365, is below the median of probabilities. The variable *matches*, instead, only preserves criterion (a). The first three columns include one lag and one lead for *noteworthy matches* dummy, with a varying set of controls (No control, Year FEs, Year and Week FEs). The fourth column reports the estimation only for the first lag, with year and week-of-the-year FEs. The last two columns report results for *matches* dummy, with year FEs and then year and week-of-the-year FEs. HAC standard errors (in parentheses), robust to both arbitrary heteroskedasticity and arbitrary autocorrelation up to 3 lags. Table referenced in Section 1.6.2. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.8: Impact of Attention on Distance, 2SLS

	$\bar{\mu}_t$							
	$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 4$	$\tau = 5$	$\tau = 6$	$\tau = 7$	$\tau = 8$
g_τ	4.177	-5.480	3.008	-8.189**	-20.95***	-8.644*	-5.031	0.201
	(8.893)	(5.293)	(8.098)	(2.989)	(3.458)	(3.758)	(8.683)	(5.253)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week-o-y FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	115	114	113	112	111	110	109	108
$KP\ F$	35.635	26.618	53.122	26.913	20.382	33.360	33.789	28.872

All variables are weekly aggregates. The dependent variable is the average distance of interceptions (KM), weighted by the proportion of migrants saved, obtained from Frontex data. The instrument is lag noteworthy matches, a dummy taking value one if a noteworthy match occurred over a week. The latter is defined as a *Serie A* match respecting the following two criteria: (a) it was played between two of the three teams in Italy that were most searched on Google during the year starting on October 2013, and (b) the ex-ante probability of its outcome, based on odds data from Bet365, is below the median of probabilities. The table reports coefficient for separate specifications, each including only one lag for attention at the week τ. All regressions include year and week-of-the-year fixed effects, partialled out. I report a KP F-stats for every estimation. HAC standard errors (in parentheses), robust to both arbitrary heteroskedasticity and arbitrary autocorrelation up to 3 lags. Table referenced in Section 1.6.2. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.9: Impact of News Attention on Distance

	Count			Weighted (Print)			Weighted (Online)		
	$\tau = 4$	$\tau = 5$	$\tau = 6$	$\tau = 4$	$\tau = 5$	$\tau = 6$	$\tau = 4$	$\tau = 5$	$\tau = 6$
$\sin^{-1} obj_\tau$	0.53	-9.32**	-5.76^{+}	-2.93	-15.6**	-20.7**	-8.99	-12.3*	-10.4^{+}
	(3.21)	(3.01)*	(3.08)	(6.40)	(6.03)	(6.85)*	(5.98)	(6.04)	(5.54)
$\sin^{-1} pos_\tau$	-4.63	0.49	0.57	-6.56	9.30	11.6	-2.39	-7.28	1.13
	(3.06)	(3.54)	(2.69)	(9.71)	(10.7)	(11.4)	(5.68)	(6.46)	(7.74)
$\sin^{-1} neg_\tau$	-0.34	6.40*	-0.63	0.12	4.78	-1.09	3.87	11.4*	-1.47
	(2.59)	(2.80)	(2.28)	(3.71)	(4.39)	(4.03)	(4.14)	(5.03)	(4.65)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-o-y FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	113	112	111	113	112	111	113	112	111

All the variables are weekly aggregates. The dependent variable is the average distance of interceptions (KM), weighted by the proportion of migrants saved, obtained from Frontex data. The independent variable is news articles by classification type and counting strategy. Columns 1 to 3 use articles count; estimations in columns 4 to 6 use only print articles and weigh them by the reach of newspapers in September 2018, according to *Accertamenti Diffusione Stampa*; estimations in columns 7 to 9 use only online articles and weigh them by the proportion of website users in September 2018, according to *Audiweb*. For each of the three subgroups, the first, second, and third columns report results when using the 4^{th}, 5^{th}, and 6^{th} lag, respectively. All regressions include year and quarter-of-the-year fixed effects. HAC standard errors (in parentheses), robust to both arbitrary heteroskedasticity and arbitrary autocorrelation up to 3 lags. Table referenced in Section 1.6.2. Significance stars on coefficients refer to baseline significance levels; significance stars on standard errors refer to Bonferroni adjusted significance levels, for nine hypotheses; P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.10: Impact of Attention on Distance: Interaction with NGO Presence

	$\hat{\mu}_t$					
	$i=1$	$i=2$	$i=3$	$i=4$	$i=5$	$i=6$
g_{t-i}	-3.844	-6.466^{+}	-10.06***	-9.360**	-14.09***	-12.87***
	(3.362)	(3.513)	(2.588)	(3.037)	(2.292)	(3.075)
mig_{t-i}^{ngo}	-29.43	-73.44*	-125.9**	-69.65	-136.1***	-74.74^{+}
	(32.86)	(33.02)	(43.87)	(43.41)	(29.49)	(38.53)
$g_{t-i} * mig_{t-i}^{ngo}$	11.25	23.70*	42.79**	25.79^{+}	47.17***	25.34*
	(11.07)	(11.24)	(14.22)	(14.42)	(10.55)	(12.52)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-o-y FEs	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
N	108	106	106	105	105	102

All variables are weekly aggregates. This table reports the impact of searches on rescue distance in interaction with NGO migrant share of rescues. Each specification has a different lag of searches and NGO presence (1 to 6) as dependent variables. All of the specifications control for year and quarter-of-the-year FEs. HAC standard errors (in parentheses), robust to both arbitrary heteroskedasticity and arbitrary autocorrelation up to 3 lags. Table referenced in Section 1.6.2. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.11: NGO and Institutional Distances

	$\hat{\mu}_t^{ngo}$			
$\hat{\mu}_t^{inst}$	0.373**	0.205*	0.137+	0.144+
	(0.121)	(0.0994)	(0.0817)	(0.0814)
Year 2016		-14.17***	-15.44***	-15.71***
		(3.395)	(2.906)	(2.915)
Year 2017		-13.45***	-16.07***	-16.46***
		(2.976)	(3.998)	(4.109)
2^{nd} quarter			4.354	4.295
			(3.462)	(3.480)
3^{rd} quarter			-4.740+	-4.968+
			(2.651)	(2.774)
4^{th} quarter			-2.864	-3.244
			(3.120)	(3.242)
g_{t-5}				1.152
				(3.019)
Constant	12.01***	25.50***	29.70***	26.54**
	(3.349)	(4.509)	(5.201)	(9.496)
N	74	74	74	74

All the variables are weekly aggregates. This table reports the relation between institutional average rescue distance and NGO operations average rescue distance. The first three specifications progressively introduce controls (No control, Year FEs, and Quarter-of-the-Year FEs). The last specification introduces the 5^{th} lag of attention as an independent variable. HAC standard errors (in parentheses), robust to both arbitrary heteroskedasticity and arbitrary autocorrelation up to 3 lags. Table referenced in Section 1.6.2. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.12: Impact of Arrivals on Attention, Other Lags

	g_t				
mig_t	0.00978	0.0116	0.0101	0.00963	0.00714
	(0.0151)	(0.0146)	(0.0142)	(0.0145)	(0.0142)
mig_{t-1}	0.0364*	0.0388*	0.0415*	0.0411*	0.0400*
	(0.0168)	(0.0196)	(0.0200)	(0.0197)	(0.0202)
mig_{t-2}		0.0118	0.0146	0.0169	0.0155
		(0.0178)	(0.0185)	(0.0180)	(0.0182)
mig_{t-3}			0.0108	0.0134	0.0153
			(0.0132)	(0.0138)	(0.0135)
mig_{t-4}				0.0108	0.0130
				(0.0114)	(0.0122)
mig_{t-5}					0.0101
					(0.0111)
Year FEs	Yes	Yes	Yes	Yes	Yes
Quarter-o-y FEs	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes
N	125	124	123	122	121

All the variables are weekly aggregates. The dependent variable is log Google searches about migration in a given week. The main dependent variables are lags of migrants' arrivals (in thousands)–representing all migrants arrived during rescue operations involving migrant boats leaving the North African coast from Libya, obtained from Frontex data. All regressions include year FEs and quarter-of-the-year FEs as a control. HAC standard errors (in parentheses), robust to both arbitrary heteroskedasticity and arbitrary autocorrelation up to 3 lags. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.13: Model Parameters

Est. Strategy	**Par.**	**Description**	**Estimate**	**90% Conf. Int.**
IV	$-\lambda$	arrival rate of incident	-0.00222	$[-0.00374, -0.000702]$
OLS	ω_0	intercept of migrant arrivals	8.60	$[8.06, 9.13]$
	ω_1	coefficient on log distance	-0.0188	$[-0.034, -0.00359]$
	ω_2	coefficient on bad weather	-1.87	$[-2.41, -1.33]$
GLS	α_0	intercept of attention eq.	2.517	$[2.312, 2.722]$
	α_1	coefficient on deaths	0.474	$[0.152, 0.797]$
	α_2	coefficient on arrivals	0.028	$[0.014, 0.042]$
	ρ_g	AR1 coefficient for error	0.776	
Freq.	Π_n	transition matrix for NGOs	(0.642,	$[0.535, 0.748]$
			0.709)	$[0.583, 0.835]$
Freq.	Π_w	transition matrix for weather	(0.571,	$[0.464, 0.679]$
			0.652)	$[0.536, 0.769]$
MLE	θ_1	stock depreciation	0.981	$[0.860, 0.999]$
	θ_2	relative importance of deaths	0.999	$[0.659, 1.000]$
	θ_3	coefficient on attention	1.293	$[0.988, 1.481]$
	θ_4	curvature on deaths and arrivals	3.176	$[2.374, 3.247]$
	θ_5	NGO cost	0.552	$[0.019, 0.635]$
Ass.	β	discount factor	0.99	

Estimated parameters, with symbol in the model, estimation strategy, and estimated value. The value for the discount factor is assumed. Errors for the utility parameters obtained with bootstrap (100 draws).

Table A.14: Model and Data Moments

Moment	**Model**	**Data**	**95% Data CI**
β in $\mu_t = \alpha + \beta g_{t-1} + \varepsilon_t$	-14.7	-17.5	$[-25, -9.98]$
β in $\mu_t = \alpha + \beta \mu_{t-1} + \varepsilon_t$	0.779	0.671	$[0.507, 0.835]$
β in $\mu_t = \alpha + \beta \ell_{t-1} + \varepsilon_t$	-0.00113	-0.00147	$[-0.00265, -0.000299]$
β in $\mu_t = \alpha + \beta d_{t-1} + \varepsilon_t$	-0.00281	-0.0111	$[-0.0428, 0.0205]$
β in $\mu_t = \alpha + \beta mig_{t-1}^{ngo,high} + \varepsilon_t$	-15.1	-16.032	$[-25.3, -6.77]$
β in $\mu_t = \alpha + \beta swell_{t-1}^{high} + \varepsilon_t$	3.883	5.69	$[-2.34, 13.7]$
β_Q^2 in $\mu_t = \alpha + \beta_Y' Y_t + \beta_Q' Q_t + \varepsilon_t$	-8.5	-4.68	$[-13.7, 4.35]$
β_Q^3 in $\mu_t = \alpha + \beta_Y' Y_t + \beta_Q' Q_t + \varepsilon_t$	-15.7	-16.3	$[-24.3, -8.22]$
β_Q^4 in $\mu_t = \alpha + \beta_Y' Y_t + \beta_Q' Q_t + \varepsilon_t$	-14.7	-17.7	$[-27.2, -8.19]$
β_Y^{2015} in $\mu_t = \alpha + \beta_Y' Y_t + \beta_Q' Q_t + \varepsilon_t$	-26.3	-34.7	$[-52.2, -17.1]$
β_Y^{2016} in $\mu_t = \alpha + \beta_Y' Y_t + \beta_Q' Q_t + \varepsilon_t$	-38.6	-56.1	$[-73.1, -39.2]$
β_Y^{2017} in $\mu_t = \alpha + \beta_Y' Y_t + \beta_Q' Q_t + \varepsilon_t$	-46.2	-60.3	$[-80.9, -39.6]$

Table comparing moments obtained from model-predicted distances and the true data. $mig_t^{ngo,high}$ is a dummy taking value 1 if the proportion of rescues performed by NGOs in a given week is higher than median. $swell_t^{high}$ is a dummy taking value 1 swell in a given period is higher than median. The vectors Y_t and Q_t are year and quarter-of-the-year FEs. The variable g_t represents log Google searches, μ_t is average rescue distance, ℓ_t are migrants' departures, and d_t are dead and missing migrants.

A.2 Frontex Data

In this section, I give an account of the procedures followed for constructing the interceptions dataset used in the paper.

A.2.1 Construction of Dataset

I obtained Frontex data on interception locations through an FOIA request under Regulation (EC) No 1049/2001 of the European Parliament and of the Council of 30 May 2001, using the portal AskTheEU. The request can be consulted at https://www.asktheeu.org/en/request/boat_interception_data_during_op_2#outgoing-9360. With a subsequent request, I obtained country of departure. These two datasets list incidents–interceptions–involving irregular migrants. They show the number of same-day incidents, along with the covariates listed above. Importantly, coordinates in the data seem to have been multiplied by the number of incidents on that day. For this reason, I made an inquiry with Frontex via email and received a corrected dataset. In the first two requests, Frontex had not agreed to publish the location of interceptions within Triton's Operational Area–a few operations occurring unusually far from the Libyan coast. However, in the subsequent email exchange, Frontex made locations for these operations available. The dataset received during the private exchange did not include the type of transport and country of departures as variables. Luckily, it was possible to match this information later. For days in which only one operation had occurred, the matching was based on the date. For days with more than one operation, I matched observations based on the number of migrants, type of detection, and type of interception. The matching process was effective, leaving out only 45 interceptions–for these observations, for them, we lack Frontex information on country of departure and type of transportation. However, this number was reduced to 3 when applying the procedure to retain only rescues for boats from Libya, explained below.

A.3 Comparison of Aggregates to Italian Coast Guard Data

The Italian Coast Guard produces aggregate data on rescue operations, reporting operations per year, and actor (CGCCP, 2017). I used it to check for inconsistencies in the aggregate number of migrants saved. For example, in 2015, Frontex data contains 134,073 migrants rescued in boats from Libya against 139,777 in Italian data; in 2016, the former contains 158,338 and the latter 162,732. These differences may be due to one of the following reasons. First, there might be some discrepancies in how the data deals with migrants who lost their lives during operations, or whose corpse was found by rescuers. Frontex data classifies these cases among total migrants and also collects them as deaths during the operation. For this reason, the number of migrants in the data I use is the number of total migrants minus the number of deaths. Italian Coast Guards might use different conventions. Second, I use an arguably 'conservative' way of assigning departures to Libya. Third, very few NGO operations might be missing from the data. Indeed, Frontex data lacked the NGO classification in 2015. As I document in the next sections of the appendix, I manually matched operations in my dataset to rescue data available prepared by one NGO, complete with location and number of migrants, and news data about interceptions and disembarkations. Using this strategy, matched Frontex data counts 18,229 migrants intercepted by NGOs against 20,063 in Italian aggregate data; in 2016, the former has 43,604 intercepted by NGOs, and the latter 46,796. There, part of the mismatch can likely be explained by the fact that data on NGO interceptions in CGCCP (2017) also includes non-Libyan interceptions; however, another part can be explained by a very small number (12) of interceptions not present in Frontex data.

A.3.1 Selection of Interceptions from Libya

As it is apparent from Figure A.1, rescue operations during the period were highly concentrated in the area of the Mediterranean Sea enclosed between Tunisia and the West coast of Libya. Also, we can visualize operations outside this area as geographical outliers, given their position. For the sake of internal validity, we drop these outliers in two ways. First, upon observing the skewness of interception longitudes and latitudes in Figure A.8, we use the matched observations–having country of departure–to extract the 99.5^{th} percentile. Second, for all matched observations, we retain only interceptions with Libya as the source country. The resulting distribution of longitudes and latitudes can be observed in Figure A.9. Finally, the geographical distribution of interceptions available in the sample is displayed in Figure A.10, showing a scatter of interceptions locations overlaid over a 2-d histogram of interception frequencies in Inverse Hyperbolic Sine units.

A.3.2 NGO Operations in 2015

In the matched Frontex dataset, according to the type of interception classification, migrants rescued during NGO operations were only 2,840 in 2015, against 20,063 in CGCCP (2017). Instead, in 2016 the former was 43,602 and the latter 46,796. MSF (in partnership with MOAS) was the only NGO actor performing interceptions during the spring and summer of 2015, except for Sea-Watch, performing few complementary actions in interceptions, because MSF was the only NGO actor with naval assets in place able to take migrants on board–and disembark them in Italy. Then, I corrected the information available in Frontex (2017), using data about NGO interceptions by MSF, publicly available on their website. I matched based on location and number of migrants, encountering no or negligible discrepancies–all documented. In a few cases, I had to complement my strategy with news data on operations available through the European Media Monitor website. In the end, I was unable to match only 12 MSF interceptions with Frontex data. As explained above, matched Frontex data counts 18,229 migrants intercepted by NGOs against 20,063 in Italian aggregate data in 2015; in 2016, the former has 43,604 intercepted by NGOs, and the latter 46,796. Again, part of the discrepancy can be explained by the fact that data on NGO interceptions in CGCCP (2017) also includes non-Libyan interceptions.

A.3.3 Commercial Ships

There is a considerable amount of misreporting of the type of actor for commercial ships' interceptions in Frontex data. Indeed, the agency classified several interceptions by commercial ships as 'Other'. An inspection of news articles revealed that this code, at times, is applied to Frontex assets' interceptions. Using news data from the European Media Monitor website I check, for every interception classified as 'Other', if it was an interception by a commercial vessel. For each date where an interception classified as 'Other' was present, I checked for the presence of articles about the rescue in main Italian news agencies (ANSA, Adnkronos, AGI) in the next three days after the operation, among articles including one of the following words: `migrant* migraz* immigra* rifugiat* clandestin*`. If the article was not present, I increased the number of sources to include all Italian news websites or the number of days. The process is documented in the dataset I manually compiled. Following this procedure, I was able to match a considerable number of operations. Now, matched Frontex data has 13,593 migrants intercepted by commercial ships against 16,158 in Italian data in 2015; in 2016, the former counts 10,152 intercepted by commercial ships, and the latter 13,888. In this case, unmatched operations can still be classified as 'Other'. However, part of the difference can still be explained by the fact that the aggregate number of interceptions by commercial vessels in CGCCP (2017) does not only include interceptions for boats from Libya. This is even more of an issue for commercial ships because their interceptions tend to occur a bit North of the usual rescue area, closer to the routes from Tunisia or Egypt.

A.4 Missing Migrants

To use Missing Migrants data, I need to extract deadly incidents that occurred to migrants leaving Africa from Libya. The country of departure is not a variable in the dataset, as this information is not readily available in most cases. Nonetheless, Missing Migrants data contains two geographical variables that can be used to this end. First, it contains a variable indicating the route followed by migrants. Second, it contains a location description in words. I use the first variable to drop all observations not included in the "Central Mediterranean Route". I select all incidents containing Libyan toponyms, Also, I include incidents displaying general toponyms of the Strait of Sicily and cases of unknown locations in the Central Mediterranean, since migrants from Libya are 91% of migration in the Central Mediterranean route during my sample period.

A.5 News Articles from Factiva

As I explained in Section 1.3.2, I retrieved articles based on the presence of at least one string referring to migration as well as a string among a list of Mediterranean toponyms. The list of string used in retrieving articles, complete with logical operators, is: (`migra*` OR `immigra*` OR `rifugiat*` OR `clandestin*` OR `richiedent* asilo`) AND (`Canale di Sicilia` OR `Sicilia` OR `Libia` OR `Lampedusa` OR `Mediterraneo`).

A.5.1 Cleaning of News Articles

To focus on news about migration and migration coverage, I excluded news about movies, books, cultural events relating to migration. Then, I excluded articles containing one or more of the following strings: `film` OR `lungometraggio` OR `cortometraggio` OR `cinema` OR `rappresentazione` OR `spettacolo` OR `premiere` OR `libr*` OR `la mostra` OR `le mostre` OR `delle mostre` OR `sulla mostra` OR `sulle mostra` OR `dalla mostra` OR `dalle mostra`.

Finally, Factiva data also contains newswires. These are available to the public online. However, newswires also give aggregations used in redacting newspapers. I exclude these since they only repeat pieces of news from elsewhere. I do so by deleting articles containing one of the two following strings: `caporedattori` OR `notizie del giorno`.

A.5.2 Implied Probabilities from Odds

Gambling odds for the event E are Euros paid back for a successful one Euro bet on E. Define the random variable R, with finite support $S \in \mathbb{R}$. Assume that the betting agency offers bets for every outcome of R in S. Suppose the agency makes a mark-up $\mathcal{M}$, equal across events with positive probability. Call o_i gambling odds of realization of $i \in \mathbb{R}$. The probability associated with the event, denoted by p_E, is:

$$p_i = \frac{1}{\mathcal{M} o_i}. \tag{A.1}$$

Where $\mathcal{M}$ is given by:

$$\mathcal{M} = \sum_{i \in S} \frac{1}{o_i}. \tag{A.2}$$

I use the previous two equations to retrieve the implied probability of the outcome that occurred from odds[1].

A.5.3 Probability of survival

By the memoryless property of the exponential distribution, we can write the probability of survival as the product of the probability of surviving in the Libyan territorial waters and the probability of surviving beyond. Call a the rescue distance for a migrant's rescue. We can write the following

$$\begin{aligned}\pi_t &= exp\left(-\lambda b\right) \int_0^{+\infty} \int_a^{+\infty} \lambda e^{-\lambda x} dx \frac{1}{\mu_t} \exp\left(-\frac{1}{\mu_t} a\right) da = \\ &= \exp\left(-\lambda b\right) \int_0^{+\infty} e^{-\lambda a} \frac{1}{\mu_t} \exp\left(-\frac{1}{\mu_t} a\right) da = \\ &= \frac{\exp\left(-\lambda b\right)}{\lambda \mu_t + 1}\end{aligned} \tag{A.3}$$

A.5.4 Departures

Consider a measure M of homogeneous migrants with wealth k. Migrants are linear in utility, and death utility is set to 0 (utility of 0 consumption). The marginal utility of consuming outside Europe is one and in $\alpha > 1$ Europe.

[1] A regression of a dummy taking value one if the home team wins on the market-implied probability of this event for all teams yields a non-significant constant. Also, it gives a coefficient on the dummy of 1.07, with a p-value lower than 0.001. Finally, the coefficient is not statistically significantly different from 1 according to an F-test–the p-value is 0.326, and the number of observations is 1140. This is evidence that market-implied probability fairs very well at representing the actual probability of outcomes.

Migrants travel if:

$$\pi\alpha(k-p) > k \tag{A.4}$$

Price paid by migrants is a linear function of the rescue probability:

$$p = k\frac{1-\pi\alpha}{\pi\alpha} \tag{A.5}$$

Or

$$p = k\frac{1}{\pi\alpha} - k \tag{A.6}$$

Smugglers face fixed cost c to provide a journey. Given the assumptions on the market and smugglers' technology, their profit is given by

$$\Pi = \frac{k}{\alpha}\frac{\exp(-\lambda b)}{\lambda\mu + 1} - k - c. \tag{A.7}$$

Then, smuggler offers his services if

$$\frac{1}{c} > (\lambda\mu + 1)\left(\frac{1}{k} + \frac{1}{\alpha}\right)\exp(\lambda b). \tag{A.8}$$

Migrants and smugglers approximate policy as:

$$\mu_t = \kappa_0 + \kappa_1\hat{\hat{\mu}}_{t-1} \tag{A.9}$$

Then, we have the following restriction on smugglers selling crossings.

$$\frac{1}{c} > [\lambda(\kappa_0 + \kappa_1\hat{\hat{\mu}}_{t-1}) + 1]\left(\frac{1}{k} + \frac{1}{\alpha}\right)\exp(\lambda b). \tag{A.10}$$

The measure of smugglers present at a given week is given by a random variable, given by the additive constant $\hat{M}_t$, and the random term ε_t, the log of which is distributed with mean 0. This implicitly defines the measure of migrants leaving Libya at a given time t.

$$M_t = \hat{M}_t\varepsilon_t F_{1/v}\left([\lambda(\kappa_0 + \kappa_1\hat{\hat{\mu}}_{t-1}) + 1]\left(\frac{1}{k} + \frac{1}{\alpha}\right)\exp(\lambda b)\right). \tag{A.11}$$

Define as w a variable taking value one if the weather is bad and zero if it is good. Assume $1/v$ is exponential with mean $\bar{v}(w)$ for $w \in 0, 1$–mean depends on the weather. Suppose $\hat{M}_t$ has mean $\hat{m}$. Then, log mean departures are given by:

$$\log(\ell_t) = \omega_0 + \omega_1\hat{\hat{\mu}}_{t-1} - \omega_2 w_t. \tag{A.12}$$

Appendix B

Appendix for Chapter 2 'Informing Risky Migration: Experimental Evidence from Guinea'

B.1 Figures

Figure B.1: Mediterranean Crossings by nationality, over time

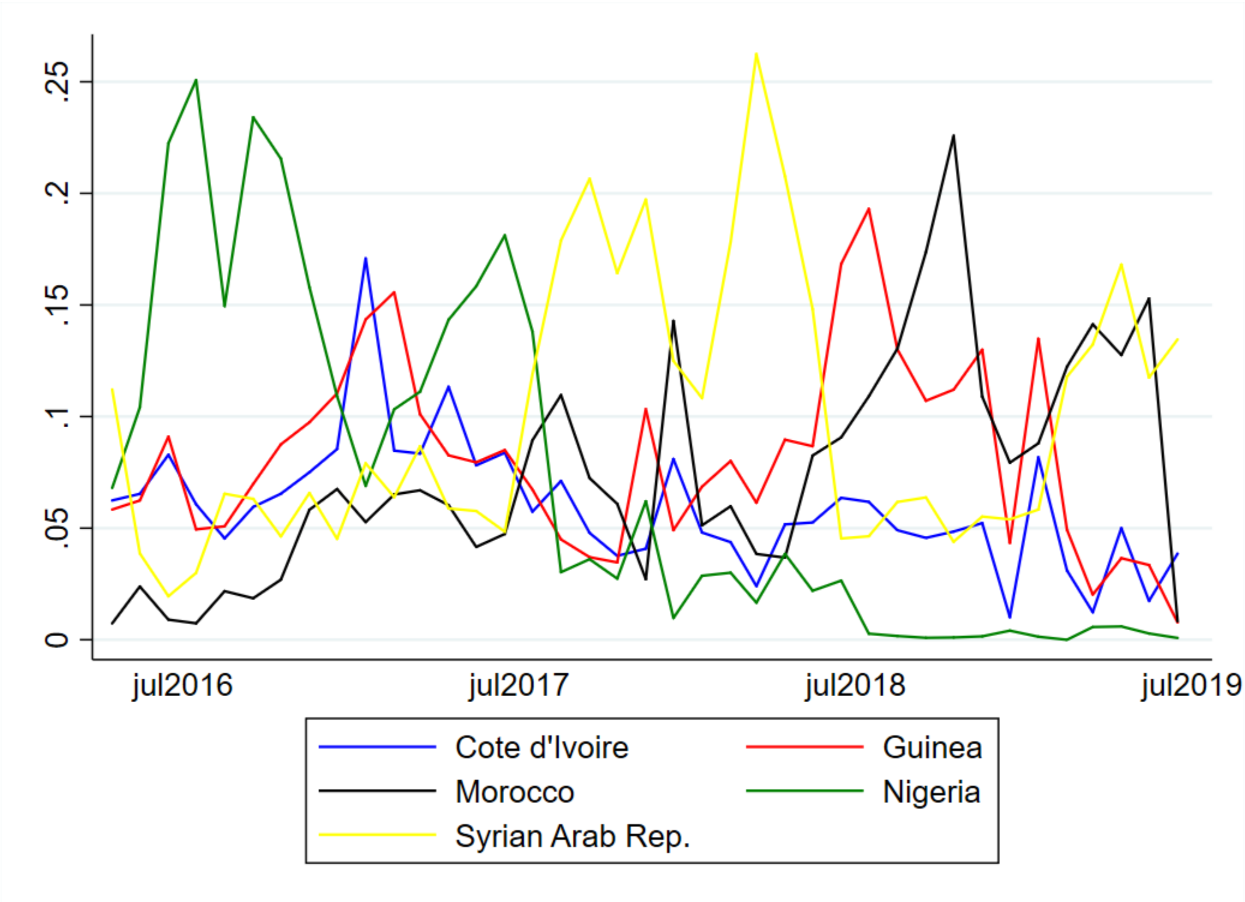
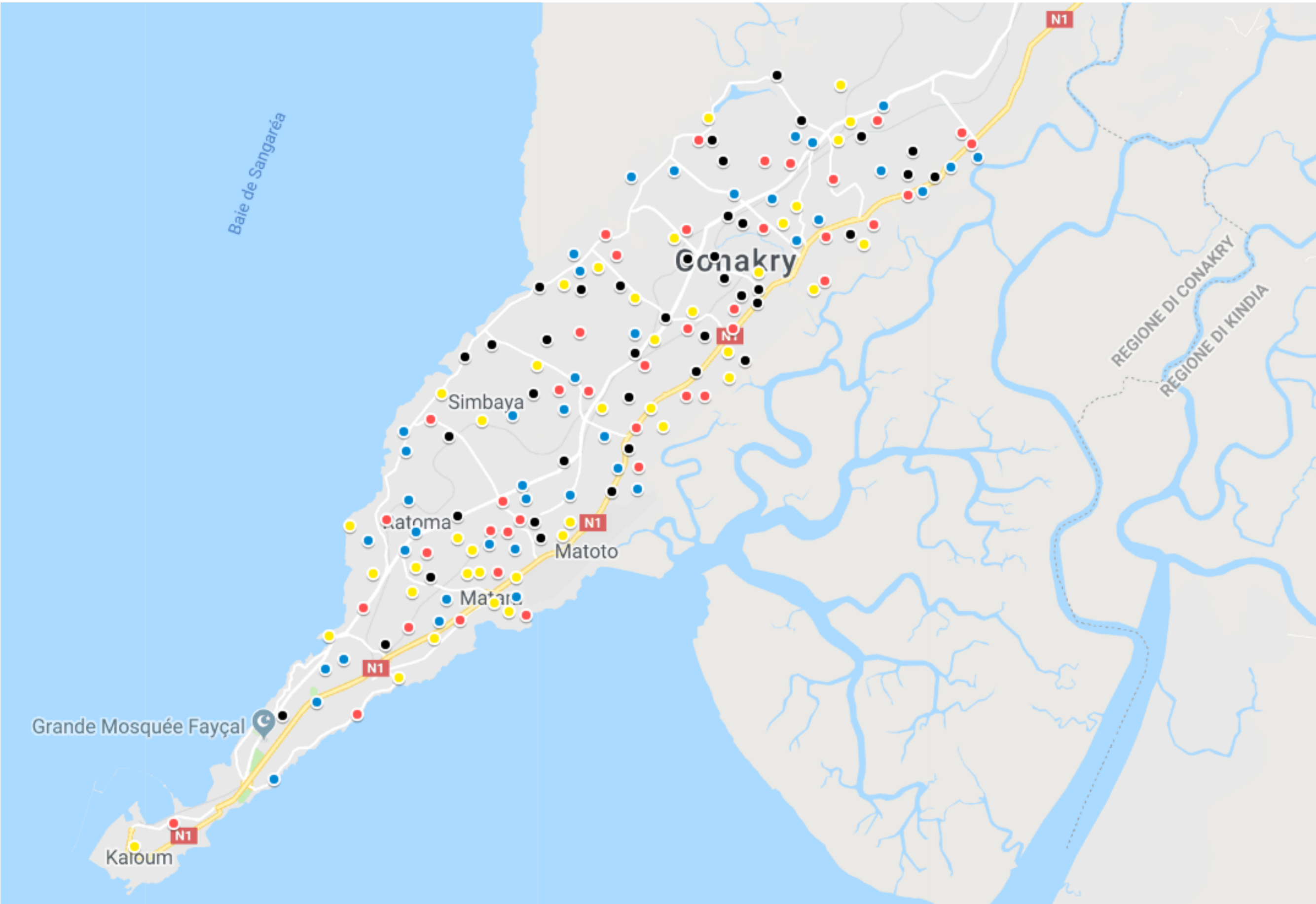


Figure B.2: Map of West Africa, Google.

Figure B.3: Control Group in black, Risk Treatment in Yellow, Econ in Blue, and Double in Red



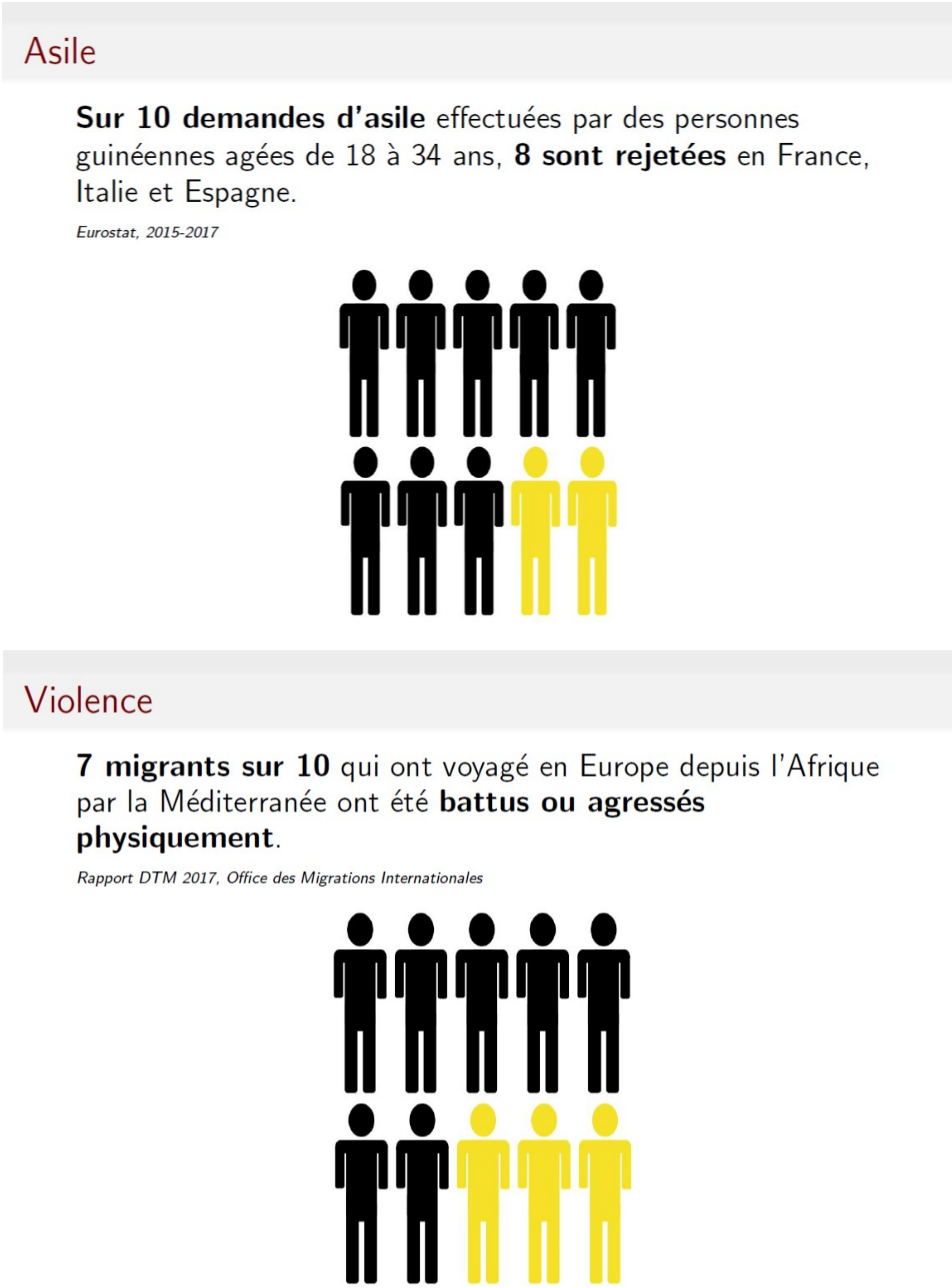


Figure B.4: Upper panel (a) reports slide from Economic Treatment, lower panel (b) reports slide from Risk Treatment. Econ slide reads 'Out of 10 asylum applications by Guineans aged 18 to 34, 8 are rejected in France, Italy, and Spain'. Risk slides read '7 out 10 migrants who travel from Africa to Europe by the Mediterranean have been beaten or physical abused'.

B.2 Tables

Table B.1: Balance Table

Variable	Control Mean	Risk-Control	Econ-Control	Double-Control
Big school	0.449	0.000	-0.000	-0.000
	(0.498)	(0.000)	(0.000)	(0.000)
Male student	0.515	-0.010	0.010	0.002
	(0.500)	(0.022)	(0.021)	(0.019)
Student's age	18.932	0.037	-0.003	0.018
	(2.007)	(0.171)	(0.164)	(0.151)
Mother some school	0.421	0.048	0.017	0.034
	(0.494)	(0.033)	(0.028)	(0.028)
Father some school	0.591	0.004	0.025	0.024
	(0.492)	(0.033)	(0.031)	(0.028)
Wealth index	-0.036	0.052	0.066	0.039
	(1.783)	(0.135)	(0.120)	(0.123)
High Durab.	0.505	0.008	-0.013	-0.015
	(0.500)	(0.035)	(0.030)	(0.031)
Expens. Sch.	0.465	0.013	0.154	0.074
	(0.499)	(0.110)	(0.111)	(0.114)
# acquaint. abroad	3.569	1.366	1.057	-0.116
	(25.315)	(1.195)	(1.352)	(0.794)
# classmates who migr.	1.359	0.061	0.130	0.474
	(4.562)	(0.177)	(0.242)	(0.363)
Wishing to migrate	0.299	-0.010	-0.003	0.009
	(0.458)	(0.023)	(0.023)	(0.025)
Planning to migr.	0.192	0.006	0.007	0.023
	(0.394)	(0.021)	(0.020)	(0.022)
Preparing to migr.	0.051	0.000	0.005	0.006
	(0.221)	(0.010)	(0.010)	(0.010)
sin^{-1} duration of the journey Ita	2.064	0.018	-0.036	0.083*
	(0.916)	(0.039)	(0.044)	(0.043)
sin^{-1} cost of the journey Ita	15.712	-0.201	-0.052	-0.257
	(4.205)	(0.205)	(0.196)	(0.212)
Probability to be beaten Ita	58.355	-1.084	-1.104	-1.596
	(28.690)	(1.448)	(1.378)	(1.416)
Probab. of being forced to work Ita	56.954	0.165	0.512	-0.266
	(31.305)	(1.355)	(1.410)	(1.449)
Probab. of being held Ita	50.748	-0.529	-0.193	-0.435
	(31.106)	(1.287)	(1.410)	(1.484)
Probab. of being sent back Ita	38.456	0.489	0.534	0.743
	(29.687)	(1.364)	(1.364)	(1.358)
Death prob. in boat Ita	45.111	0.264	1.766	0.100
	(29.814)	(1.215)	(1.391)	(1.433)
Death prob. bef. boat Ita	40.204	0.052	0.661	-0.771
	(28.779)	(1.141)	(1.209)	(1.328)
sin^{-1} duration of the journey Spa	2.031	-0.027	0.006	0.036
	(0.899)	(0.040)	(0.046)	(0.043)
sin^{-1} cost of the journey Spa	15.633	-0.112	0.025	-0.157
	(4.388)	(0.209)	(0.187)	(0.212)
Probability to be beaten Spa	49.693	0.069	1.113	-0.214
	(29.975)	(1.353)	(1.462)	(1.502)
Probab. of being forced to work Spa	50.531	-1.135	0.266	0.426
	(31.384)	(1.278)	(1.389)	(1.442)
Probab. of being held Spa	47.126	-1.809	-0.559	-0.636
	(30.796)	(1.149)	(1.260)	(1.302)
Probab. of being sent back Spa	38.427	-0.108	-0.329	0.371
	(28.822)	(1.175)	(1.188)	(1.235)
Death prob. in boat Spa	41.476	-0.716	0.544	0.505
	(29.079)	(1.223)	(1.205)	(1.287)
Death prob. bef. boat Spa	38.358	-1.028	-0.217	-0.001
	(28.945)	(1.065)	(1.141)	(1.284)
sin^{-1} expected wage at dest.	15.150	-0.025	-0.029	0.113
	(2.387)	(0.105)	(0.103)	(0.099)

Prob. of finding a job	34.009	-0.648	-0.938	-0.109
	(27.388)	(0.985)	(1.000)	(0.992)
Asylum prob., if requested	33.090	-1.213	-1.743	-1.308
	(28.223)	(1.243)	(1.184)	(1.374)
Prob. of continuing studies	29.539	-1.379	-1.612	0.090
	(26.362)	(1.376)	(1.313)	(1.343)
Prob. of becoming citizen	31.930	-0.734	-0.620	0.243
	(28.532)	(1.288)	(1.299)	(1.353)
Prob. of having ret. 5yrs	29.377	0.199	0.371	1.804
	(27.570)	(1.287)	(1.402)	(1.443)
sin^{-1} expected liv. cost at dest.	7.526	0.024	0.045	-0.036
	(1.892)	(0.078)	(0.072)	(0.071)
Perc. in favor of migr. at destination	39.452	-0.115	-1.071	0.781
	(28.598)	(1.167)	(1.169)	(1.296)
Prob. receiving fin. help	34.680	-1.418	-1.336	0.292
	(32.920)	(1.351)	(1.288)	(1.715)
Observations	1,809	3,693	3,713	3,599

(1) Obtained as average of routes through Italy and Spain.
Errors clustered at school level, stratum dummy included as control.
$+ p < 0.1$, $* p < 0.05$, $** p < 0.01$, $*** p < 0.001$.

Table B.2: Table attrition number of observations by treatment arm and round

	All	Control	Risk	Econ	Double
Baseline	7387	1809	1884	1904	1790
Treated	2730	0	920	915	895
Fraction at Baseline	.37	0	.488	.481	.5
Follow Up 1 (tablet)	4479	1166	1103	1156	1054
Fraction at Baseline	.606	.645	.585	.607	.589
Follow Up 2 (tablet)	2381	660	537	599	585
Fraction at Baseline	.322	.365	.285	.315	.327
Follow Up 2 (subject)	7142	1755	1830	1825	1732
Fraction at Baseline	.967	.97	.971	.959	.968
Follow Up 2 (contact)	7207	1772	1841	1845	1749
Fraction at Baseline	.976	.98	.977	.969	.977
Follow Up 2 (SSS)	7345	1801	1870	1893	1781
Fraction at Baseline	.994	.996	.993	.994	.995
Follow Up 2 (phone)	7367	1805	1879	1897	1786
Fraction at Baseline	.997	.998	.997	.996	.998

Table B.3: Attrited at 1^{st} follow-up, treatment and controls

	1 = Attrited at follow-up		
Risk Treatment	0.0602**	0.0521*	0.0560*
	(0.0291)	(0.0286)	(0.0286)
Economic Treatment	0.0381	0.0340	0.0435
	(0.0353)	(0.0354)	(0.0355)
Double Treatment	0.0557	0.0461	0.0485
	(0.0341)	(0.0343)	(0.0350)
Big school	0.0270	0.0324	0.0384
	(0.0234)	(0.0233)	(0.0287)
Wishing to migrate		-0.00349	0.00224
		(0.0208)	(0.0223)
Planning to migr.		0.0415*	0.0349
		(0.0241)	(0.0261)
Preparing to migr.		0.0435	0.0163
		(0.0297)	(0.0335)
sin^{-1} duration of the journey Ita		0.00889	0.00859
		(0.00738)	(0.00779)
sin^{-1} cost of the journey Ita		-0.00383*	-0.00347
		(0.00194)	(0.00215)
Probability to be beaten Ita		-0.000575**	-0.000277
		(0.000242)	(0.000264)
Death prob. in boat Ita		-0.000848***	-0.000705**
		(0.000254)	(0.000274)
Death prob. bef. boat Ita		0.000493*	0.000215
		(0.000297)	(0.000319)
sin^{-1} duration of the journey Spa		-0.00388	-0.0111
		(0.00709)	(0.00774)
sin^{-1} cost of the journey Spa		-0.00100	-0.000300
		(0.00187)	(0.00208)
Probability to be beaten Spa		-0.0000393	-0.000189
		(0.000267)	(0.000280)
Death prob. in boat Spa		0.0000716	0.0000735
		(0.000304)	(0.000324)
Death prob. bef. boat Spa		0.000310	0.000525*
		(0.000295)	(0.000309)
sin^{-1} expected wage at dest.		-0.000402	-0.00199

	(0.00263)	(0.00273)
Prob. of finding a job	0.000219	0.000283
	(0.000244)	(0.000277)
Asylum prob., if requested	-0.000573**	-0.000630**
	(0.000256)	(0.000268)
Prob. of continuing studies	-0.000257	-0.000116
	(0.000306)	(0.000323)
Prob. of becoming citizen	0.0000517	-0.000158
	(0.000251)	(0.000268)
Prob. of having ret. 5yrs	0.000163	0.000215
	(0.000259)	(0.000270)
sin^{-1} expected liv. cost at dest.	0.000230	-0.000567
	(0.00294)	(0.00335)
Perc. in favor of migr. at destination	0.000100	0.000312
	(0.000217)	(0.000240)
Prob. receiving fin. help	0.000731***	0.000577**
	(0.000224)	(0.000238)
School size		0.00000234
		(0.0000465)
Male student		0.0252*
		(0.0142)
Student's age		0.0157***
		(0.00450)
Mother some school		0.0108
		(0.0152)
Father some school		-0.00568
		(0.0141)
Wealth index		0.000278
		(0.00492)
Wealth index		0
		(.)
High Durab.		-0.00766
		(0.0169)
Expens. Sch.		0.00792
		(0.0252)
# acquaint. abroad		0.000210

			(0.000276)
# classmates who migr.			0.0000390
			(0.00127)
Constant	0.341***	0.421***	0.107
	(0.0291)	(0.0643)	(0.112)
Observations	7387	7140	6295

Errors are clustered at the school level. P-values are denoted as follows: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.4: No School Survey at 2^{nd} follow-up, treatment and controls

	1 = Attrited at follow-up		
Risk Treatment	0.0803	0.0849*	0.0790
	(0.0408)	(0.0411)	(0.0419)
Economic Treatment	0.0501	0.0487	0.0469
	(0.0407)	(0.0414)	(0.0408)
Double Treatment	0.0379	0.0430	0.0392
	(0.0445)	(0.0446)	(0.0450)
Big school	0.0209	0.0208	-0.00319
	(0.0296)	(0.0297)	(0.0346)
Wishing to migrate		-0.0217	-0.000890
		(0.0206)	(0.0218)
Planning to migr.		0.0297	0.00770
		(0.0259)	(0.0268)
Preparing to migr.		0.0213	0.0104
		(0.0267)	(0.0279)
sin^{-1} duration of the journey Ita		0.00312	0.00344
		(0.00727)	(0.00790)
sin^{-1} cost of the journey Ita		0.00121	0.00232
		(0.00184)	(0.00201)
Probability to be beaten Ita		-0.0000504	0.000142
		(0.000248)	(0.000279)
Death prob. in boat Ita		-0.0000824	-0.0000503
		(0.000247)	(0.000265)
Death prob. bef. boat Ita		0.000511	0.000406
		(0.000283)	(0.000306)
sin^{-1} duration of the journey Spa		-0.00705	-0.0124

	(0.00781)	(0.00837)
sin^{-1} cost of the journey Spa	-0.000949	-0.000769
	(0.00194)	(0.00210)
Probability to be beaten Spa	0.000180	0.000176
	(0.000249)	(0.000278)
Death prob. in boat Spa	0.000419	0.000393
	(0.000299)	(0.000311)
Death prob. bef. boat Spa	-0.000637*	-0.000551
	(0.000299)	(0.000289)
sin^{-1} expected wage at dest.	0.00354	0.00112
	(0.00278)	(0.00292)
Prob. of finding a job	-0.000110	-0.000108
	(0.000269)	(0.000276)
Asylum prob., if requested	-0.00000978	-0.0000628
	(0.000228)	(0.000232)
Prob. of continuing studies	0.000115	0.000236
	(0.000290)	(0.000300)
Prob. of becoming citizen	-0.000542*	-0.000636*
	(0.000265)	(0.000269)
Prob. of having ret. 5yrs	-0.000264	-0.000203
	(0.000218)	(0.000230)
sin^{-1} expected liv. cost at dest.	0.00328	0.00440
	(0.00285)	(0.00297)
Perc. in favor of migr. at destination	-0.0000651	0.0000419
	(0.000197)	(0.000213)
Prob. receiving fin. help	0.000374	0.000324

		(0.000201)	(0.000211)
School size			0.0000501
			(0.0000544)
Male student			0.0125
			(0.0128)
Student's age			0.0429***
			(0.00411)
Mother attended school			0.0142
			(0.0139)
Father attended school			0.0190
			(0.0138)
Wealth index			0.00580
			(0.00404)
# acquaint. abroad			0.000419***
			(0.000116)
# classmates who migr.			-0.00181
			(0.00122)
Constant	0.624***	0.579***	-0.275**
	(0.0341)	(0.0545)	(0.103)
2^{nd} F.U. Cont.	0.64	0.64	0.64
N	7376	7218	6343

Standard errors in parentheses

Errors are clustered at the school level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.5: No School or Phone Survey at 2^{nd} follow-up, treatment and controls

	1 = Attrited at follow-up		
Risk Treatment	-0.00268	-0.000195	0.000267
	(0.00672)	(0.00681)	(0.00693)
Economic Treatment	0.00966	0.00893	0.00818
	(0.00731)	(0.00727)	(0.00691)
Double Treatment	0.000420	0.000430	0.00372
	(0.00636)	(0.00631)	(0.00667)
Big school	0.00132	0.00347	0.00952
	(0.00490)	(0.00486)	(0.00659)
Wishing to migrate		0.000424	0.00169
		(0.00674)	(0.00721)
Planning to migr.		-0.00595	-0.00200
		(0.00776)	(0.00849)
Preparing to migr.		0.0213	0.0137
		(0.0121)	(0.0130)
sin^{-1} duration of the journey Ita		0.000103	0.000369
		(0.00294)	(0.00309)
sin^{-1} cost of the journey Ita		-0.00113	-0.00129
		(0.000755)	(0.000846)
Probability to be beaten Ita		-0.000110	-0.0000922
		(0.0000934)	(0.000102)
Death prob. in boat Ita		-0.0000363	-0.0000438
		(0.0000974)	(0.0000984)
Death prob. bef. boat Ita		0.000224*	0.000218
		(0.000108)	(0.000111)
sin^{-1} duration of the journey Spa		0.00250	0.00251

	(0.00236)	(0.00233)
sin^{-1} cost of the journey Spa	-0.000532	-0.000313
	(0.000720)	(0.000773)
Probability to be beaten Spa	0.0000236	0.0000723
	(0.0000994)	(0.000104)
Death prob. in boat Spa	0.0000581	0.0000348
	(0.0000855)	(0.0000901)
Death prob. bef. boat Spa	-0.000232**	-0.000240*
	(0.0000888)	(0.0000924)
sin^{-1} expected wage at dest.	0.00309**	0.00194
	(0.00106)	(0.00112)
Prob. of finding a job	-0.000149	-0.0000746
	(0.0000910)	(0.0000990)
Asylum prob., if requested	0.0000271	0.0000481
	(0.0000839)	(0.0000914)
Prob. of continuing studies	-0.0000166	-0.0000165
	(0.0000992)	(0.000109)
Prob. of becoming citizen	0.0000403	-0.0000381
	(0.000102)	(0.000102)
Prob. of having ret. 5yrs	0.0000548	0.0000532
	(0.0000782)	(0.0000793)
sin^{-1} expected liv. cost at dest.	-0.00136	-0.00107
	(0.000936)	(0.000997)
Perc. in favor of migr. at destination	0.0000587	0.0000278
	(0.0000773)	(0.0000789)
Prob. receiving fin. help	0.0000644	0.0000755

		(0.0000660)	(0.0000720)
School size			-0.0000165
			(0.00000989)
Male student			-0.00552
			(0.00462)
Student's age			0.00103
			(0.001000)
Mother attended school			-0.00317
			(0.00398)
Father attended school			0.00100
			(0.00432)
Wealth index			0.00155
			(0.00122)
# acquaint. abroad			-0.0000315
			(0.0000258)
# classmates who migr.			0.0000335
			(0.000383)
Constant	0.0292***	0.0405*	0.0247
	(0.00496)	(0.0169)	(0.0245)
2^{nd} F.U. Cont.	0.030	0.030	0.030
N	7376	7218	6343

Standard errors in parentheses

Errors are clustered at the school level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.6: No School, Phone, or Contact Survey at 2^{nd} follow-up, treatment and controls

	1 = Attrited at follow-up		
Risk Treatment	-0.000594	0.00181	0.00152
	(0.00526)	(0.00515)	(0.00543)
Economic Treatment	0.00661	0.00592	0.00678
	(0.00643)	(0.00601)	(0.00615)
Double Treatment	-0.00146	-0.00136	0.000248
	(0.00538)	(0.00505)	(0.00539)
Big school	0.000412	0.00288	0.00548
	(0.00399)	(0.00377)	(0.00561)
Wishing to migrate		-0.0000823	0.0000656
		(0.00496)	(0.00540)
Planning to migr.		-0.00752	-0.00656
		(0.00537)	(0.00598)
Preparing to migr.		0.0171	0.0179
		(0.00884)	(0.0104)
sin^{-1} duration of the journey Ita		0.000460	0.00104
		(0.00230)	(0.00252)
sin^{-1} cost of the journey Ita		-0.000923	-0.000885
		(0.000636)	(0.000734)
Probability to be beaten Ita		-0.0000761	-0.0000463
		(0.0000790)	(0.0000871)
Death prob. in boat Ita		-0.0000144	-0.0000467
		(0.0000628)	(0.0000684)
Death prob. bef. boat Ita		0.0000444	0.0000295
		(0.0000696)	(0.0000741)

sin^{-1} duration of the journey Spa	0.00175	0.00222
	(0.00187)	(0.00196)
sin^{-1} cost of the journey Spa	-0.000357	-0.000469
	(0.000579)	(0.000665)
Probability to be beaten Spa	0.0000194	0.0000124
	(0.0000676)	(0.0000726)
Death prob. in boat Spa	0.0000310	0.0000327
	(0.0000596)	(0.0000624)
Death prob. bef. boat Spa	-0.000135*	-0.000147*
	(0.0000577)	(0.0000615)
sin^{-1} expected wage at dest.	0.00166*	0.00153
	(0.000767)	(0.000828)
Prob. of finding a job	-0.0000449	0.00000509
	(0.0000710)	(0.0000791)
Asylum prob., if requested	0.0000528	0.0000604
	(0.0000648)	(0.0000736)
Prob. of continuing studies	-0.00000505	-0.0000333
	(0.0000665)	(0.0000758)
Prob. of becoming citizen	-0.0000124	-0.0000569
	(0.0000674)	(0.0000744)
Prob. of having ret. 5yrs	0.0000528	0.0000391
	(0.0000615)	(0.0000641)
sin^{-1} expected liv. cost at dest.	-0.000650	-0.000471
	(0.000716)	(0.000770)
Perc. in favor of migr. at destination	0.0000767	0.0000967
	(0.0000547)	(0.0000602)
Prob. receiving fin. help	0.0000168	0.0000407

		(0.0000463)	(0.0000504)
School size			-0.00000712
			(0.00000897)
Male student			-0.00966**
			(0.00343)
Student's age			0.0000909
			(0.000738)
Mother attended school			0.00192
			(0.00322)
Father attended school			-0.00202
			(0.00323)
Wealth index			0.000359
			(0.000897)
# acquaint. abroad			-0.0000252
			(0.0000190)
# classmates who migr.			-0.000104
			(0.000132)
Constant	0.0158***	0.0252	0.0279
	(0.00415)	(0.0145)	(0.0220)
2^{nd} F.U. Cont.	0.016	0.016	0.016
N	7376	7218	6343

Standard errors in parentheses

Errors are clustered at the school level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.7: No School, Phone, Contact, or Short School Survey at 2^{nd} follow-up, treatment and controls

	1 = Attrited at follow-up		
Risk Treatment	-0.000739	0.000379	0.000541
	(0.00280)	(0.00255)	(0.00294)
Economic Treatment	-0.00286	-0.00175	-0.00203
	(0.00214)	(0.00175)	(0.00196)
Double Treatment	-0.00276	-0.00180	-0.00173
	(0.00231)	(0.00194)	(0.00222)
Big school	-0.000809	-0.000228	-0.00183
	(0.00160)	(0.00148)	(0.00176)
Wishing to migrate		0.00208	0.00237
		(0.00267)	(0.00299)
Planning to migr.		-0.000713	-0.000724
		(0.00281)	(0.00320)
Preparing to migr.		-0.00413*	-0.00429*
		(0.00187)	(0.00214)
sin^{-1} duration of the journey Ita		0.000444	0.000561
		(0.000662)	(0.000790)
sin^{-1} cost of the journey Ita		-0.000336	-0.000383
		(0.000359)	(0.000431)
Probability to be beaten Ita		-0.0000166	-0.0000240
		(0.0000298)	(0.0000371)
Death prob. in boat Ita		0.0000757*	0.0000866*
		(0.0000303)	(0.0000351)
Death prob. bef. boat Ita		-0.0000199	-0.0000239
		(0.0000376)	(0.0000432)

sin^{-1} duration of the journey Spa	-0.000172	-0.000320
	(0.000725)	(0.000812)
sin^{-1} cost of the journey Spa	-0.000202	-0.000239
	(0.000315)	(0.000383)
Probability to be beaten Spa	0.00000210	0.00000181
	(0.0000262)	(0.0000316)
Death prob. in boat Spa	-0.0000124	-0.0000130
	(0.0000228)	(0.0000273)
Death prob. bef. boat Spa	-0.00000816	-0.0000150
	(0.0000299)	(0.0000328)
sin^{-1} expected wage at dest.	-0.000101	-0.000123
	(0.000304)	(0.000363)
Prob. of finding a job	-0.0000187	-0.0000191
	(0.0000226)	(0.0000256)
Asylum prob., if requested	0.0000169	0.0000221
	(0.0000300)	(0.0000345)
Prob. of continuing studies	0.0000289	0.0000246
	(0.0000239)	(0.0000270)
Prob. of becoming citizen	0.00000808	0.00000884
	(0.0000221)	(0.0000249)
Prob. of having ret. 5yrs	-0.0000101	-0.0000154
	(0.0000220)	(0.0000259)
sin^{-1} expected liv. cost at dest.	-0.000178	-0.000164
	(0.000320)	(0.000364)
Perc. in favor of migr. at destination	0.0000181	0.0000197
	(0.0000275)	(0.0000308)
Prob. receiving fin. help	0.00000150	0.00000852

		(0.0000203)	(0.0000233)
School size			0.00000450
			(0.00000321)
Male student			-0.00359*
			(0.00171)
Student's age			0.000246
			(0.000456)
Mother attended school			-0.00306
			(0.00180)
Father attended school			0.00125
			(0.00221)
Wealth index			0.000302
			(0.000356)
# acquaint. abroad			-0.0000125
			(0.00000740)
# classmates who migr.			0.0000253
			(0.0000728)
Constant	0.00484*	0.0106	0.0100
	(0.00237)	(0.00754)	(0.0115)
2^{nd} F.U. Cont.	0.0044	0.0044	0.0044
N	7376	7218	6343

Standard errors in parentheses

Errors are clustered at the school level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.8: Out of Guinea at 2^{nd} F. U.

	(1) Only Interviewed Subject	(2) Previous and Contacts	(3) Previous and St. + Adm.	(4) Previous and Phone On
Risk T.	-0.00077	-0.0043	-0.0026	-0.0017
	(0.0039)	(0.0047)	(0.0051)	(0.0056)
Econ. T.	-0.00074	0.0011	0.0031	0.0024
	(0.0032)	(0.0045)	(0.0045)	(0.0049)
Double T.	-0.0011	-0.00096	-0.00039	-0.0015
	(0.0033)	(0.0046)	(0.0045)	(0.0047)
Strata	0.0030	0.0039	0.0042	0.0036
	(0.0023)	(0.0032)	(0.0033)	(0.0037)
Constant	0.0022	0.0092*	0.0091	0.012*
	(0.0035)	(0.0053)	(0.0055)	(0.0063)
2^{nd} F. U. Cont. Mean	0.0068	0.015	0.016	0.018
N	7142	7207	7345	7367

Table B.9: Out of Conakry at 2^{nd} F. U.

	(1) Only Interviewed Subject	(2) Previous and Contacts	(3) Previous and St. + Adm.	(4) Previous and Phone On
Risk T.	0.0068	0.0032	0.0026	0.0026
	(0.0093)	(0.0097)	(0.0100)	(0.0100)
Econ. T.	-0.014*	-0.013	-0.012	-0.012
	(0.0075)	(0.0080)	(0.0081)	(0.0081)
Double T.	0.000077	0.00063	0.000056	0.000056
	(0.0092)	(0.0099)	(0.0099)	(0.0099)
Strata	0.0095	0.011	0.010	0.010
	(0.0061)	(0.0066)	(0.0067)	(0.0067)
Constant	0.038***	0.044***	0.046***	0.046***
	(0.011)	(0.012)	(0.012)	(0.012)
2^{nd} F. U. Cont. Mean	0.052	0.061	0.062	0.062
N	7142	7249	7355	7355

Table B.10: Migration intentions at 1^{st} F. U.

	Wish	Plan	Prepare
Risk Treatment	-0.0505***	-0.0313**	-0.00176
	(0.0166)	(0.0150)	(0.00691)
Econ Treatment	-0.0403**	-0.0184	-0.00984
	(0.0175)	(0.0157)	(0.00750)
Double Treatment	-0.0479***	-0.0334**	-0.0103
	(0.0169)	(0.0152)	(0.00782)
Big school	-0.00750	-0.0148	-0.0100*
	(0.0122)	(0.0107)	(0.00531)
Outcome at Baseline	0.365***	0.312***	0.234***
	(0.0148)	(0.0184)	(0.0288)
Constant	0.155***	0.110***	0.0372***
	(0.0155)	(0.0135)	(0.00642)
1^{st} F. U. Cont. Mean	0.256	0.160	0.0420
N	4475	4475	4475

(1) is outcome *wishing to migrate*, (2) is *planning to migrate*, (3) is *preparing*. Errors are clustered at the school level. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.11: Migration intentions at 2^{nd} F. U.

	Wish	Plan	Prepare
Risk Treatment	0.00172	-0.00388	-0.00637
	(0.0197)	(0.0238)	(0.00984)
Econ Treatment	-0.0568**	-0.0160	-0.00875
	(0.0222)	(0.0216)	(0.00847)
Double Treatment	-0.000350	0.0138	0.00370
	(0.0213)	(0.0250)	(0.00912)
Big school	0.0315**	-0.000889	0.00165
	(0.0145)	(0.0169)	(0.00613)
Outcome at Baseline	0.182***	0.133***	0.0568***
	(0.0128)	(0.0133)	(0.0154)
Constant	0.461***	0.129***	0.0443***
	(0.0192)	(0.0161)	(0.00705)
2^{nd} F. U. Cont. Mean	0.532	0.154	0.0480
N	7218	7209	7208

(1) is outcome *wishing to migrate*, (2) is *planning to migrate*, (3) is *preparing*. Errors are clustered at the school level. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.12: Migration intentions at 2^{nd} F. U., restricted to non-attrited at 1^{st}

	Wish	Plan	Prepare
Risk Treatment	-0.00782	-0.00799	0.000472
	(0.0249)	(0.0231)	(0.00862)
Econ Treatment	-0.0726***	-0.0141	-0.00324
	(0.0264)	(0.0204)	(0.00814)
Double Treatment	-0.0259	0.000882	0.00699
	(0.0239)	(0.0233)	(0.0102)
Big school	0.0175	-0.0109	0.000853
	(0.0180)	(0.0164)	(0.00625)
Outcome at Basel.	0.207***	0.149***	0.0735***
	(0.0159)	(0.0167)	(0.0229)
Constant	0.459***	0.122***	0.0319***
	(0.0226)	(0.0155)	(0.00649)
2^{nd} F. U. Cont. Mean	0.532	0.154	0.0480
N	4411	4407	4406

(1) is outcome *wishing to migrate*, (2) is *planning to migrate*, (3) is *preparing*. Errors are clustered at the school level. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.13: Risk perceptions for route through Italy at 1^{st} F. U.

	(1) $sinh^{-1}$ Journey Duration	(2) $sinh^{-1}$ Journey Cost	(3) Being Beaten	(4) Forced to Work	(5) Being Kidnap-ped	(6) Death before boat	(7) Death in boat	(8) Sent Back	(9) PCA Risk
Risk Treat.	0.30	-0.13	9.48	5.59	7.10	9.37	10.3	6.65	0.67
	(0.045)***	(0.17)	(1.25)***	(1.34)***	(1.35)***	(1.33)***	(1.35)***	(1.33)***	(0.090)***
	[0.00]***	[0.42]	[0.00]***	[0.00]***	[0.00]***	[0.00]***	[0.00]***	[0.00]***	
Econ Treat.	0.057	-0.21	6.58	3.72	5.54	5.29	5.27	8.88	0.50
	(0.045)	(0.15)	(1.24)***	(1.35)***	(1.35)***	(1.35)***	(1.27)***	(1.41)***	(0.081)***
	[0.34]	[0.34]	[0.00]***	[0.02]**	[0.00]***	[0.00]***	[0.00]***	[0.00]***	
Double Treat.	0.22	-0.52	10.7	4.99	10.1	10.3	11.1	9.21	0.79
	(0.055)***	(0.19)***	(1.67)***	(1.60)***	(1.47)***	(1.51)***	(1.51)***	(1.28)***	(0.11)***
	[0.00]***	[0.02]**	[0.00]***	[0.00]***	[0.00]***	[0.00]***	[0.00]***	[0.00]***	
Big school	-0.0077	0.27	2.42	2.07	1.76	1.09	1.76	3.29	0.16
	(0.033)	(0.13)**	(1.08)**	(1.09)*	(1.11)	(1.06)	(1.07)	(1.04)***	(0.072)**
Basel. outc.	0.26	0.27	0.33	0.36	0.38	0.36	0.37	0.37	0.53
	(0.021)***	(0.023)***	(0.015)***	(0.015)***	(0.015)***	(0.015)***	(0.016)***	(0.016)***	(0.014)***
Constant	1.67	11.7	31.1	31.0	26.6	21.8	23.4	20.8	-0.44
	(0.056)***	(0.40)***	(1.25)***	(1.36)***	(1.18)***	(1.23)***	(1.26)***	(1.23)***	(0.070)***
1^{st} F.U. Cont.	2.20	16.1	52.3	53.0	47.4	37.0	41.3	37.0	-0.30
N	4472	4430	4469	4469	4468	4468	4467	4469	4418

Legend: (1) duration of journey in $sinh^{-1}$ months (winsorized at 5^{th} perc.), (2) journey cost in $sinh^{-1}$ euros (winsorized at 5^{th} perc.), (3) probability of being beaten, (4) probability of being forced to work, (5) probability of being kidnapped, (6) probability of dying before travel by boat, (7) probability of dying during travel by boat, (8) probability of being sent back, (9) PCA aggregator for risk perceptions. 1^{st} F.U. Cont. represents average in control group at midline. Errors are clustered at school level in round brackets. Fwer p-values in square brackets. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.14: Risk perceptions for route through Italy at 2^{nd} F. U.

	(1) $sinh^{-1}$ Journey Duration	(2) $sinh^{-1}$ Journey Cost	(3) Being Beaten	(4) Forced to Work	(5) Being Kidnap-ped	(6) Death before boat	(7) Death in boat	(8) Sent Back	(9) PCA Risk
Risk Treat.	0.046	0.015	1.90	1.56	0.28	0.94	2.57	0.80	0.093
	(0.085)	(0.25)	(1.80)	(1.92)	(2.25)	(1.83)	(2.02)	(2.28)	(0.14)
	[0.98]	[0.99]	[0.85]	[0.93]	[0.99]	[0.98]	[0.73]	[0.98]	
Econ Treat.	-0.20	0.24	3.82	1.93	0.65	-0.26	2.16	3.20	0.12
	(0.081)**	(0.21)	(1.72)**	(1.85)	(1.98)	(1.95)	(2.05)	(2.00)	(0.13)
	[0.13]	[0.71]	[0.18]	[0.71]	[0.93]	[0.93]	[0.71]	[0.45]	
Double Treat.	0.074	-0.23	5.85	4.44	5.82	4.71	7.40	4.02	0.45
	(0.086)	(0.27)	(2.02)***	(1.92)**	(2.22)***	(2.04)**	(2.18)***	(2.35)*	(0.15)***
	[0.64]	[0.64]	[0.05]**	[0.12]	[0.07]*	[0.12]	[0.01]***	[0.28]	
Big school	0.013	0.34	1.25	1.05	0.86	0.63	0.94	-0.48	0.055
	(0.057)	(0.17)**	(1.29)	(1.30)	(1.43)	(1.34)	(1.45)	(1.47)	(0.091)
Basel. outc.	0.13	0.24	0.27	0.23	0.27	0.27	0.25	0.27	0.37
	(0.027)***	(0.026)***	(0.022)***	(0.023)***	(0.023)***	(0.025)***	(0.027)***	(0.023)***	(0.025)***
Constant	2.14	11.6	36.5	38.2	33.5	27.6	29.5	28.2	-0.27
	(0.082)***	(0.45)***	(2.09)***	(2.20)***	(2.25)***	(1.94)***	(2.15)***	(2.08)***	(0.12)**
2^{nd} F.U. Cont.	2.42	15.5	52.6	51.3	47.2	38.3	40.9	38.4	-0.28
N	2377	2363	2373	2372	2371	2372	2371	2372	2355

Legend: (1) duration of journey in $sinh^{-1}$ months (winsorized at 5^{th} perc.), (2) journey cost in $sinh^{-1}$ euros (winsorized at 5^{th} perc.), (3) probability of being beaten, (4) probability of being forced to work, (5) probability of being kidnapped, (6) probability of dying before travel by boat, (7) probability of dying during travel by boat, (8) probability of being sent back, (9) PCA aggregator for risk perceptions. 2^{nd} F.U. Cont. represents average in control group at midline. Errors are clustered at school level in round brackets. Fwer p-values in square brackets. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.15: Risk perceptions for route through Spain at 1^{st} F. U.

	(1) $sinh^{-1}$ Journey Duration	(2) $sinh^{-1}$ Journey Cost	(3) Being Beaten	(4) Forced to Work	(5) Being Kidnap-ped	(6) Death before boat	(7) Death in boat	(8) Sent Back	(9) PCA Risk
Risk Treat.	0.26	0.019	8.93	7.45	9.55	10.1	9.26	6.45	0.76
	$(0.049)^{***}$	(0.17)	$(1.31)^{***}$	$(1.45)^{***}$	$(1.39)^{***}$	$(1.47)^{***}$	$(1.35)^{***}$	$(1.30)^{***}$	$(0.097)^{***}$
	$[0.00]^{***}$	[0.91]	$[0.00]^{***}$	$[0.00]^{***}$	$[0.00]^{***}$	$[0.00]^{***}$	$[0.00]^{***}$	$[0.00]^{***}$	
Econ Treat.	0.072	-0.26	5.40	5.45	6.26	6.55	5.65	7.41	0.53
	(0.049)	(0.17)	$(1.31)^{***}$	$(1.28)^{***}$	$(1.35)^{***}$	$(1.46)^{***}$	$(1.33)^{***}$	$(1.45)^{***}$	$(0.092)^{***}$
	[0.25]	[0.25]	$[0.00]^{***}$	$[0.00]^{***}$	$[0.00]^{***}$	$[0.00]^{***}$	$[0.00]^{***}$	$[0.00]^{***}$	
Double Treat.	0.17	-0.28	10.0	8.70	11.3	9.96	11.0	9.10	0.87
	$(0.055)^{***}$	(0.19)	$(1.51)^{***}$	$(1.67)^{***}$	$(1.61)^{***}$	$(1.50)^{***}$	$(1.46)^{***}$	$(1.40)^{***}$	$(0.11)^{***}$
	$[0.01]^{***}$	[0.14]	$[0.00]^{***}$	$[0.00]^{***}$	$[0.00]^{***}$	$[0.00]^{***}$	$[0.00]^{***}$	$[0.00]^{***}$	
Big school	0.027	0.28	1.13	1.86	2.41	0.79	0.55	0.78	0.11
	(0.035)	$(0.13)^{**}$	(1.06)	$(1.10)^{*}$	$(1.10)^{**}$	(1.06)	(1.06)	(1.06)	(0.075)
Basel. outc.	0.26	0.27	0.38	0.37	0.37	0.39	0.40	0.36	0.52
	$(0.018)^{***}$	$(0.022)^{***}$	$(0.016)^{***}$	$(0.015)^{***}$	$(0.015)^{***}$	$(0.016)^{***}$	$(0.017)^{***}$	$(0.016)^{***}$	$(0.016)^{***}$
Constant	1.63	11.4	27.2	26.8	23.9	20.0	23.0	23.1	-0.29
	$(0.054)^{***}$	$(0.38)^{***}$	$(1.34)^{***}$	$(1.46)^{***}$	$(1.40)^{***}$	$(1.41)^{***}$	$(1.32)^{***}$	$(1.23)^{***}$	$(0.080)^{***}$
1^{st} F.U. Cont.	2.18	15.8	47.1	46.8	43.2	35.4	40.1	37.5	-0.20
N	4468	4433	4463	4464	4463	4463	4459	4459	4420

Legend: (1) duration of journey in $sinh^{-1}$ months (winsorized at 5^{th} perc.), (2) journey cost in $sinh^{-1}$ euros (winsorized at 5^{th} perc.), (3) probability of being beaten, (4) probability of being forced to work, (5) probability of being kidnapped, (6) probability of dying before travel by boat, (7) probability of dying during travel by boat, (8) probability of being sent back, (9) PCA aggregator for risk perceptions. 1^{st} F.U. Cont. represents average in control group at midline. Errors are clustered at school level in round brackets. Fwer p-values in square brackets. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.16: Risk perceptions for route through Spain at 2^{nd} F. U.

	(1) $sinh^{-1}$ Journey Duration	(2) $sinh^{-1}$ Journey Cost	(3) Being Beaten	(4) Forced to Work	(5) Being Kidnap-ped	(6) Death before boat	(7) Death in boat	(8) Sent Back	(9) PCA Risk
Risk Treat.	0.042	-0.12	1.86	0.85	0.95	1.20	1.92	1.71	0.11
	(0.095)	(0.33)	(1.76)	(1.93)	(2.25)	(2.29)	(2.22)	(2.26)	(0.15)
	[0.98]	[0.98]	[0.83]	[0.98]	[0.98]	[0.97]	[0.89]	[0.93]	
Econ Treat.	-0.25	0.15	2.36	1.99	1.17	0.28	-0.37	2.51	0.068
	(0.084)***	(0.26)	(1.68)	(1.92)	(2.07)	(2.14)	(1.91)	(2.03)	(0.14)
	[0.04]**	[0.93]	[0.56]	[0.72]	[0.93]	[0.96]	[0.96]	[0.63]	
Double Treat.	0.038	-0.33	6.32	4.81	4.47	3.10	2.92	3.10	0.35
	(0.096)	(0.32)	(2.06)***	(2.11)**	(2.43)*	(2.48)	(2.53)	(2.43)	(0.18)**
	[0.71]	[0.58]	[0.02]**	[0.12]	[0.26]	[0.58]	[0.58]	[0.58]	
Big school	-0.0062	-0.13	1.10	1.52	2.08	0.13	0.44	0.28	0.067
	(0.063)	(0.23)	(1.30)	(1.39)	(1.54)	(1.55)	(1.58)	(1.60)	(0.11)
Basel. outc.	0.14	0.21	0.25	0.22	0.24	0.29	0.25	0.28	0.36
	(0.026)***	(0.030)***	(0.023)***	(0.021)***	(0.023)***	(0.024)***	(0.022)***	(0.021)***	(0.025)***
Constant	2.20	12.1	33.2	34.9	32.6	27.5	30.3	27.7	-0.089
	(0.093)***	(0.51)***	(1.80)***	(1.87)***	(2.12)***	(2.21)***	(2.07)***	(1.81)***	(0.12)
2^{nd} F.U. Cont.	2.50	15.4	46.1	46.5	45.0	38.4	40.7	38.5	-0.079
N	2373	2355	2370	2367	2367	2366	2366	2366	2348

Legend: (1) duration of journey in $sinh^{-1}$ months (winsorized at 5^{th} perc.), (2) journey cost in $sinh^{-1}$ euros (winsorized at 5^{th} perc.), (3) probability of being beaten, (4) probability of being forced to work, (5) probability of being kidnapped, (6) probability of dying before travel by boat, (7) probability of dying during travel by boat, (8) probability of being sent back, (9) PCA aggregator for risk perceptions. 2^{nd} F.U. Cont. represents average in control group at midline. Errors are clustered at school level in round brackets. Fwer p-values in square brackets. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.17: Perceptions about econ. outcomes at 1^{st} F. U.

	(1) Finding Job	(2) Contin. Studies	(3) Becom. Citiz.	(4) Return 5 yrs	(5) Finan. Help	(6) Getting Asyl.	(7) Favor Migr.	(8) $sinh^{-1}$ Liv. Cost	(9) $sinh^{-1}$ Wage	(10) PCA econ
Risk Treat.	-5.12	-3.32	-5.48	2.15	-4.33	-3.53	-2.00	0.00031	-0.084	-0.31
	(1.60)**	(1.67)*	(1.62)***	(1.41)	(1.78)*	(1.65)*	(1.45)	(0.080)	(0.12)	(0.12)*
	[0.02]*	[0.24]	[0.01]**	[0.44]	[0.13]	[0.19]	[0.44]	[1.00]	[0.73]	
Econ Treat.	-8.24	-3.98	-6.32	5.35	-5.31	-7.37	-2.17	-0.086	-0.026	-0.41
	(1.66)***	(1.54)*	(1.61)***	(1.43)***	(1.79)**	(1.54)***	(1.66)	(0.096)	(0.11)	(0.12)**
	[0.00]***	[0.04]*	[0.00]**	[0.00]**	[0.01]*	[0.00]***	[0.48]	[0.64]	[0.81]	
Double Treat.	-9.87	-6.93	-8.06	2.52	-7.86	-8.98	-3.91	-0.14	-0.17	-0.64
	(1.44)***	(1.41)***	(1.58)***	(1.59)	(1.63)***	(1.50)***	(1.65)*	(0.095)	(0.11)	(0.12)***
	[0.00]***	[0.00]***	[0.00]***	[0.33]	[0.00]***	[0.00]***	[0.08]	[0.33]	[0.33]	
Big school	2.14	2.37	2.44	2.00	2.62	2.25	1.99	-0.079	0.19	0.21
	(1.14)	(1.15)*	(1.15)*	(1.08)	(1.21)*	(1.11)*	(1.15)	(0.064)	(0.089)*	(0.088)*
Basel. outc.	0.28	0.31	0.26	0.24	0.28	0.21	0.21	0.12	0.23	0.37
	(0.018)***	(0.017)***	(0.015)***	(0.018)***	(0.016)***	(0.016)***	(0.016)***	(0.016)***	(0.020)***	(0.019)***
Constant	27.8	22.3	25.1	25.1	25.8	28.8	31.3	6.68	11.7	0.21
	(1.29)***	(1.18)***	(1.29)***	(1.24)***	(1.49)***	(1.31)***	(1.39)***	(0.15)***	(0.32)***	(0.088)*
1^{st} F.U. Cont.	38.6	32.7	34.9	33.4	37.0	37.0	40.8	7.54	15.2	0.35
N	4450	4443	4443	4438	4433	4430	4403	4390	4444	4356

Legend: (1) probability of finding job, (2) probability of continuing studies (3) probability of becoming a citizen, (4) probability of having returned after 5 years, (5) probability that govt at destination gives financial help, (6) probability of getting asylum, if requested, (7) percentage in favor of migration at destination, (8) expected wage at destination in $sinh^{-1}$ euros (winsorized at 5^{th} perc.), (9) expected living cost at destination in $sinh^{-1}$ euros (winsorized at 5^{th} perc.), (10) PCA aggregator for perceptions about economic outcomes. Errors are clustered at school level. 1^{st} F.U. Cont. represents average in control group at midline. Errors are clustered at school level in round brackets. Fwer p-values in square brackets. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.18: Perceptions about econ. outcomes at 2^{nd} F. U.

	(1) Finding Job	(2) Contin. Studies	(3) Becom. Citiz.	(4) Return 5 yrs	(5) Finan. Help	(6) Getting Asyl.	(7) Favor Migr.	(8) $sinh^{-1}$ Liv. Cost	(9) $sinh^{-1}$ Wage	(10) PCA econ
Risk Treat.	-2.90	-3.57	-4.79	-0.15	-2.93	-2.23	1.89	0.15	-0.080	-0.23
	(1.86)	(1.54)*	(2.16)*	(2.50)	(2.28)	(2.14)	(1.90)	(0.13)	(0.18)	(0.14)
	[0.61]	[0.23]	[0.25]	[0.96]	[0.71]	[0.76]	[0.76]	[0.75]	[0.89]	
Econ Treat.	-6.08	-5.43	-5.75	-0.57	-5.93	-3.95	-1.64	0.31	-0.18	-0.41
	(1.65)***	(1.61)***	(2.29)*	(2.44)	(1.96)**	(1.87)*	(1.50)	(0.13)*	(0.18)	(0.13)**
	[0.01]**	[0.01]*	[0.09]	[0.81]	[0.03]*	[0.14]	[0.63]	[0.11]	[0.63]	
Double Treat.	-2.83	-3.22	-2.95	2.90	-3.38	-2.55	3.20	0.16	0.087	-0.13
	(1.76)	(1.95)	(2.33)	(2.38)	(2.25)	(2.19)	(1.84)	(0.15)	(0.19)	(0.15)
	[0.54]	[0.54]	[0.69]	[0.69]	[0.54]	[0.69]	[0.52]	[0.69]	[0.69]	
Big school	-0.51	-2.30	-0.55	-0.88	-3.34	-0.20	-2.03	-0.13	0.11	-0.14
	(1.18)	(1.25)	(1.54)	(1.61)	(1.52)*	(1.45)	(1.27)	(0.097)	(0.13)	(0.10)
Basel. outc.	0.17	0.16	0.17	0.15	0.19	0.12	0.12	0.062	0.14	0.23
	(0.024)***	(0.021)***	(0.020)***	(0.022)***	(0.021)***	(0.022)***	(0.021)***	(0.019)**	(0.023)***	(0.023)***
Constant	28.9	29.8	29.7	30.5	31.9	31.8	35.2	6.95	13.5	0.35
	(1.70)***	(1.48)***	(2.06)***	(2.00)***	(2.00)***	(1.74)***	(1.54)***	(0.18)***	(0.39)***	(0.11)**
2^{nd} F.U. Cont.	34.3	32.9	34.8	34.4	36.5	35.4	39.0	7.35	15.6	0.28
N	2355	2350	2350	2348	2339	2338	2327	2322	2353	2309

Legend: (1) probability of finding job, (2) probability of continuing studies (3) probability of becoming a citizen, (4) probability of having returned after 5 years, (5) probability that govt at destination gives financial help, (6) probability of getting asylum, if requested, (7) percentage in favor of migration at destination, (8) expected wage at destination in $sinh^{-1}$ euros (winsorized at 5^{th} perc.), (9) expected living cost at destination in $sinh^{-1}$ euros (winsorized at 5^{th} perc.), (10) PCA aggregator for perceptions about economic outcomes. Errors are clustered at school level. 2^{nd} F.U. Cont. represents average in control group at midline. Errors are clustered at school level in round brackets. Fwer p-values in square brackets. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.19: Impacts on Kling (2007) at 1^{st} F. U. Indexes

	(1) Kling Cost+ Ita	(2) Kling Cost- Ita	(3) Kling Cost+ Spa	(4) Kling Cost- Spa
Risk Treat.	0.243***	0.251***	0.262***	0.259***
	(0.0285)	(0.0295)	(0.0301)	(0.0322)
Econ Treat.	0.159***	0.171***	0.164***	0.179***
	(0.0264)	(0.0255)	(0.0303)	(0.0300)
Double Treat.	0.260***	0.284***	0.278***	0.289***
	(0.0358)	(0.0348)	(0.0378)	(0.0366)
Big school	0.0595**	0.0422*	0.0464*	0.0301
	(0.0239)	(0.0233)	(0.0250)	(0.0246)
Basel. outcome	0.513***	0.517***	0.505***	0.509***
	(0.0150)	(0.0157)	(0.0158)	(0.0159)
Constant	-0.116***	-0.127***	-0.0781***	-0.0749***
	(0.0221)	(0.0225)	(0.0254)	(0.0262)
1^{st} F.U. Cont. Mean	-0.067	-0.095	-0.045	-0.057
N	4418	4418	4420	4420

Dependent variable in (1) is aggregator of Italy risk perceptions based on Kling (2007) using positive cost, (2) uses negative cost. (3) and (4) are the same, for Spain. (5) is Kling aggregator for perceptions about economic outcomes. 1^{st} F.U. Cont. represents average in control group at midline.Errors are clustered at school level. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.20: Impacts on Kling (2007) at 2^{nd} F. U. Indexes

	(1) Kling Cost+ Ita	(2) Kling Cost- Ita	(3) Kling Cost+ Spa	(4) Kling Cost- Spa
Risk Treat.	0.0352	0.0303	0.0351	0.0409
	(0.0492)	(0.0500)	(0.0550)	(0.0555)
Econ Treat.	0.0210	0.00722	-0.00123	-0.00928
	(0.0452)	(0.0467)	(0.0514)	(0.0506)
Double Treat.	0.138**	0.149***	0.100	0.117*
	(0.0536)	(0.0522)	(0.0630)	(0.0618)
Big school	0.0311	0.0109	0.0185	0.0256
	(0.0323)	(0.0324)	(0.0386)	(0.0387)
Basel. outcome	0.340***	0.370***	0.336***	0.361***
	(0.0268)	(0.0244)	(0.0255)	(0.0239)
Constant	-0.0479	-0.0306	0.0156	0.0243
	(0.0429)	(0.0420)	(0.0440)	(0.0413)
2^{nd} F.U. Cont. Mean	-0.046	-0.042	0.016	0.027
N	2355	2355	2348	2348

Dependent variable in (1) is aggregator of Italy risk perceptions based on Kling (2007) using positive cost, (2) uses negative cost. (3) and (4) are the same, for Spain. (5) is Kling aggregator for perceptions about economic outcomes. 2^{nd} F.U. Cont. represents average in control group at midline.Errors are clustered at school level. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.21: Balance Table (Only High Fees)

Variable	Control Mean	Risk-Control	Econ-Control	Double-Control
Big school	0.290	-0.000	0.000	0.000
	(0.454)	(0.000)	(0.000)	(0.000)
Male student	0.504	-0.008	0.008	0.013
	(0.500)	(0.032)	(0.029)	(0.027)
Student's age	18.560	0.161	0.054	0.292
	(1.887)	(0.205)	(0.165)	(0.177)
Mother some school	0.479	0.079	-0.023	0.010
	(0.500)	(0.047)	(0.039)	(0.041)
Father some school	0.658	0.001	-0.020	-0.019
	(0.475)	(0.046)	(0.042)	(0.042)
Wealth index	0.177	0.103	0.083	-0.015
	(1.735)	(0.191)	(0.166)	(0.177)
High Durab.	0.566	0.005	-0.028	-0.026
	(0.496)	(0.055)	(0.040)	(0.044)
Expens. Sch.	0.771	0.069	0.107	0.101
	(0.421)	(0.130)	(0.116)	(0.129)
# acquaint. abroad	4.105	2.366	-0.679	-0.524
	(36.109)	(2.176)	(1.644)	(1.715)
# classmates who migr.	1.211	0.465	0.017	0.471
	(4.457)	(0.276)	(0.227)	(0.467)
Wishing to migrate	0.268	0.049	0.017	0.026
	(0.443)	(0.033)	(0.030)	(0.034)
Planning to migr.	0.162	0.045	0.020	0.039
	(0.369)	(0.030)	(0.024)	(0.029)
Preparing to migr.	0.043	0.012	-0.004	0.005
	(0.203)	(0.015)	(0.011)	(0.013)
sin^{-1} duration of the journey Ita	1.997	0.064	-0.034	0.116**
	(0.839)	(0.049)	(0.052)	(0.054)
sin^{-1} cost of the journey Ita	15.963	-0.234	-0.155	-0.320
	(3.949)	(0.285)	(0.234)	(0.248)
Probability to be beaten Ita	59.354	-0.700	-1.004	-0.494
	(28.288)	(2.320)	(2.103)	(1.997)
Probab. of being forced to work Ita	58.797	1.230	0.851	-0.590
	(30.670)	(2.079)	(1.961)	(2.073)
Probab. of being held Ita	52.367	-0.022	0.121	-1.564
	(30.428)	(2.035)	(2.116)	(2.012)
Probab. of being sent back Ita	38.202	2.330	1.419	-0.113
	(29.480)	(2.097)	(1.864)	(1.861)
Death prob. in boat Ita	46.208	0.354	1.474	-0.783
	(29.225)	(1.920)	(2.112)	(2.346)
Death prob. bef. boat Ita	41.008	-0.926	-0.088	-1.995
	(28.319)	(1.692)	(1.779)	(1.940)
sin^{-1} duration of the journey Spa	1.966	0.053	-0.010	0.055
	(0.830)	(0.049)	(0.051)	(0.052)
sin^{-1} cost of the journey Spa	15.824	-0.031	0.058	-0.099
	(4.242)	(0.275)	(0.221)	(0.246)
Probability to be beaten Spa	50.823	-0.020	0.835	-0.859
	(29.838)	(2.146)	(2.219)	(2.274)
Probab. of being forced to work Spa	51.133	-0.166	1.563	-0.210
	(31.146)	(1.844)	(1.912)	(1.973)
Probab. of being held Spa	47.740	-1.476	-0.049	-1.806
	(30.557)	(1.862)	(1.901)	(1.883)
Probab. of being sent back Spa	38.206	0.009	-0.335	-0.336
	(28.053)	(1.795)	(1.574)	(1.528)
Death prob. in boat Spa	41.425	-0.207	1.592	0.561
	(28.805)	(1.677)	(1.850)	(2.057)
Death prob. bef. boat Spa	38.524	-0.991	-0.784	-1.229
	(28.701)	(1.406)	(1.630)	(1.780)
sin^{-1} expected wage at dest.	15.131	-0.124	-0.146	0.002
	(2.250)	(0.151)	(0.136)	(0.149)
Prob. of finding a job	32.935	0.272	-0.895	-0.158
	(27.381)	(1.516)	(1.280)	(1.275)
Asylum prob., if requested	33.461	-1.925	-3.171*	-3.000

	(28.810)	(1.934)	(1.755)	(2.015)
Prob. of continuing studies	28.493	-0.878	-1.750	-0.129
	(25.798)	(2.246)	(1.837)	(1.962)
Prob. of becoming citizen	30.373	-1.207	-0.398	-0.598
	(27.949)	(2.019)	(1.776)	(1.964)
Prob. of having ret. 5yrs	29.023	-0.904	-0.442	0.085
	(27.503)	(1.883)	(1.949)	(2.065)
sin^{-1} expected liv. cost at dest.	7.564	0.023	-0.061	-0.111
	(1.895)	(0.114)	(0.090)	(0.087)
Perc. in favor of migr. at destination	38.711	-0.099	-1.959	-0.385
	(28.451)	(1.956)	(1.664)	(1.843)
Prob. receiving fin. help	34.481	-0.665	-1.416	-0.454
	(33.052)	(2.386)	(2.067)	(2.721)
Observations	841	1,730	2,010	1,806

(1) Obtained as average of routes through Italy and Spain.
Errors clustered at school level, stratum dummy included as control.
$+\ p < 0.1$, $*\ p < 0.05$, $**\ p < 0.01$, $***\ p < 0.001$.

Table B.22: Balance Table (Only Low Fees)

Variable	Control Mean	Risk-Control	Econ-Control	Double-Control
Big school	0.588	0.000	0.000	-0.000
	(0.492)	(0.000)	(0.000)	(0.000)
Male student	0.525	-0.012	0.019	-0.017
	(0.500)	(0.030)	(0.033)	(0.027)
Student's age	19.266	-0.081	0.073	-0.294
	(2.054)	(0.177)	(0.203)	(0.194)
Mother some school	0.371	0.019	0.055	0.053
	(0.483)	(0.032)	(0.033)	(0.034)
Father some school	0.534	0.006	0.056	0.061*
	(0.499)	(0.033)	(0.042)	(0.035)
Wealth index	-0.220	0.005	-0.032	0.090
	(1.805)	(0.153)	(0.138)	(0.151)
High Durab.	0.452	0.010	-0.011	-0.012
	(0.498)	(0.033)	(0.037)	(0.032)
Expens. Sch.	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
# acquaint. abroad	3.108	0.431	3.577	0.247
	(8.510)	(1.196)	(3.108)	(0.856)
# classmates who migr.	1.486	-0.291	0.498	0.673
	(4.649)	(0.207)	(0.535)	(0.689)
Wishing to migrate	0.326	-0.062**	-0.019	0.010
	(0.469)	(0.029)	(0.032)	(0.034)
Planning to migr.	0.218	-0.028	0.009	0.028
	(0.413)	(0.027)	(0.028)	(0.030)
Preparing to migr.	0.059	-0.010	0.027	0.017
	(0.236)	(0.013)	(0.016)	(0.014)
sin^{-1} duration of the journey Ita	2.123	-0.020	0.016	0.079
	(0.975)	(0.055)	(0.065)	(0.065)
sin^{-1} cost of the journey Ita	15.495	-0.180	-0.045	-0.233
	(4.404)	(0.272)	(0.303)	(0.338)
Probability to be beaten Ita	57.491	-1.439	-1.389	-3.183
	(29.021)	(1.735)	(1.414)	(2.023)
Probab. of being forced to work Ita	55.360	-0.859	-0.996	-0.424
	(31.773)	(1.583)	(1.624)	(2.095)
Probab. of being held Ita	49.346	-1.055	-1.808	0.074
	(31.631)	(1.511)	(1.465)	(2.201)
Probab. of being sent back Ita	38.676	-1.137	-0.221	1.588
	(29.878)	(1.731)	(1.940)	(2.138)
Death prob. in boat Ita	44.161	0.152	2.224	0.540
	(30.297)	(1.522)	(1.584)	(1.711)
Death prob. bef. boat Ita	39.508	0.933	1.699	0.694
	(29.168)	(1.538)	(1.549)	(1.880)
sin^{-1} duration of the journey Spa	2.086	-0.099*	0.064	0.031
	(0.953)	(0.057)	(0.075)	(0.063)
sin^{-1} cost of the journey Spa	15.468	-0.189	-0.132	-0.213
	(4.505)	(0.282)	(0.304)	(0.339)
Probability to be beaten Spa	48.714	0.120	1.342	0.410
	(30.074)	(1.687)	(1.681)	(2.084)
Probab. of being forced to work Spa	50.010	-1.997	-1.502	1.259
	(31.596)	(1.717)	(1.752)	(2.292)
Probab. of being held Spa	46.595	-2.117	-1.178	0.667
	(31.006)	(1.385)	(1.498)	(1.973)
Probab. of being sent back Spa	38.618	-0.192	-0.165	1.067
	(29.483)	(1.548)	(1.765)	(2.012)
Death prob. in boat Spa	41.520	-1.162	-0.694	0.603
	(29.328)	(1.791)	(1.617)	(1.735)
Death prob. bef. boat Spa	38.215	-1.070	0.795	1.198
	(29.168)	(1.596)	(1.629)	(1.981)
sin^{-1} expected wage at dest.	15.165	0.058	0.119	0.196
	(2.500)	(0.129)	(0.147)	(0.129)
Prob. of finding a job	34.938	-1.408	0.196	0.622
	(27.374)	(1.250)	(1.410)	(1.520)
Asylum prob., if requested	32.771	-0.658	-0.333	0.139

	(27.717)	(1.540)	(1.512)	(1.963)
Prob. of continuing studies	30.442	-1.795	-0.726	0.548
	(26.820)	(1.661)	(2.014)	(1.864)
Prob. of becoming citizen	33.272	-0.286	-0.346	1.336
	(28.974)	(1.458)	(1.965)	(1.795)
Prob. of having ret. 5yrs	29.682	1.202	1.533	3.495*
	(27.638)	(1.700)	(2.196)	(1.948)
sin^{-1} expected liv. cost at dest.	7.494	0.024	0.204*	0.064
	(1.889)	(0.107)	(0.120)	(0.117)
Perc. in favor of migr. at destination	40.091	-0.106	0.798	2.260
	(28.724)	(1.380)	(1.696)	(1.734)
Prob. receiving fin. help	34.852	-2.066	-1.242	1.630
	(32.823)	(1.486)	(1.799)	(2.232)
Observations	968	1,963	1,703	1,793

(1) Obtained as average of routes through Italy and Spain.
Errors clustered at school level, stratum dummy included as control.
$+ \ p < 0.1$, $* \ p < 0.05$, $** \ p < 0.01$, $*** \ p < 0.001$.

Table B.23: Balance Table (Only High Durables)

Variable	Control Mean	Risk-Control	Econ-Control	Double-Control
Big school	0.426	0.000	-0.000	0.000
	(0.495)	(0.000)	(0.000)	(0.000)
Male student	0.465	0.035	0.041	0.003
	(0.499)	(0.028)	(0.026)	(0.027)
Student's age	18.650	0.202	0.073	0.148
	(1.913)	(0.196)	(0.172)	(0.170)
Mother some school	0.488	0.035	-0.002	0.021
	(0.500)	(0.039)	(0.030)	(0.029)
Father some school	0.633	0.014	0.031	0.036
	(0.482)	(0.036)	(0.033)	(0.031)
Wealth index	1.254	0.026	0.073	0.071
	(0.966)	(0.065)	(0.065)	(0.065)
High Durab.	1.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Expens. Sch.	0.413	0.060	0.160	0.104
	(0.493)	(0.110)	(0.110)	(0.118)
# acquaint. abroad	3.572	3.746**	2.243	0.678
	(8.859)	(1.833)	(1.427)	(0.718)
# classmates who migr.	1.403	0.219	0.057	0.520
	(4.591)	(0.243)	(0.240)	(0.339)
Wishing to migrate	0.301	-0.011	0.005	-0.014
	(0.459)	(0.032)	(0.035)	(0.033)
Planning to migr.	0.188	0.010	0.025	0.009
	(0.391)	(0.027)	(0.028)	(0.031)
Preparing to migr.	0.055	-0.004	0.001	-0.009
	(0.229)	(0.013)	(0.014)	(0.014)
sin^{-1} duration of the journey Ita	2.021	0.045	-0.020	0.079
	(0.915)	(0.047)	(0.053)	(0.048)
sin^{-1} cost of the journey Ita	15.614	0.096	0.003	-0.358
	(4.277)	(0.227)	(0.249)	(0.255)
Probability to be beaten Ita	58.309	-0.013	-2.467	0.311
	(28.017)	(1.830)	(1.737)	(1.844)
Probab. of being forced to work Ita	57.965	0.812	-0.742	0.544
	(30.430)	(1.729)	(1.827)	(2.058)
Probab. of being held Ita	50.347	0.420	-0.096	1.451
	(30.105)	(1.695)	(1.849)	(1.929)
Probab. of being sent back Ita	38.698	1.260	-0.862	1.084
	(29.294)	(1.623)	(1.859)	(1.558)
Death prob. in boat Ita	46.257	0.243	0.577	0.597
	(29.594)	(1.743)	(1.887)	(1.767)
Death prob. bef. boat Ita	40.929	0.527	-0.691	-0.288
	(28.411)	(1.404)	(1.691)	(1.607)
sin^{-1} duration of the journey Spa	2.016	-0.024	-0.006	0.019
	(0.876)	(0.045)	(0.055)	(0.048)
sin^{-1} cost of the journey Spa	15.593	0.073	0.069	-0.220
	(4.413)	(0.254)	(0.232)	(0.253)
Probability to be beaten Spa	50.572	0.723	-0.841	-0.234
	(29.470)	(1.568)	(1.715)	(1.738)
Probab. of being forced to work Spa	50.693	0.626	-0.065	1.758
	(30.694)	(1.660)	(1.677)	(2.012)
Probab. of being held Spa	47.114	0.128	-1.725	0.128
	(29.965)	(1.482)	(1.522)	(1.656)
Probab. of being sent back Spa	39.398	0.231	-2.611	0.708
	(28.776)	(1.590)	(1.743)	(1.569)
Death prob. in boat Spa	43.168	-0.958	-1.771	-0.919
	(28.971)	(1.662)	(1.731)	(1.615)
Death prob. bef. boat Spa	39.184	-0.228	-1.725	0.643
	(28.884)	(1.297)	(1.620)	(1.455)
sin^{-1} expected wage at dest.	15.076	-0.048	0.064	0.216
	(2.378)	(0.131)	(0.127)	(0.146)
Prob. of finding a job	34.912	-3.005**	-1.316	0.168
	(27.770)	(1.471)	(1.467)	(1.541)
Asylum prob., if requested	32.635	-0.250	-1.121	-0.961

	(27.511)	(1.514)	(1.361)	(1.634)
Prob. of continuing studies	29.658	-1.647	-1.499	0.853
	(25.936)	(1.612)	(1.289)	(1.651)
Prob. of becoming citizen	31.540	-0.831	-0.484	2.141
	(27.510)	(1.764)	(1.394)	(1.801)
Prob. of having ret. 5yrs	29.011	1.096	1.000	1.376
	(26.655)	(1.472)	(1.564)	(1.571)
sin^{-1} expected liv. cost at dest.	7.592	-0.031	-0.060	-0.071
	(1.881)	(0.100)	(0.098)	(0.099)
Perc. in favor of migr. at destination	39.111	1.012	-0.629	1.145
	(27.970)	(1.639)	(1.628)	(1.601)
Prob. receiving fin. help	34.227	-1.223	-1.151	0.585
	(32.253)	(1.670)	(1.711)	(2.079)
Observations	884	1,761	1,788	1,702

(1) Obtained as average of routes through Italy and Spain.
Errors clustered at school level, stratum dummy included as control.
$+ \ p < 0.1$, $* \ p < 0.05$, $** \ p < 0.01$, $*** \ p < 0.001$.

Table B.24: Balance Table (Only Low Durables)

Variable	Control Mean	Risk-Control	Econ-Control	Double-Control
Big school	0.460	-0.000	-0.000	-0.000
	(0.499)	(0.000)	(0.000)	(0.000)
Male student	0.569	-0.046	-0.026	-0.011
	(0.496)	(0.032)	(0.028)	(0.026)
Student's age	19.179	-0.003	-0.086	-0.145
	(2.067)	(0.176)	(0.190)	(0.169)
Mother some school	0.355	0.038	0.039	0.047
	(0.479)	(0.033)	(0.030)	(0.033)
Father some school	0.544	-0.015	0.022	0.019
	(0.498)	(0.036)	(0.035)	(0.035)
Wealth index	-1.352	0.036	0.124	0.087
	(1.429)	(0.100)	(0.089)	(0.092)
High Durab.	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Expens. Sch.	0.302	0.015	0.160	0.112
	(0.459)	(0.106)	(0.109)	(0.111)
# acquaint. abroad	3.565	-1.118	-0.102	-0.876
	(34.861)	(1.376)	(1.739)	(1.314)
# classmates who migr.	1.315	-0.108	0.202	0.409
	(4.535)	(0.226)	(0.398)	(0.450)
Wishing to migrate	0.298	-0.011	-0.014	0.016
	(0.457)	(0.025)	(0.024)	(0.028)
Planning to migr.	0.196	-0.005	-0.013	0.019
	(0.397)	(0.022)	(0.020)	(0.024)
Preparing to migr.	0.044	0.001	0.009	0.006
	(0.205)	(0.010)	(0.011)	(0.009)
sin^{-1} duration of the journey Ita	2.100	-0.032	-0.060	0.058
	(0.910)	(0.045)	(0.050)	(0.053)
sin^{-1} cost of the journey Ita	15.854	-0.507*	-0.097	-0.234
	(4.079)	(0.270)	(0.236)	(0.279)
Probability to be beaten Ita	58.706	-1.706	-0.171	-3.353*
	(29.059)	(1.834)	(1.637)	(1.750)
Probab. of being forced to work Ita	56.274	0.228	1.475	-0.836
	(31.926)	(1.796)	(1.897)	(1.721)
Probab. of being held Ita	51.448	-0.917	-0.460	-2.030
	(31.800)	(1.727)	(1.920)	(1.854)
Probab. of being sent back Ita	38.151	0.316	1.737	0.660
	(30.035)	(1.534)	(1.437)	(1.782)
Death prob. in boat Ita	44.029	0.657	2.847*	-0.043
	(29.891)	(1.514)	(1.587)	(1.661)
Death prob. bef. boat Ita	39.823	-1.020	1.559	-1.390
	(29.051)	(1.636)	(1.647)	(1.636)
sin^{-1} duration of the journey Spa	2.041	-0.044	0.015	0.023
	(0.918)	(0.050)	(0.054)	(0.053)
sin^{-1} cost of the journey Spa	15.728	-0.323	-0.049	-0.167
	(4.298)	(0.242)	(0.209)	(0.248)
Probability to be beaten Spa	48.371	-0.022	3.301*	0.484
	(30.325)	(1.724)	(1.811)	(1.765)
Probab. of being forced to work Spa	50.013	-2.009	1.280	-0.349
	(31.965)	(1.764)	(1.902)	(1.753)
Probab. of being held Spa	46.908	-3.025*	0.868	-1.177
	(31.392)	(1.569)	(1.835)	(1.582)
Probab. of being sent back Spa	37.097	-0.122	2.115	0.639
	(28.720)	(1.422)	(1.372)	(1.446)
Death prob. in boat Spa	39.560	-0.816	2.976*	1.830
	(28.953)	(1.467)	(1.540)	(1.560)
Death prob. bef. boat Spa	37.459	-1.864	1.234	-0.689
	(28.923)	(1.412)	(1.465)	(1.593)
sin^{-1} expected wage at dest.	15.244	-0.019	-0.125	0.013
	(2.358)	(0.134)	(0.130)	(0.117)
Prob. of finding a job	33.321	1.314	-0.453	-0.552
	(27.143)	(1.182)	(1.261)	(1.241)

Asylum prob., if requested	33.260	-1.816	-1.723	-1.154
	(28.638)	(1.645)	(1.577)	(1.723)
Prob. of continuing studies	29.846	-1.308	-1.934	-0.940
	(26.855)	(1.774)	(1.849)	(1.733)
Prob. of becoming citizen	32.508	-0.733	-0.874	-1.655
	(29.605)	(1.555)	(1.820)	(1.598)
Prob. of having ret. 5yrs	29.872	-0.978	-0.099	1.771
	(28.382)	(1.731)	(1.857)	(1.883)
sin^{-1} expected liv. cost at dest.	7.462	0.058	0.138	-0.005
	(1.898)	(0.110)	(0.098)	(0.096)
Perc. in favor of migr. at destination	39.757	-1.196	-1.180	0.385
	(28.904)	(1.424)	(1.428)	(1.617)
Prob. receiving fin. help	35.532	-1.302	-1.844	0.039
	(33.693)	(1.706)	(1.661)	(2.028)
Observations	867	1,704	1,807	1,720

(1) Obtained as average of routes through Italy and Spain.
Errors clustered at school level, stratum dummy included as control.
$+\ p < 0.1$, $*\ p < 0.05$, $**\ p < 0.01$, $*\!*\!*\ p < 0.001$.

Table B.25: Out of Guinea at 2^{nd} F. U. Interacted with High Fees Dummy

	(1) Only Interviewed Subject	(2) Previous and Contacts	(3) Previous and Stud. + Adm.	(4) Previous and Phone On
Risk T.	-0.0011	-0.0043	-0.0022	-0.0023
	(0.0026)	(0.0047)	(0.0052)	(0.0056)
Econ. T.	-0.0044**	-0.0061	-0.0071*	-0.010**
	(0.0019)	(0.0040)	(0.0042)	(0.0048)
Double T.	-0.0020	-0.0032	-0.0030	-0.0061
	(0.0030)	(0.0057)	(0.0058)	(0.0062)
Expens. Sch.	0.0050	0.0071	0.0058	0.0041
	(0.0054)	(0.0065)	(0.0065)	(0.0068)
Risk T. × Expens. Sch.	0.00057	-0.00020	-0.00096	0.0013
	(0.0082)	(0.0097)	(0.010)	(0.011)
	[0.94]	[0.59]	[0.72]	[0.91]
Econ. T. × Expens. Sch.	0.0047	0.0100	0.015*	0.019**
	(0.0061)	(0.0083)	(0.0082)	(0.0087)
	[0.96]	[0.59]	[0.26]	[0.21]
Double T. × Expens. Sch.	0.0011	0.0032	0.0041	0.0079
	(0.0065)	(0.0089)	(0.0089)	(0.0091)
	[0.87]	[1.00]	[0.88]	[0.79]
Strata	0.0020	0.0025	0.0029	0.0024
	(0.0020)	(0.0030)	(0.0031)	(0.0033)
Constant	0.0014	0.0080	0.0083	0.012*
	(0.0033)	(0.0052)	(0.0053)	(0.0064)
2^{nd} F. U. Cont. Mean	0.0068	0.015	0.016	0.018
N	7142	7207	7345	7367

Table B.26: Out of Conakry at 2^{nd} F. U. Interacted with High Fees Dummy

	(1) Only Interviewed Subject	(2) Previous and Contacts	(3) Previous and Stud. + Adm.	(4) Previous and Phone On
Risk T.	0.0083	0.0032	0.0019	0.0019
	(0.013)	(0.014)	(0.014)	(0.014)
Econ. T.	-0.018*	-0.020*	-0.023**	-0.023**
	(0.011)	(0.011)	(0.011)	(0.011)
Double T.	-0.0094	-0.010	-0.011	-0.011
	(0.012)	(0.014)	(0.014)	(0.014)
Expens. Sch.	-0.0071	-0.0056	-0.0066	-0.0066
	(0.012)	(0.012)	(0.013)	(0.013)
Risk T. × Expens. Sch.	-0.0030	0.00014	0.0017	0.0017
	(0.018)	(0.019)	(0.020)	(0.020)
	[0.68]	[0.80]	[0.79]	[0.79]
Econ. T. × Expens. Sch.	0.0079	0.013	0.019	0.019
	(0.015)	(0.016)	(0.016)	(0.016)
	[0.35]	[0.54]	[0.72]	[0.72]
Double T. × Expens. Sch.	0.019	0.021	0.021	0.021
	(0.018)	(0.020)	(0.020)	(0.020)
	[0.49]	[0.45]	[0.46]	[0.46]
Strata	0.011*	0.011*	0.011	0.011
	(0.0063)	(0.0068)	(0.0069)	(0.0069)
Constant	0.039***	0.046***	0.048***	0.048***
	(0.012)	(0.013)	(0.013)	(0.013)
2^{nd} F. U. Cont. Mean	0.052	0.061	0.062	0.062
N	7142	7249	7355	7355

Table B.27: Out of Guinea at 2^{nd} F. U. Interacted with High Durables Dummy

	(1) Only Interviewed Subject	(2) Previous and Contacts	(3) Previous and Stud. + Adm.	(4) Previous and Phone On
Risk T.	-0.0082***	-0.017***	-0.018***	-0.016***
	(0.0029)	(0.0052)	(0.0054)	(0.0060)
Econ. T.	-0.0016	-0.0067	-0.0078	-0.0079
	(0.0039)	(0.0063)	(0.0063)	(0.0064)
Double T.	-0.0011	-0.0045	-0.0032	-0.0032
	(0.0044)	(0.0065)	(0.0066)	(0.0069)
Wealthy (Durables)	-0.0026	-0.0097	-0.011*	-0.011*
	(0.0037)	(0.0059)	(0.0061)	(0.0061)
Risk T. × Wealthy (Durables)	0.014**	0.027***	0.031***	0.029***
	(0.0063)	(0.0090)	(0.0097)	(0.010)
	[0.34]	[0.20]	[0.12]	[0.12]
Econ. T. × Wealthy (Durables)	0.0016	0.016**	0.022***	0.023***
	(0.0053)	(0.0079)	(0.0082)	(0.0083)
	[1.00]	[0.13]	[0.020]**	[0.020]**
Double T. × Wealthy (Durables)	0.00041	0.0079	0.0065	0.0067
	(0.0059)	(0.0096)	(0.0097)	(0.0099)
	[0.88]	[0.63]	[0.63]	[0.62]
Strata	0.0028	0.0047	0.0045	0.0046
	(0.0023)	(0.0032)	(0.0033)	(0.0035)
Constant	0.0039	0.013*	0.014**	0.015**
	(0.0040)	(0.0066)	(0.0068)	(0.0071)
2^{nd} F. U. Cont. Mean	0.0068	0.015	0.016	0.018
N	6758	6819	6943	6961

Table B.28: Out of Conakry at 2^{nd} F. U. Interacted with High Durables Dummy

	(1) Only Interviewed Subject	(2) Previous and Contacts	(3) Previous and Stud. + Adm.	(4) Previous and Phone On
Risk T.	-0.0023	-0.012	-0.013	-0.013
	(0.014)	(0.015)	(0.014)	(0.014)
Econ. T.	-0.019*	-0.023*	-0.024**	-0.024**
	(0.010)	(0.012)	(0.012)	(0.012)
Double T.	-0.012	-0.017	-0.015	-0.015
	(0.012)	(0.014)	(0.014)	(0.014)
Wealthy (Durables)	-0.023**	-0.030***	-0.030***	-0.030***
	(0.010)	(0.012)	(0.012)	(0.012)
Risk T. × Wealthy (Durables)	0.026	0.038*	0.041**	0.041**
	(0.018)	(0.020)	(0.020)	(0.020)
	[0.062]*	[0.050]*	[0.053]*	[0.053]*
Econ. T. × Wealthy (Durables)	0.0094	0.022	0.027*	0.027*
	(0.013)	(0.015)	(0.014)	(0.014)
	[0.36]	[0.88]	[0.81]	[0.81]
Double T. × Wealthy (Durables)	0.021	0.032*	0.029*	0.029*
	(0.015)	(0.017)	(0.016)	(0.016)
	[0.43]	[0.19]	[0.23]	[0.23]
Strata	0.012**	0.014**	0.014**	0.014**
	(0.0061)	(0.0065)	(0.0065)	(0.0065)
Constant	0.046***	0.054***	0.055***	0.055***
	(0.012)	(0.014)	(0.014)	(0.014)
2^{nd} F. U. Cont. Mean	0.052	0.061	0.062	0.062
N	6758	6854	6951	6951

Table B.29: Migration Intentions at 2^{nd} F. U. Interacted with High Fees Dummy

	(1) Wish to Migrate	(2) Planning to Migrate	(3) Prepare to Migrate
Risk T.	0.016	-0.026	-0.0066
	(0.026)	(0.032)	(0.0096)
Econ. T.	-0.066**	-0.060**	-0.018*
	(0.031)	(0.030)	(0.0100)
Double T.	0.032	0.025	0.0089
	(0.029)	(0.038)	(0.012)
Expens. Sch.	0.065**	-0.0058	0.021
	(0.030)	(0.032)	(0.014)
Risk T. × Expens. Sch.	-0.031	0.047	-0.00013
	(0.038)	(0.048)	(0.020)
	[0.58]	[0.55]	[0.70]
Econ. T. × Expens. Sch.	-0.0013	0.072*	0.0091
	(0.043)	(0.042)	(0.016)
	[0.022]**	[0.67]	[0.50]
Double T. × Expens. Sch.	-0.069	-0.019	-0.013
	(0.042)	(0.051)	(0.018)
	[0.21]	[0.87]	[0.79]
Outcome at Basel.	0.18***	0.13***	0.059***
	(0.013)	(0.013)	(0.015)
Strata	0.023	-0.0046	-0.0020
	(0.014)	(0.017)	(0.0056)
Constant	0.41***	0.14***	0.038***
	(0.032)	(0.029)	(0.011)
2^{nd} F. U. Cont. Mean	0.53	0.15	0.048
N	7218	7209	7208

Table B.30: Migration Intentions at 2^{nd} F. U. Interacted with High Durables Dummy

	(1) Wish to Migrate	(2) Planning to Migrate	(3) Prepare to Migrate
Risk T.	-0.020	-0.021	-0.025***
	(0.024)	(0.027)	(0.0094)
Econ. T.	-0.049*	-0.034	-0.021**
	(0.027)	(0.027)	(0.0098)
Double T.	-0.0036	0.020	0.0043
	(0.022)	(0.030)	(0.010)
Wealthy (Durables)	-0.016	-0.019	-0.0092
	(0.024)	(0.018)	(0.0077)
Risk T. × Wealthy (Durables)	0.065**	0.042	0.042***
	(0.031)	(0.027)	(0.015)
	[0.098]*	[0.46]	[0.19]
Econ. T. × Wealthy (Durables)	-0.0060	0.048**	0.035***
	(0.035)	(0.024)	(0.012)
	[0.069]*	[0.56]	[0.14]
Double T. × Wealthy (Durables)	0.0045	-0.014	0.0055
	(0.032)	(0.027)	(0.013)
	[0.98]	[0.81]	[0.37]
Outcome at Basel.	0.18***	0.13***	0.054***
	(0.013)	(0.014)	(0.017)
Strata	0.031**	-0.0050	-0.00098
	(0.015)	(0.017)	(0.0056)
Constant	0.44***	0.14***	0.047***
	(0.030)	(0.028)	(0.011)
2^{nd} F. U. Cont. Mean	0.53	0.15	0.048
N	6832	6825	6824

Table B.31: Risk perceptions for route through Italy at 2^{nd} F. U. (Only High Fees)

	(1) $sinh^{-1}$ Journey Duration	(2) $sinh^{-1}$ Journey Cost	(3) Being Beaten	(4) Forced to Work	(5) Being Kidnap-ped	(6) Death before boat	(7) Death in boat	(8) Sent Back	(9) PCA Risk
Risk Treat.	0.14	-0.041	3.55	2.49	4.28	4.33	4.69	2.37	0.27
	(0.13)	(0.31)	(2.68)	(3.07)	(3.63)	(2.74)	(3.36)	(3.66)	(0.23)
	[0.78]	[0.89]	[0.69]	[0.81]	[0.73]	[0.58]	[0.68]	[0.81]	
Econ Treat.	-0.075	0.10	4.63	1.06	2.45	3.14	4.54	4.64	0.26
	(0.12)	(0.25)	$(2.53)^{*}$	(2.40)	(2.66)	(2.66)	(2.98)	(2.90)	(0.18)
	[0.92]	[0.92]	[0.41]	[0.92]	[0.84]	[0.76]	[0.57]	[0.54]	
Double Treat.	0.13	0.13	8.54	5.37	8.72	8.16	9.83	6.13	0.67
	(0.12)	(0.28)	$(2.87)^{***}$	$(2.70)^{*}$	$(3.27)^{***}$	$(3.03)^{***}$	$(3.61)^{***}$	$(3.65)^{*}$	$(0.23)^{***}$
	[0.50]	[0.70]	$[0.05]^{*}$	[0.23]	$[0.07]^{*}$	$[0.07]^{*}$	$[0.07]^{*}$	[0.30]	
Big school	-0.010	0.23	0.46	1.07	1.21	2.19	1.16	-0.86	0.089
	(0.075)	(0.19)	(2.08)	(2.04)	(2.26)	(1.93)	(2.33)	(2.22)	(0.15)
Basel. outc.	0.14	0.26	0.27	0.21	0.25	0.28	0.23	0.29	0.36
	$(0.038)^{***}$	$(0.034)^{***}$	$(0.029)^{***}$	$(0.027)^{***}$	$(0.030)^{***}$	$(0.035)^{***}$	$(0.037)^{***}$	$(0.032)^{***}$	$(0.034)^{***}$
Constant	2.01	11.5	36.2	39.1	31.4	23.1	27.7	25.9	-0.45
	$(0.13)^{***}$	$(0.61)^{***}$	$(3.45)^{***}$	$(3.33)^{***}$	$(3.66)^{***}$	$(2.76)^{***}$	$(3.80)^{***}$	$(3.47)^{***}$	$(0.20)^{**}$
2^{nd} F.U. Cont.	2.28	15.8	52.2	51.9	45.3	35.5	38.9	36.6	-0.38
N	1260	1255	1260	1259	1259	1259	1259	1261	1253

Legend: (1) duration of journey in $sinh^{-1}$ months (winsorized at 5^{th} perc.), (2) journey cost in $sinh^{-1}$ euros (winsorized at 5^{th} perc.), (3) probability of being beaten, (4) probability of being forced to work, (5) probability of being kidnapped, (6) probability of dying before travel by boat, (7) probability of dying during travel by boat, (8) probability of being sent back, (9) PCA aggregator for risk perceptions. 2^{nd} F.U. Cont. represents average in control group at midline. Errors are clustered at school level in round brackets. Fwer p-values in square brackets. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.32: Risk perceptions for route through Italy at 2^{nd} F. U. (Only Low Fees)

	(1) $sinh^{-1}$ Journey Duration	(2) $sinh^{-1}$ Journey Cost	(3) Being Beaten	(4) Forced to Work	(5) Being Kidnap-ped	(6) Death before boat	(7) Death in boat	(8) Sent Back	(9) PCA Risk
Risk Treat.	-0.050	0.094	0.54	1.07	-3.03	-2.14	0.48	-0.86	-0.063
	(0.096)	(0.38)	(2.46)	(2.52)	(2.81)	(2.24)	(2.25)	(2.85)	(0.17)
	[1.00]	[1.00]	[1.00]	[1.00]	[0.89]	[0.93]	[1.00]	[1.00]	
Econ Treat.	-0.33	0.32	2.90	3.45	-0.15	-3.28	0.19	1.97	0.016
	$(0.096)^{***}$	(0.33)	(2.36)	(3.12)	(2.97)	(2.57)	(2.99)	(3.08)	(0.19)
	$[0.03]^{**}$	[0.82]	[0.77]	[0.78]	[1.00]	[0.77]	[1.00]	[0.88]	
Double Treat.	0.030	-0.76	2.45	3.27	3.02	1.77	5.03	1.73	0.24
	(0.12)	$(0.39)^{*}$	(2.79)	(2.84)	(2.89)	(2.53)	$(2.32)^{**}$	(2.80)	(0.18)
	[0.84]	[0.33]	[0.84]	[0.80]	[0.83]	[0.84]	[0.26]	[0.84]	
Big school	0.10	0.32	2.10	0.67	1.17	0.043	1.88	0.61	0.070
	(0.080)	(0.28)	(1.94)	(1.98)	(2.11)	(1.72)	(1.90)	(2.21)	(0.13)
Basel. outc.	0.12	0.21	0.26	0.24	0.28	0.26	0.28	0.24	0.38
	$(0.039)^{***}$	$(0.039)^{***}$	$(0.033)^{***}$	$(0.039)^{***}$	$(0.037)^{***}$	$(0.035)^{***}$	$(0.039)^{***}$	$(0.033)^{***}$	$(0.038)^{***}$
Constant	2.25	11.8	37.1	37.5	34.9	31.0	30.5	30.5	-0.13
	$(0.093)^{***}$	$(0.67)^{***}$	$(2.84)^{***}$	$(3.13)^{***}$	$(2.93)^{***}$	$(2.35)^{***}$	$(2.48)^{***}$	$(2.54)^{***}$	(0.15)
2^{nd} F.U. Cont.	2.55	15.2	52.9	50.6	49.0	41.0	42.9	40.0	-0.18
N	1117	1108	1113	1113	1112	1113	1112	1111	1102

Legend: (1) duration of journey in $sinh^{-1}$ months (winsorized at 5^{th} perc.), (2) journey cost in $sinh^{-1}$ euros (winsorized at 5^{th} perc.), (3) probability of being beaten, (4) probability of being forced to work, (5) probability of being kidnapped, (6) probability of dying before travel by boat, (7) probability of dying during travel by boat, (8) probability of being sent back, (9) PCA aggregator for risk perceptions. 2^{nd} F.U. Cont. represents average in control group at midline. Errors are clustered at school level in round brackets. Fwer p-values in square brackets. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.33: Risk perceptions for route through Spain at 2^{nd} F. U. (Only High Fees)

	(1) $sinh^{-1}$ Journey Duration	(2) $sinh^{-1}$ Journey Cost	(3) Being Beaten	(4) Forced to Work	(5) Being Kidnap-ped	(6) Death before boat	(7) Death in boat	(8) Sent Back	(9) PCA Risk
Risk Treat.	0.12	-0.15	2.20	3.15	5.32	1.80	1.08	2.61	0.20
	(0.15)	(0.48)	(2.48)	(2.60)	(3.61)	(3.71)	(3.13)	(3.41)	(0.23)
	[0.90]	[0.93]	[0.90]	[0.76]	[0.60]	[0.93]	[0.93]	[0.90]	
Econ Treat.	-0.26	-0.10	2.57	3.52	3.68	2.15	0.91	2.81	0.16
	(0.13)**	(0.29)	(2.00)	(2.27)	(2.77)	(2.95)	(2.53)	(2.63)	(0.18)
	[0.28]	[0.94]	[0.62]	[0.50]	[0.62]	[0.84]	[0.94]	[0.67]	
Double Treat.	-0.041	0.20	8.90	8.20	8.12	4.23	4.14	4.73	0.52
	(0.14)	(0.31)	(2.97)***	(2.73)***	(3.47)**	(3.79)	(3.63)	(3.52)	(0.26)**
	[0.81]	[0.81]	[0.05]**	[0.05]**	[0.15]	[0.65]	[0.65]	[0.58]	
Big school	-0.072	0.039	0.44	0.61	1.53	0.20	0.52	-1.01	0.038
	(0.080)	(0.28)	(1.90)	(1.89)	(2.24)	(2.26)	(2.34)	(2.42)	(0.16)
Basel. outc.	0.16	0.24	0.24	0.21	0.22	0.29	0.22	0.27	0.34
	(0.034)***	(0.046)***	(0.033)***	(0.030)***	(0.033)***	(0.034)***	(0.034)***	(0.032)***	(0.037)***
Constant	2.19	11.8	32.4	34.3	30.5	25.5	29.9	27.8	-0.21
	(0.14)***	(0.72)***	(2.64)***	(2.45)***	(3.42)***	(3.40)***	(3.19)***	(3.02)***	(0.19)
2^{nd} F.U. Cont.	2.45	15.7	44.4	45	41.7	36.7	39.0	37.1	-0.23
N	1260	1256	1259	1259	1259	1259	1259	1260	1254

Legend: (1) duration of journey in $sinh^{-1}$ months (winsorized at 5^{th} perc.), (2) journey cost in $sinh^{-1}$ euros (winsorized at 5^{th} perc.), (3) probability of being beaten, (4) probability of being forced to work, (5) probability of being kidnapped, (6) probability of dying before travel by boat, (7) probability of dying during travel by boat, (8) probability of being sent back, (9) PCA aggregator for risk perceptions. 2^{nd} F.U. Cont. represents average in control group at midline. Errors are clustered at school level in round brackets. Fwer p-values in square brackets. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.34: Risk perceptions for route through Spain at 2^{nd} F. U. (Only Low Fees)

	(1) $sinh^{-1}$ Journey Duration	(2) $sinh^{-1}$ Journey Cost	(3) Being Beaten	(4) Forced to Work	(5) Being Kidnap-ped	(6) Death before boat	(7) Death in boat	(8) Sent Back	(9) PCA Risk
Risk Treat.	-0.023	-0.053	1.22	-1.10	-2.82	0.30	2.23	0.80	0.021
	(0.11)	(0.44)	(2.48)	(2.83)	(2.62)	(2.83)	(3.05)	(3.01)	(0.21)
	[1.00]	[1.00]	[0.99]	[0.99]	[0.84]	[1.00]	[0.96]	[1.00]	
Econ Treat.	-0.20	0.47	3.51	0.34	-0.36	-1.52	-1.30	2.71	0.034
	(0.13)	(0.46)	(2.88)	(3.30)	(3.14)	(3.33)	(3.04)	(3.65)	(0.25)
	[0.52]	[0.78]	[0.70]	[0.99]	[0.99]	[0.94]	[0.94]	[0.84]	
Double Treat.	0.13	-1.05	3.23	0.70	0.64	2.20	1.77	0.93	0.17
	(0.13)	$(0.47)^{**}$	(2.79)	(3.12)	(3.19)	(3.15)	(3.39)	(3.11)	(0.24)
	[0.80]	[0.19]	[0.70]	[0.97]	[0.97]	[0.89]	[0.94]	[0.97]	
Big school	0.090	-0.52	3.06	2.76	3.90	1.14	1.36	2.29	0.17
	(0.099)	(0.36)	(2.08)	(2.22)	$(2.25)^{*}$	(2.27)	(2.45)	(2.61)	(0.17)
Basel. outc.	0.13	0.18	0.26	0.22	0.26	0.28	0.28	0.29	0.38
	$(0.041)^{***}$	$(0.039)^{***}$	$(0.034)^{***}$	$(0.031)^{***}$	$(0.031)^{***}$	$(0.034)^{***}$	$(0.028)^{***}$	$(0.026)^{***}$	$(0.033)^{***}$
Constant	2.23	12.6	33.6	35.8	34.3	29.0	30.1	27.8	0.0025
	$(0.13)^{***}$	$(0.72)^{***}$	$(2.54)^{***}$	$(2.83)^{***}$	$(2.48)^{***}$	$(2.91)^{***}$	$(2.76)^{***}$	$(2.32)^{***}$	(0.16)
2^{nd} F.U. Cont.	2.54	15.1	47.6	48.0	48.0	40.0	42.2	39.8	0.064
N	1113	1099	1111	1108	1108	1107	1107	1106	1094

Legend: (1) duration of journey in $sinh^{-1}$ months (winsorized at 5^{th} perc.), (2) journey cost in $sinh^{-1}$ euros (winsorized at 5^{th} perc.), (3) probability of being beaten, (4) probability of being forced to work, (5) probability of being kidnapped, (6) probability of dying before travel by boat, (7) probability of dying during travel by boat, (8) probability of being sent back, (9) PCA aggregator for risk perceptions. 2^{nd} F.U. Cont. represents average in control group at midline. Errors are clustered at school level in round brackets. Fwer p-values in square brackets. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.35: Perceptions about econ. outcomes at 2^{nd} F. U. (Only High Fees)

	(1) Finding Job	(2) Contin. Studies	(3) Becom. Citiz.	(4) Return 5 yrs	(5) Finan. Help	(6) Getting Asyl.	(7) Favor Migr.	(8) $sinh^{-1}$ Liv. Cost	(9) $sinh^{-1}$ Wage	(10) PCA econ
Risk Treat.	-0.15	-6.15	-1.73	0.41	-2.97	-0.69	-0.069	0.35	-0.19	-0.19
	(2.16)	(2.11)**	(2.54)	(3.39)	(2.81)	(2.85)	(2.70)	(0.17)*	(0.26)	(0.16)
	[1.00]	[0.08]	[0.98]	[1.00]	[0.88]	[1.00]	[1.00]	[0.30]	[0.98]	
Econ Treat.	-2.81	-5.51	-2.88	-1.88	-4.63	-4.90	-3.09	0.54	-0.0086	-0.33
	(1.70)	(2.12)*	(2.56)	(3.31)	(2.26)*	(2.51)	(1.98)	(0.16)**	(0.23)	(0.15)*
	[0.48]	[0.12]	[0.60]	[0.83]	[0.31]	[0.35]	[0.48]	[0.04]*	[0.96]	
Double Treat.	-0.95	-4.94	-1.48	2.03	-3.30	-3.22	-0.60	0.27	0.073	-0.18
	(2.10)	(2.52)	(2.82)	(3.29)	(2.66)	(3.04)	(2.26)	(0.18)	(0.26)	(0.19)
	[0.99]	[0.42]	[0.99]	[0.99]	[0.81]	[0.88]	[0.99]	[0.69]	[0.99]	
Big school	0.60	-0.92	0.24	-1.96	-2.33	0.029	-1.24	-0.060	0.089	-0.070
	(1.34)	(1.70)	(2.01)	(1.95)	(1.85)	(1.91)	(1.51)	(0.14)	(0.19)	(0.13)
Basel. outc.	0.16	0.16	0.21	0.18	0.20	0.13	0.15	0.086	0.14	0.25
	(0.032)***	(0.031)***	(0.028)***	(0.031)***	(0.027)***	(0.031)***	(0.028)***	(0.026)**	(0.033)***	(0.031)***
Constant	26.8	30.1	25.9	30.9	30.3	31.9	35.0	6.53	13.2	0.30
	(1.87)***	(2.25)***	(2.44)***	(3.07)***	(2.38)***	(2.54)***	(2.34)***	(0.22)***	(0.58)***	(0.14)*
2^{nd} F.U. Cont.	32.6	33.9	32.8	34.8	35.5	36.1	40.3	7.13	15.5	0.26
N	1254	1252	1252	1252	1248	1250	1244	1243	1252	1238

Legend: (1) probability of finding job, (2) probability of continuing studies (3) probability of becoming a citizen, (4) probability of having returned after 5 years, (5) probability that govt at destination gives financial help, (6) probability of getting asylum, if requested, (7) percentage in favor of migration at destination, (8) expected wage at destination in $sinh^{-1}$ euros (winsorized at 5^{th} perc.), (9) expected living cost at destination in $sinh^{-1}$ euros (winsorized at 5^{th} perc.), (10) PCA aggregator for perceptions about economic outcomes. Errors are clustered at school level. 2^{nd} F.U. Cont. represents average in control group at midline. Errors are clustered at school level in round brackets. Fwer p-values in square brackets. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.36: Perceptions about econ. outcomes at 2^{nd} F. U. (Only Low Fees)

	(1) Finding Job	(2) Contin. Studies	(3) Becom. Citiz.	(4) Return 5 yrs	(5) Finan. Help	(6) Getting Asyl.	(7) Favor Migr.	(8) $sinh^{-1}$ Liv. Cost	(9) $sinh^{-1}$ Wage	(10) PCA econ
Risk Treat.	-5.16	-1.41	-7.30	-0.43	-3.09	-3.14	3.58	-0.048	-0.037	-0.26
	(2.77)	(2.22)	(3.34)*	(3.56)	(3.49)	(3.07)	(2.62)	(0.18)	(0.24)	(0.22)
	[0.43]	[0.95]	[0.28]	[0.99]	[0.88]	[0.84]	[0.69]	[0.99]	[0.99]	
Econ Treat.	-10.5	-6.35	-9.22	1.43	-7.90	-2.56	-0.046	0.083	-0.41	-0.55
	(2.83)***	(2.48)*	(3.80)*	(3.83)	(3.19)*	(3.04)	(2.49)	(0.20)	(0.30)	(0.21)*
	[0.02]*	[0.15]	[0.15]	[0.97]	[0.15]	[0.86]	[0.99]	[0.97]	[0.63]	
Double Treat.	-4.35	-1.01	-3.76	3.73	-3.06	-1.72	7.96	0.12	0.13	-0.036
	(2.67)	(2.98)	(3.60)	(3.50)	(3.60)	(3.07)	(2.89)**	(0.22)	(0.27)	(0.24)
	[0.57]	[0.98]	[0.85]	[0.85]	[0.91]	[0.98]	[0.11]	[0.98]	[0.98]	
Big school	-1.64	-4.33	-1.14	0.15	-4.46	-1.14	-3.21	-0.14	0.23	-0.24
	(1.93)	(1.98)*	(2.70)	(2.82)	(2.61)	(2.36)	(2.07)	(0.15)	(0.18)	(0.18)
Basel. outc.	0.18	0.16	0.13	0.12	0.17	0.10	0.091	0.035	0.13	0.21
	(0.036)***	(0.030)***	(0.029)***	(0.032)***	(0.034)***	(0.033)**	(0.033)**	(0.027)	(0.034)***	(0.033)***
Constant	30.4	29.2	33.0	30.6	33.2	32.1	35.5	7.34	13.7	0.39
	(2.46)***	(2.02)***	(3.06)***	(2.63)***	(3.07)***	(2.42)***	(1.95)***	(0.24)***	(0.55)***	(0.16)*
2^{nd} F.U. Cont.	36.0	32.0	36.6	34.0	37.4	34.7	37.8	7.55	15.6	0.31
N	1101	1098	1098	1096	1091	1088	1083	1079	1101	1071

Legend: (1) probability of finding job, (2) probability of continuing studies (3) probability of becoming a citizen, (4) probability of having returned after 5 years, (5) probability that govt at destination gives financial help, (6) probability of getting asylum, if requested, (7) percentage in favor of migration at destination, (8) expected wage at destination in $sinh^{-1}$ euros (winsorized at 5^{th} perc.), (9) expected living cost at destination in $sinh^{-1}$ euros (winsorized at 5^{th} perc.), (10) PCA aggregator for perceptions about economic outcomes. Errors are clustered at school level. 2^{nd} F.U. Cont. represents average in control group at midline. Errors are clustered at school level in round brackets. Fwer p-values in square brackets. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.37: Impacts on Kling (2007) at 2^{nd} F. U. Indexes (Only High Fees)

	(1) Kling Cost+ Ita	(2) Kling Cost- Ita	(3) Kling Cost+ Spa	(4) Kling Cost- Spa
Risk Treat.	0.0962	0.0956	0.0689	0.0765
	(0.0810)	(0.0850)	(0.0812)	(0.0848)
Econ Treat.	0.0762	0.0701	0.0176	0.0226
	(0.0629)	(0.0674)	(0.0633)	(0.0660)
Double Treat.	0.218***	0.209**	0.156*	0.145
	(0.0803)	(0.0827)	(0.0908)	(0.0886)
Big school	0.0346	0.0211	0.00571	0.00427
	(0.0512)	(0.0507)	(0.0556)	(0.0550)
Basel. outcome	0.333***	0.361***	0.312***	0.349***
	(0.0374)	(0.0363)	(0.0369)	(0.0351)
Constant	-0.107	-0.104	-0.0160	-0.0123
	(0.0709)	(0.0716)	(0.0648)	(0.0651)
2^{nd} F.U. Cont. Mean	-0.087	-0.10	-0.027	-0.033
N	1253	1253	1254	1254

Dependent variable in (1) is aggregator of Italy risk perceptions based on Kling (2007) using positive cost, (2) uses negative cost. (3) and (4) are the same, for Spain. (5) is Kling aggregator for perceptions about economic outcomes. 2^{nd} F.U. Cont. represents average in control group at midline.Errors are clustered at school level. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.38: Impacts on Kling (2007) at 2^{nd} F. U. Indexes (Only Low Fees)

	(1) Kling Cost+ Ita	(2) Kling Cost- Ita	(3) Kling Cost+ Spa	(4) Kling Cost- Spa
Risk Treat.	-0.0203	-0.0304	0.00394	0.00341
	(0.0604)	(0.0564)	(0.0753)	(0.0713)
Econ Treat.	-0.0282	-0.0459	0.00282	-0.0247
	(0.0670)	(0.0665)	(0.0882)	(0.0850)
Double Treat.	0.0540	0.0957	0.0372	0.0885
	(0.0667)	(0.0588)	(0.0824)	(0.0825)
Big school	0.0465	0.0264	0.0509	0.0777
	(0.0457)	(0.0435)	(0.0604)	(0.0610)
Basel. outcome	0.348***	0.381***	0.359***	0.367***
	(0.0397)	(0.0338)	(0.0352)	(0.0330)
Constant	-0.000242	0.0253	0.0404	0.0525
	(0.0529)	(0.0469)	(0.0607)	(0.0524)
2^{nd} F.U. Cont. Mean	-0.0080	0.014	0.056	0.082
N	1102	1102	1094	1094

Dependent variable in (1) is aggregator of Italy risk perceptions based on Kling (2007) using positive cost, (2) uses negative cost. (3) and (4) are the same, for Spain. (5) is Kling aggregator for perceptions about economic outcomes. 2^{nd} F.U. Cont. represents average in control group at midline.Errors are clustered at school level. P-values are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Appendix C

Appendix for Chapter 3 'Third Party Interest, Resource Value, and the Likelihood of Conflict'

C.1 Figures

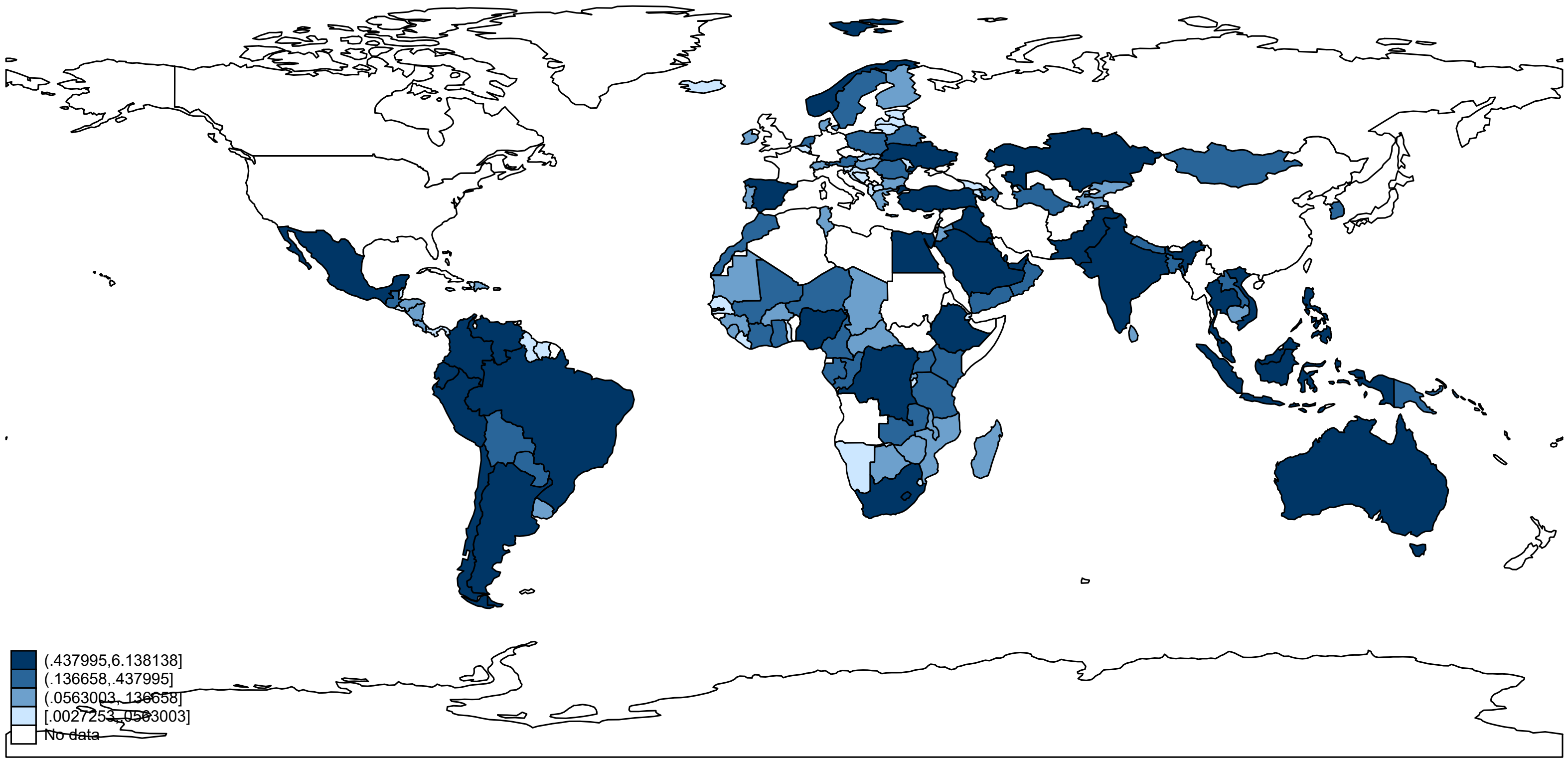


Figure C.1: Natural Capital by country in 2014 in 10^{12} \$, source: World Bank. Referenced in Section 3.5.1.

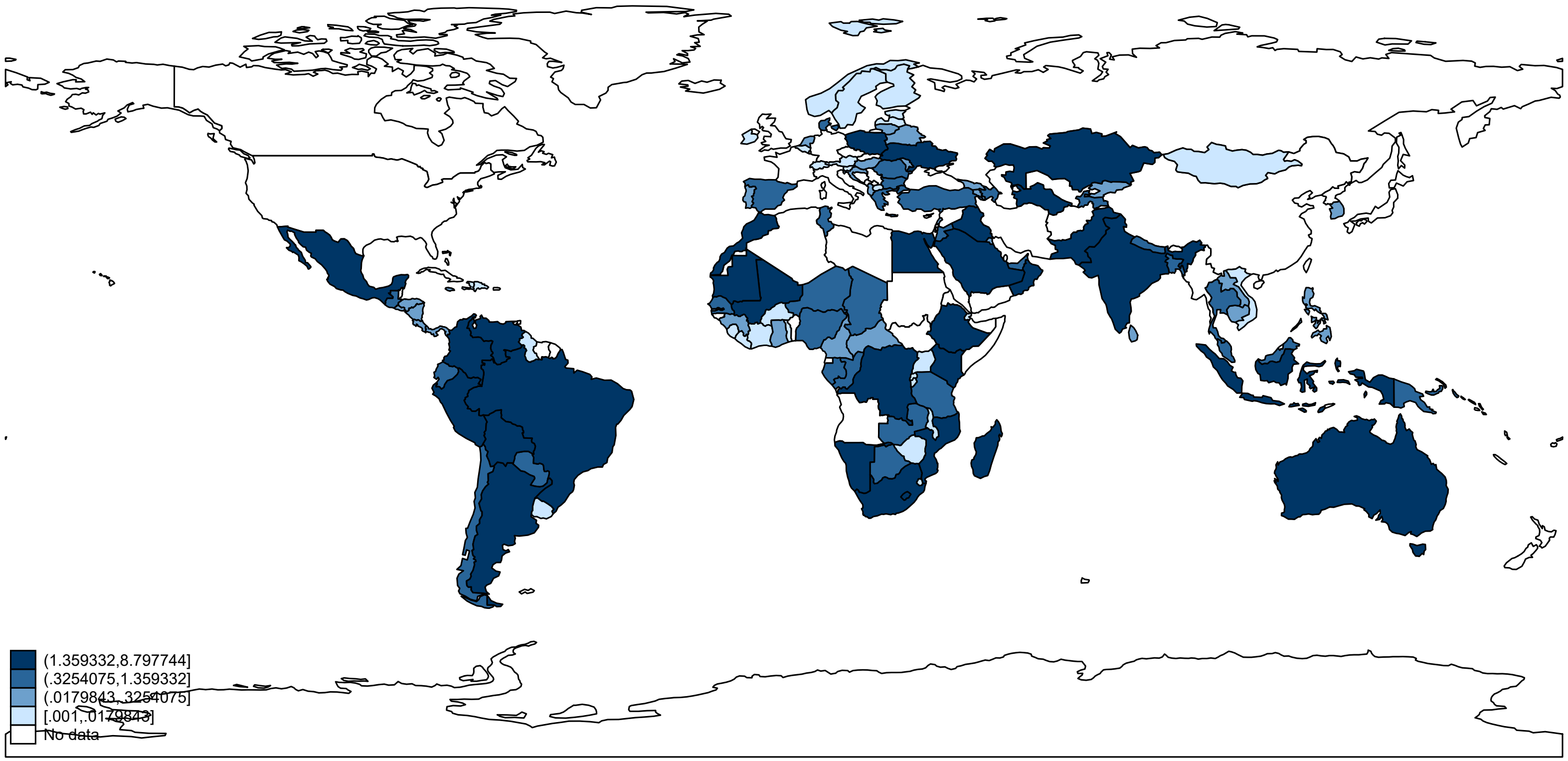


Figure C.2: Sedimentary basins Volumes in $10km^3$ \$, source: CRUST 1.0. Referenced in Section 3.5.1.

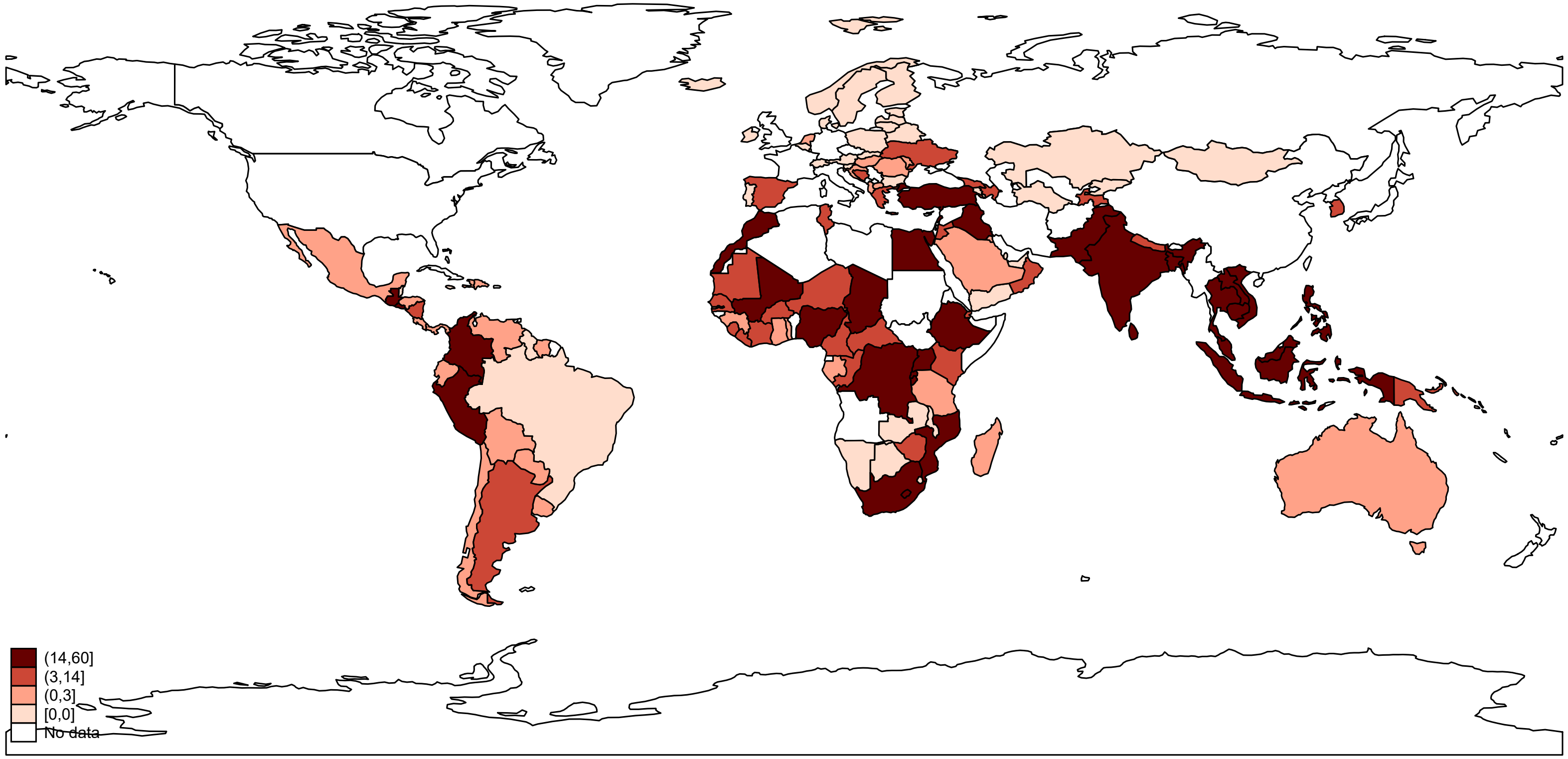


Figure C.3: Total number of conflict years by country from 1950 till 2000, source: UCDP/PRIO. Conflict is defines as at least 25 battle-related deaths. Referenced in Section 3.5.1.

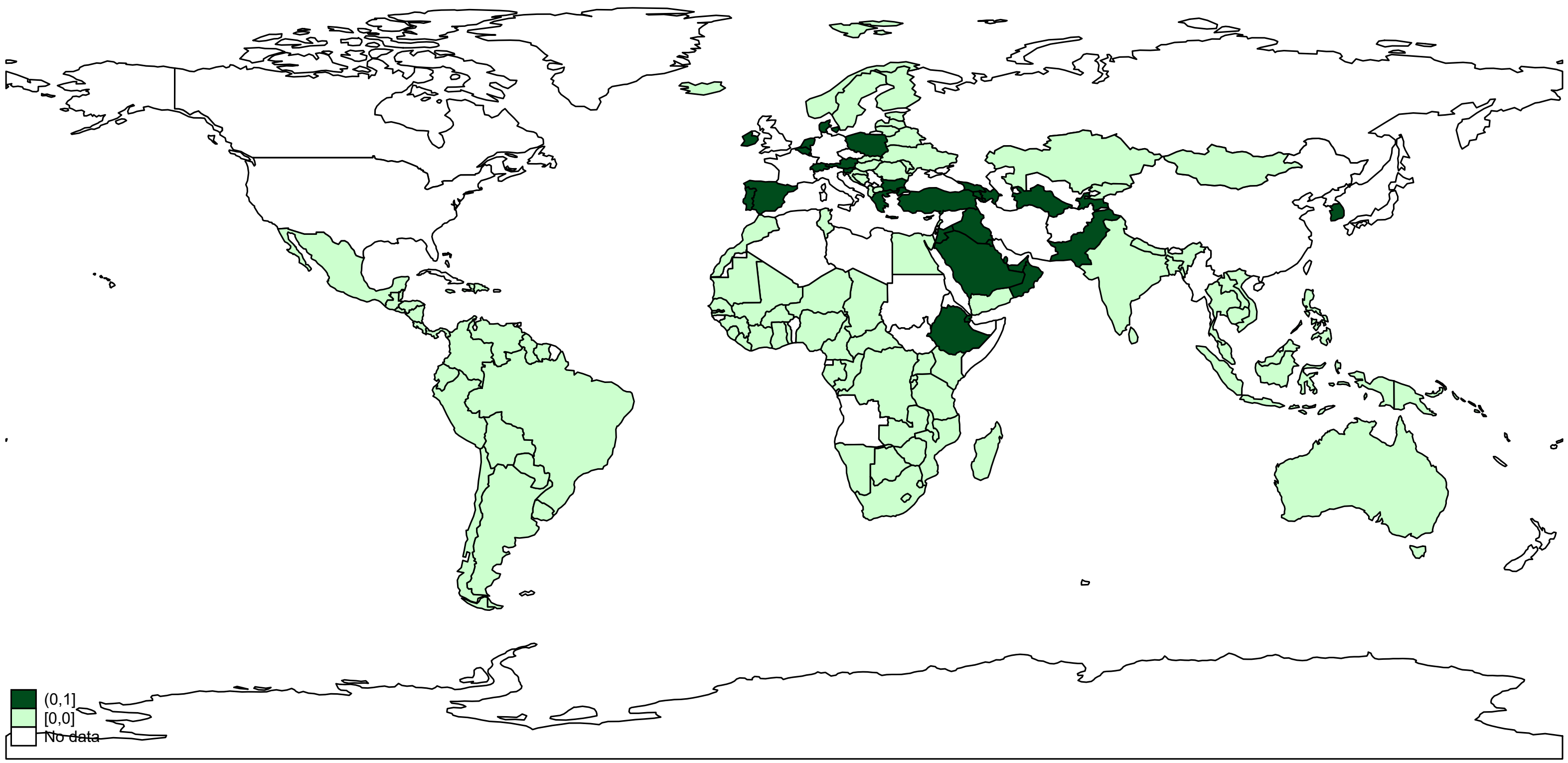


Figure C.4: Countries with 1000 or more US DoD employees or neighbouring to them in dark color, source: DMDC. Referenced in Section 3.5.1.

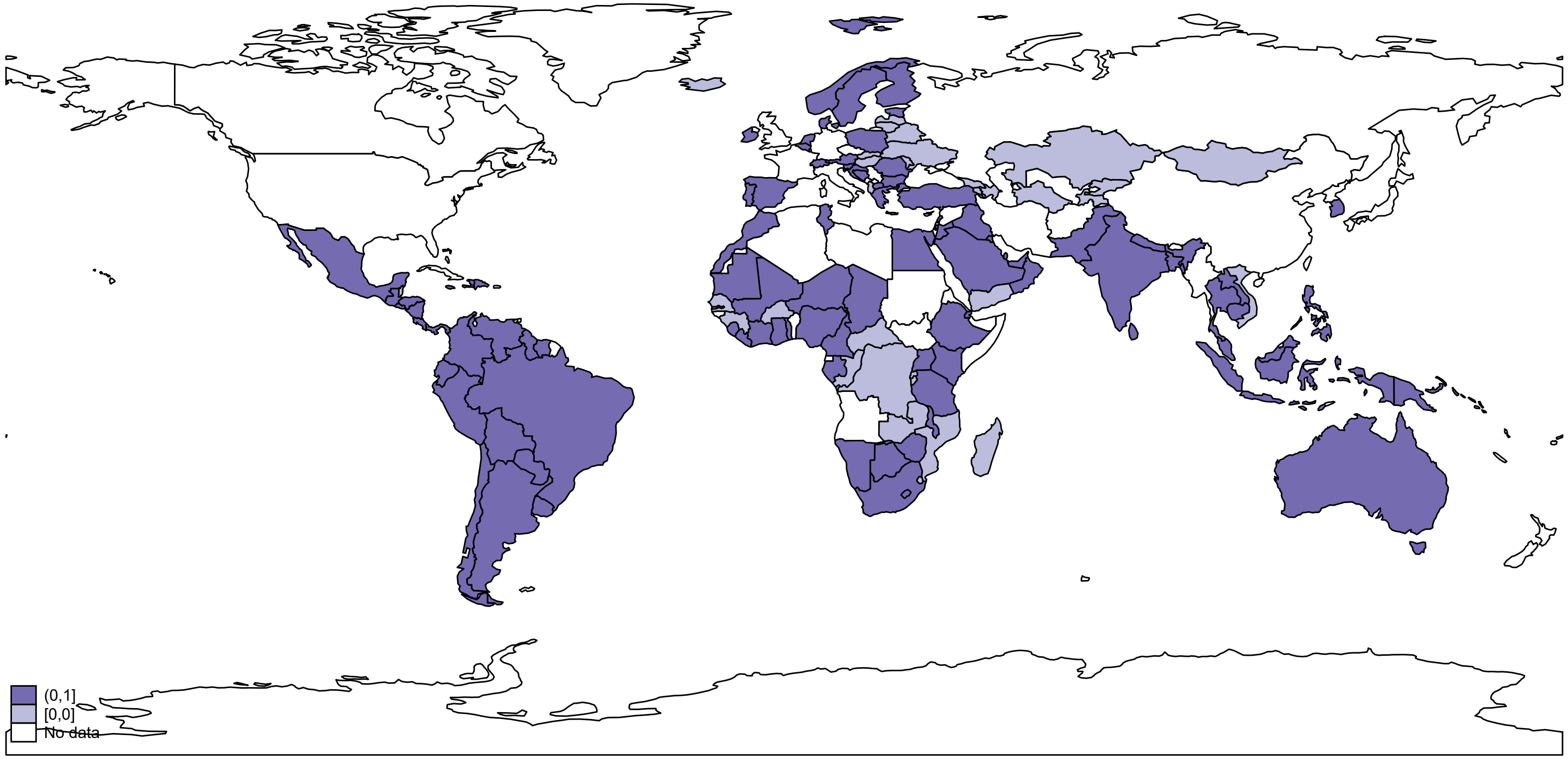


Figure C.5: US arms importers in dark color, source: SIPRI. Referenced in Section 3.5.1.

C.2 Tables

Table C.1: Impact of Resources on Conflict

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Conf.	Conf.	H. Conf.	H. Conf.	Conf.	Conf.	H. Conf.	H. Conf.
Nat. Cap.	0.125**	0.133**	0.0477*	0.0580**				
	(0.0622)	(0.0658)	(0.0248)	(0.0286)				
Sq. Nat. Cap.	-0.0179**	-0.0172*	-0.00719**	-0.00755*				
	(0.00905)	(0.00913)	(0.00363)	(0.00396)				
Sed. Vol.					0.0884***	0.101***	0.0219*	0.0303**
					(0.0285)	(0.0312)	(0.0123)	(0.0150)
Sq. Sed. Vol.					-0.0120***	-0.0176***	-0.00309**	-0.00500***
					(0.00334)	(0.00404)	(0.00141)	(0.00179)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Continent FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geo Controls	No	Yes	No	Yes	No	Yes	No	Yes
Peak	3.49	3.87	3.32	3.84	3.67	2.88	3.55	3.03
N	6426	6102	6426	6102	6426	6102	6426	6102

Outcomes in (1), (2), (5), and (6) is conflict dummies, defined as episodes with at least 25 battle-related deaths. Other columns have High-Intensity conflict episodes as an outcome, defined as episodes with at least 1,000 battle-related deaths. First four columns have natural capital as the main independent variable, measured in trillions of constant dollars, while last four have sedimentary basins, measured in tens of cubic Kilometers. This table is referenced in Section 3.5.3. Errors are clustered at the country level. P-values are denoted as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.2: Impact of Resources on Conflict, Countries with at Least 1,000 DoD Employees or their Neighbors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Conf.	Conf.	H. Conf.	H. Conf.	Conf.	Conf.	H. Conf.	H. Conf.
Nat. Cap.	0.205*	0.162*	0.0972*	0.0976**				
	(0.109)	(0.0855)	(0.0558)	(0.0446)				
Sq. Nat. Cap.	-0.0298*	-0.0351***	-0.0142*	-0.0169***				
	(0.0152)	(0.0101)	(0.00779)	(0.00555)				
Sed. Vol.					0.187***	0.239***	0.0782**	0.114***
					(0.0668)	(0.0726)	(0.0384)	(0.0359)
Sq. Sed. Vol.					-0.0247***	-0.0294***	-0.0106**	-0.0121***
					(0.00800)	(0.00507)	(0.00474)	(0.00266)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Continent FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geo Controls	No	Yes	No	Yes	No	Yes	No	Yes
Peak	3.44	2.31	3.41	2.88	3.77	4.07	3.70	4.72
N	1566	1512	1566	1512	1566	1512	1566	1512

Outcomes in (1), (2), (5), and (6) is conflict dummies, defined as episodes with at least 25 battle-related deaths. Other columns have High-Intensity conflict episodes as an outcome, defined as episodes with at least 1,000 battle-related deaths. First four columns have natural capital as the main independent variable, measured in trillions of constant dollars, while last four have sedimentary basins, measured in tens of cubic Kilometers. This table is referenced in Section 3.5.3. Errors are clustered at the country level. P-values are denoted as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.3: Impact of Resources on Conflict, Countries without and not bordering with others having at least 1,000 DoD Employees

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Conf.	Conf.	H. Conf.	H. Conf.	Conf.	Conf.	H. Conf.	H. Conf.
Nat. Cap.	0.0891	0.133*	0.0249	0.0376*				
	(0.0732)	(0.0717)	(0.0231)	(0.0212)				
Sq. Nat. Cap.	-0.0120	-0.00929	-0.00356	-0.00229				
	(0.0113)	(0.00965)	(0.00345)	(0.00292)				
Sed. Vol.					0.0808***	0.0783**	0.0140	0.0126
					(0.0274)	(0.0334)	(0.0105)	(0.0146)
Sq. Sed. Vol.					-0.0112***	-0.0148***	-0.00213*	-0.00240
					(0.00326)	(0.00552)	(0.00119)	(0.00222)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Continent FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geo Controls	No	Yes	No	Yes	No	Yes	No	Yes
Peak	3.71	7.15	3.50	8.22	3.60	2.65	3.27	2.62
N	4860	4590	4860	4590	4860	4590	4860	4590

Outcomes in (1), (2), (5), and (6) is conflict dummies, defined as episodes with at least 25 battle-related deaths. Other columns have High-Intensity conflict episodes as an outcome, defined as episodes with at least 1,000 battle-related deaths. First four columns have natural capital as the main independent variable, measured in trillions of constant dollars, while last four have sedimentary basins, measured in tens of cubic Kilometers. This table is referenced in Section 3.5.3. Errors are clustered at the country level. P-values are denoted as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.4: Impact of Resources on Conflict, US Arms Importers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Conf.	Conf.	H. Conf.	H. Conf.	Conf.	Conf.	H. Conf.	H. Conf.
Nat. Cap.	0.103	0.132**	0.0376	0.0588**				
	(0.0660)	(0.0654)	(0.0260)	(0.0267)				
Sq. Nat. Cap.	-0.0154*	-0.0162*	-0.00579	-0.00703*				
	(0.00937)	(0.00916)	(0.00377)	(0.00378)				
Sed. Vol.					0.0931***	0.101***	0.0213	0.0313**
					(0.0290)	(0.0352)	(0.0130)	(0.0152)
Sq. Sed. Vol.					-0.0124***	-0.0163***	-0.00300**	-0.00432**
					(0.00339)	(0.00476)	(0.00146)	(0.00191)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Continent FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geo Controls	No	Yes	No	Yes	No	Yes	No	Yes
Peak	3.35	4.08	3.25	4.18	3.76	3.10	3.55	3.62
N	4806	4590	4806	4590	4806	4590	4806	4590

Outcomes in (1), (2), (5), and (6) is conflict dummies, defined as episodes with at least 25 battle-related deaths. Other columns have High-Intensity conflict episodes as an outcome, defined as episodes with at least 1,000 battle-related deaths. First four columns have natural capital as the main independent variable, measured in trillions of constant dollars, while last four have sedimentary basins, measured in tens of cubic Kilometers. This table is referenced in Section 3.5.3. Errors are clustered at the country level. P-values are denoted as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.5: Impact of Resources on Conflict, Not US Arms Importers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Conf.	Conf.	H. Conf.	H. Conf.	Conf.	Conf.	H. Conf.	H. Conf.
Nat. Cap.	0.425*	0.0115	0.291*	0.0912				
	(0.257)	(0.189)	(0.164)	(0.118)				
Sq. Nat. Cap.	-0.275	0.160	-0.183	0.00982				
	(0.262)	(0.155)	(0.169)	(0.0925)				
Sed. Vol.					0.0498	0.00744	0.0230	0.00300
					(0.0765)	(0.0503)	(0.0416)	(0.0269)
Sq. Sed. Vol.					-0.00682	0.00124	-0.00320	-0.000186
					(0.0105)	(0.00671)	(0.00565)	(0.00357)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Continent FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geo Controls	No	Yes	No	Yes	No	Yes	No	Yes
Peak	0.77	-0.036	0.79	-4.64	3.65	-3.01	3.59	8.05
N	1620	1512	1620	1512	1620	1512	1620	1512

Outcomes in (1), (2), (5), and (6) is conflict dummies, defined as episodes with at least 25 battle-related deaths. Other columns have High-Intensity conflict episodes as an outcome, defined as episodes with at least 1,000 battle-related deaths. First four columns have natural capital as the main independent variable, measured in trillions of constant dollars, while last four have sedimentary basins, measured in tens of cubic Kilometers. This table is referenced in Section 3.5.3. Errors are clustered at the country level. P-values are denoted as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C.3 Proofs of Section 3.2

C.3.1 Proof of Proposition 3.2.1

The probability that there is war is:

$$\mathbb{P}(war; v) = F_P(p_w\Pi_P(0)) + (p_w F_P\Pi_P(v) - F_P(p_w\Pi_P(0)))\left[1 - F_T\left(p_w\Pi_T(v)\right)\right] \quad \text{(C.1)}$$

The derivative of the probability is:

$$\frac{\partial}{\partial v}\mathbb{P}(war; v) = \left(F\left(p_w\Pi_P(0)\right) - F(p_w\Pi_P(v))\right) f(p_w\Pi_T(v))p_w\Pi_T'(v) + \quad \text{(C.2)}$$

$$p_w\Pi_P'(v) f\left(p_w\Pi_P(v)\right)\left[1 - F\left(p_w\Pi_T(v)\right)\right] \quad \text{(C.3)}$$

it is bigger than zero if and only if:

$$\left[1 - F\left(p_w\Pi_T(v)\right)\right] p_w\Pi_P'(v) f\left(p_w\Pi_P(v)\right) > \left(F\left(p_w\Pi_P(v)\right) - F(p_w\Pi_P(0))\right) f(p_w\Pi_T(v))p_w\Pi_T'(v) \quad \text{(C.4)}$$

Rewrite the condition above to get (I omit the arguments of the functions whenever they are clear, for ease of reading):

$$(F_P - F_P(0))f_T\Big(\left[1 - F_T\right]\frac{\Pi_P'}{\Pi_T'}\frac{f_P}{(F_P - F_P(0))f_T} - 1\Big) > 0$$

The sign of the derivative is driven by the term in brackets. So we have to check when:

$$\left[1 - F_T\right]\frac{\Pi_P'}{\Pi_T'}\frac{f_P}{(F_P - F_P(0))f_T} > 1$$

By *RC*, we have that $\lim_{v\to 0}\Pi_P/\Pi_T = \lim_{v\to 0}\Pi_P'/\Pi_T'$ is finite, so they are asymptotically equivalent. The same holds if $v \to \infty$.

Case $v \to 0$ Using a Taylor expansion of the denominator around 0, so that: $F_P(p_w\Pi_P) - F_P(0) \sim f_P(p_w\Pi_P)p_w\Pi_P$ we can rewrite the LHS as:

$$\left[1 - F_T\right]\frac{\Pi_P'}{\Pi_T'}\frac{1}{\Pi_P f_T}$$

because by *RC* $f_T\Pi_P \sim f_T\Pi_T \to 0$ and so the fraction diverges. So the derivative is positive.

Case $v \to \infty$

If $f_T(M) > 0$ then the thesis follows.

If $f_T(M) = 0$, by *RC* the function $G(x) := 1 - F_T(1/x)$ has a derivative $G'(x) = f_T(1/x)(1/x^2)$ which is strictly increasing in x. Hence:

$$G(x) - G(0) \leq G'(x)x$$

that is:

$$1 - F_T(1/x) \leq f_T(1/x)(1/x^2)x$$

so

$$1 - F_T \leq \Pi_T f_T$$

hence $\frac{1-F_T}{f_T} f_P \leq \Pi_T f_P \to 0$ and so the derivative is negative. This concludes the proof of the first part.

For the second part, note that we can rewrite the FOC as:

$$\frac{\Pi_P'(v)}{\Pi_T'(v)} \frac{f_P}{F_P - F_P(0)} > \frac{f_T}{[1 - F_T]}$$

Under the log-concavity $\frac{f_P()}{F_P()}$ is decreasing and $\frac{f_T()}{[1-F_T()]}$ is increasing, so under DRM there is a unique zero of the first order condition, hence a unique maximum.

C.3.2 Proof of Proposition 3.2.2

For the sake of simplicity, we do the proof in the simple case of $suppF_i = [0, M]$, $M < \infty$ and f_i bounded and bounded away from zero. The arguments can be extended to the other cases as in the baseline.

The expected gain from a war for P is $p_w \Pi_P (1 - F_T(p_w \Pi_T)) - \varepsilon_P$. Then there are also here three types of equilibria:

- If $p_w \Pi_P (1 - F_T((p_w)\Pi_T)) < \varepsilon_P$, P never wants to attack and there is no war;
- If $p_w \Pi_P (1 - F_T((p_w)\Pi_T)) > \varepsilon_P$ then P attacks and there is war. If in addition $(p_w)\Pi_T(v) > \varepsilon_T$ then there is intervention, otherwise there is no intervention.

So, the probability of war is:

$$P(w) = F_P(p_w \Pi_P (1 - F_T((p_w)\Pi_T)))$$

The derivative is (omitting the arguments):

$$f_P \left(p_w \Pi_P'(1 - F_T) - p_w \Pi_P f_T(p_w) \Pi_T'\right)$$

This is bigger than zero if and only if:

$$\frac{\Pi_P'(v)}{\Pi_T'(v)} > \Pi_P(v) \frac{f_T}{(1 - F_T)}(p_w)$$

If f is log-concave the RHS is monotone increasing. If we use the assumptions above we have that it increases from 0 to ∞; moreover, we get that the LHS is bounded and weakly decreasing. So as above there is one maximum and the function is hump shaped.

C.4 Proofs of Section 3.3

C.4.1 Proof of Proposition 3.3.1

Since the behavior of the third party does not change, this means that we have 2 cases: if T intervenes, there is no offer and no war. If T does not intervene, there is an offer. The probability of conflict is:

$$\mathbb{P}(war; v) = (1 - F_T(p_w\Pi_T))P(P \text{ does not accept})$$

R offers x in exchange to not enter into the conflict. P does not accept if $x < p_w\Pi_P - \varepsilon$, or $p_w\Pi_P - x > \varepsilon_P$. In this case the optimal trasfer is the solution of:

$$\begin{aligned}
&\max_x \int^{p_w\Pi_P - x}(1-p_w)\Pi_R f_P \mathrm{d}\varepsilon_P + \int_{p_w\Pi_P - x}(\Pi_R - x) f_P \mathrm{d}\varepsilon_P \\
&= \max \Pi_R - p_w\Pi_R F_P(p_w\Pi_P - x) + (\Pi_R - x)(1 - F_P(p_w\Pi_P - x))
\end{aligned}$$

taking the FOC we get:

$$x = p_w\Pi_R - \frac{1 - F_P}{f_P}$$

whenever x is positive.

To check if the result on the hump shape holds we need to study $P(war) = P(\varepsilon_T > p_w\Pi_T)P(\varepsilon_P < p_w\Pi_P - x)$, and in particular $p_w\Pi_P - x$. If this is increasing, there is the hump shape, otherwise not. If F_P is uniform:

$$x = \frac{p_w(\Pi_R + \Pi_P) - 1}{2}$$

and

$$p_w\Pi_P - x = \frac{p_w(\Pi_P - \Pi_R) + 1}{2}$$

whenever $p_w\frac{\Pi_R+\Pi_P-1}{2} > 0$, that is whenever $\Pi_R + \Pi_P$ are high enough. In particular if $v = 0$ then $p_w\Pi_P - x = 0$ and $x = 0$. In particular if $\Pi_P - \Pi_R$ is increasing then there can be conflict, and the hump shape follows from Proposition 3.2.1. If $\Pi_P - \Pi_R$ is decreasing then the probability of conflict is 0 if $v = 0$ and decreasing, so it is always zero.

R does not know the type of T In the case P does not know the type of T we obtain a very similar result. The optimal offer is:

$$x = p_w(1 - F_T)\Pi_R - \frac{1 - F_P}{f_P}$$

With uniform distribution:

$$x = (1 - F_T)p_w\frac{\Pi_R + \Pi_P - 1}{2}$$

$P(war) = F_P\left((1 - F_T)p_w\Pi_P - x\right)$ and the threshold is: $(1 - F_T)p_w\frac{\Pi_P - \Pi_R + 1}{2}$ again depends on $\Pi_P - \Pi_R$.

C.5 Proofs of Section 3.4

C.5.1 Proof of proposition 3.4.1

We calculate the equilibrium price, assuming all problems have an interior solution. The FOC is:

$$\Omega_T \alpha (g_T)^{\alpha-1} = p \tag{C.5}$$

that is

$$p = \frac{\alpha\Omega}{g_T^{1-\alpha}} = \frac{\alpha\Omega}{(R_M + R_R)^{1-\alpha}} \tag{C.6}$$

where we already used the market clearing condition $g_T = R_R + R_M$. The equilibrium profits are as follows. Call Π_P the profit of the predator when it seizes the resource. Since in this case war occurs for sure:

$$\pi_P = \frac{\alpha\Omega}{(R_M + \eta R_R)^{1-\alpha}} \eta R_R$$

$$\pi_T = \Omega(R_M + R_R)^\alpha - \frac{\alpha\Omega}{(R_M + R_R)^{1-\alpha}}(R_M + R_R) = (1-\alpha)\Omega(R_M + R_R)^\alpha$$

If there is war instead:

$$p(war) = \frac{\alpha\Omega}{g_T^{1-\alpha}} = \frac{\alpha\Omega}{(R_M + \eta R_R)^{1-\alpha}} \tag{C.7}$$

$$\pi_P(war) = \frac{\alpha\Omega}{(R_M + \eta R_R)^{1-\alpha}} \eta R_R \tag{C.8}$$

$$\pi_T(war) = (1-\alpha)\Omega(R_M + \eta R_R)^\alpha \tag{C.9}$$

Now solve the first part of the model by backward induction:
third party intervenes after attack if:

$$\Pi_T(I|A) > p\Pi_T(NI|A) + (1-p)\Pi_T(NI|A)$$

that is $p(\Pi_T(I|A) - \Pi_T(NI|A)) > 0$. That is:

$$\varepsilon_T < p\left((1-\alpha)\Omega(R_M + R_R)^\alpha - (1-\alpha)\Omega(R_M + \eta R_R)^\alpha\right)$$

so T intervenes if and only if $p(1-\alpha)\Omega\left((R_M + R_R)^\alpha - (R_M + \eta R_R)^\alpha\right) > \varepsilon_T$

Knowing that T will not intervene, P will attack if:

$$p\frac{\alpha\Omega}{(R_M + \eta R_R)^{1-\alpha}} \eta R_R > \varepsilon_P$$

C.5.2 Proof of Corollary 1

The derivatives are:

$$\Pi_P' = p\alpha\Omega\eta\frac{R_M + \alpha\eta R_R}{(R_M + \eta R_R)^{2-\alpha}}$$

$$\Pi_T' = p(1-\alpha)\Omega\alpha\left((R_M + R_R)^{\alpha-1} - \eta(R_M + \eta R_R)^{\alpha-1}\right)$$

The first is obviously positive. To check the second, notice that is positive if and only if:

$$(R_M + R_R)^{\alpha-1} > \eta(R_M + \eta R_R)^{\alpha-1}$$

that is:

$$(R_M + \eta R_R)^{1-\alpha} > \eta(R_M + R_R)^{1-\alpha}$$

$$R_M + \eta R_R > \eta^{\frac{1}{1-\alpha}}(R_M + R_R)$$

$$R_M(1 - \eta^{\frac{1}{1-\alpha}}) + R_R\eta(1 - \eta^{\frac{1}{1-\alpha}-1}) > 0$$

and $\frac{1}{1-\alpha} - 1 > 0$ so $\eta^{\frac{1}{1-\alpha}-1} < 1$ and this inequality is true.

The ratio of marginal payoffs is:

$$\frac{\Pi_P'}{\Pi_T'} = \frac{R_M + (\eta - 1 + \alpha)R_R}{(R_M + \eta R_R)^{2-\alpha}\left((R_M + R_R)^{\alpha-1} - \eta(R_M + \eta R_R)^{\alpha-1}\right)}$$

Taking the derivative, we find that it is decreasing if and only if:

$$(\alpha-1)R_M\left(R_M + \eta R_R\right)^{\alpha-3}\left(\left(R_M + R_R\right)^{\alpha-2}\left((2\eta - 1)R_M + \eta R_R(\alpha(\eta - 1) + 1)\right) - \eta^2\left(R_M + \eta R_R\right)^{\alpha-1}\right) <$$

Manipulating this expression, we find that this is true if and only if

$$R_M > (1-\alpha)\frac{\eta}{1-\eta}R_R$$

C.5.3 Proof of Corollary 2

The the derivatives of the payoffs with respect to this parameter are the following:

$$\frac{\partial \Pi_P}{\partial R_M} = -\frac{(1-\alpha)\alpha\Omega\eta R_R}{(R_M + \eta R_R)^{2-\alpha}} < 0$$

$$\frac{\partial \Pi_T}{\partial R_M} = \alpha(1-\alpha)\Omega\left((R_M + R_R)^{\alpha-1} - (R_M + \eta R_R)^{\alpha-1}\right) < 0$$

To see in that specification AI holds, we can just consider a $-R_M$ as a measure of value. Then, both payoffs are differentiable and increasing in the resource value.

However, we have a clear maximum level of the payoffs when $R_M = 0$. Hence, condition AI holds whenever the maximum war costs M is below these two natural thresholds.

$$\Pi_P(0) = \alpha\Omega(\eta R_R)^\alpha$$

$$\Pi_T(0) = (1-\alpha)\Omega(1-\eta^\alpha)R_R^\alpha$$