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Three Essays on Entrepreneurial Strategies: Entry, Exit and Scale-up

PhD in Business Administration and Management

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Student's Advisor:
Alfonso Gambardella

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Abstract

The purpose of my dissertation is to study successful entrepreneurial strategies related to different stages of a venture's lifecycle. The document is divided into three chapters, each focused on distinct phases of a start-up process: growth, divestment/exit, and entry. Chapter 1 studies the relative advantages of a growth strategy based on the creation of different organizational entities - business group growth - over traditional company growth. I provide a formal model that clarifies the circumstances under which group growth is more advantageous than traditional company growth and test my theory using a longitudinal dataset of more than 4000 Italian first-time entrepreneurs. Chapter 2 studies the behavior and exit decision of entrepreneurs owning more than one company - portfolio entrepreneurs. Building on the literature on intertemporal economies of scope, I explore how the opportunity to reinvest resources across businesses affects the entrepreneur's performance threshold. I use a sample of more than 6,000 entrepreneurs, spanning all the companies they created over their lifetimes, to test the hypotheses derived from the theory. Finally, chapter 3 studies how small start-ups can challenge bigger incumbents and enter new markets. Building on an in-depth industry study in which an "opportunity-rich, resource-poor" new company disrupted the incumbent competitors, I draw important theoretical implications for the disruptive innovation literature and demand-side approach to strategy.

Table of Contents

Chapter 1:
Company Growth or Business Growth? Business Group Formation as a Strategic Growth Option

ABSTRACT

Successful entrepreneurs can grow their business in two ways. They can increase the size of their original company or create other companies (different legal entities). We call the former company growth and the latter business group growth. We provide a formal model that clarifies the circumstances under which group growth is more advantageous than traditional company growth and test our hypotheses using a longitudinal dataset of more than 4000 Italian first-time entrepreneurs. Our theory posits that entrepreneurs who opt for group growth can more easily attract external resources in their business and grow faster. The novelty of the study is the focus on the individual-the entrepreneur- rather than the company as the focal unit of analysis to study business growth, and the antecedents of business group formation.

INTRODUCTION

In the extensive literature on entrepreneurial growth most studies either confound the spaces of entrepreneurs and firms, or focus exclusively on the space of firms (Sarasvathy 2013), though substantial fractions of entrepreneurs create and manage more than one company (Birley and Westhead 1993; Rosa 1998; Iacobucci and Rosa 2010). In this paper we want to explore the advantages of an entrepreneurial growth strategy based on the creation of a group of different companies over traditional dimensional growth. We refer to the former as business group growth and the latter as company growth. The former mode of growth leads to the creation of business groups: - a set of companies that are legally distinct but belong to the same person (Iacobucci and Rosa 2010; Westhead and Wright 1998). Business groups traditionally have been associated with large firms, and there is a significant body of literature on the nature, management, and performance of large business groups (Chang, 2006; Morck and Yeung, 2003). However, despite the diffusion of business group structure, we lack empirical evidence regarding the antecedents of this organizational form in the context of entrepreneurial ventures (Iacobucci and Rosa 2010).

Managing the growth process of a new business is complex (Hellmann et al. 2016). Most of the time, it requires the match between an entrepreneur with a brilliant business idea and external resource providers who believe in the idea. Many entrepreneurs do not want to open their company to external investors/partners and, thus, expand their business because of the fear of losing control, facing partners with different goals/visions, being accountable to others (McKenna and Oritt, 1981; O'Farrell and Hitchens 1988). At the same time, it is extremely risky for external resource providers to invest in a new company due to low transparency and moral hazard (Burchardt et al. 2016). The creation of separate legal entities organized as a business group mitigates the above problems. We argue that, under some circumstances, entrepreneurs who expand their business as a business group instead of a single legal entity can access more external resources and grow faster.

In this paper we present a formal model showing that a group growth is more effective than normal company growth in environments characterized by high risk of partner opportunistic behavior. We test our hypothesis using a longitudinal dataset of Italian entrepreneurs. We follow a matched sample of entrepreneurs who created their first company in 2003 for 10 years. Our findings are in line with the theoretical model. Entrepreneurs who decide to grow their business as a group of separate companies can expand it at a faster pace than other entrepreneurs. This effect is stronger in cities characterized by a high "partner risk" and low institutional quality. In addition, we found evidence that this mode of growth is more common when access to traditional resources like credit is constrained.

We believe that this paper contributes to the literature on strategy and entrepreneurship in several aspects. First, this paper contributes to the literature on the organization design of young ventures (Beckman and Burton 2008; Colombo and Grilli 2013), showing how a specific organizational structure -business group- influences the growth rate of a new venture. The innovation of the paper is to use the entrepreneur rather than the business as the focal unit of analysis. This novel perspective allows us to capture a phenomenon –business group growth- frequently overlooked by previous research. In addition, by focusing on the early stages of a new venture, this paper can shed light on how large business groups form and evolve (Iacobucci and Rosa 2010; Manikandam and Ramachandran 2014). Finally, this paper provides empirical evidence about some theoretical intuitions developed by Almeida and Wolfenzon (2006) and Lechner and

Leyronas (2009) regarding the advantages of a business group structure in attracting external resources.

THEORETICAL BACKGROUND

Business Growth in Strategy and Entrepreneurship

Ever since Penrose (1959) pioneering work, firm growth has been one of the central themes of strategy research. The field has explored extensively the different growth strategies companies can pursue, and their relative advantages. Companies can diversify their business to redeploy their valuable resources or stick to their main market to leverage core competences (Prahalad and Hamel 1990). Firms can either enter new markets organically through internal development or acquire a firm that is already established, depending on the firm's set of resources and capabilties (Lieberman and Lee 2009). Most of these theories have studied firm growth adopting an organization-level perspective and focus on large multi-division companies. However, in the context of entrepreneurship and small businesses, the growth strategy of a firm is an individual-level decision of the founder, and personal preferences play a big role. Entrepreneurship literature discovered that founders have different growth attitudes (Wiklund et al. 2003). Some entrepreneurs do not want to grow their business because they expect less control and more problems with a bigger company. However, contrary to its strategy counterpart, entrepreneurship literature on business growth never really investigated the different types of growth strategies available to entrepreneurs, and studied growth as a unitary concept (Sarasvathy et al. 2013). The goal of this paper is to provide a theoretical framework, grounded at the founder level, that can explain under which circumstances an entrepreneur might prefer to grow its business as a group of separate companies over one single organizational entity. In this context, the creation of a business group becomes the antecedent and determinant of business growth.

Business Group Growth: Main Benefits

Business groups traditionally have been associated with large firms (Mahmood and Mitchell 2004; Manikandan et al. 2014), and most of the studies in the related literature explore the advantages of group affiliation on firm performance (Locorotondo et al. 2015). These advantages include the creation of an efficient internal capital and labor market where transaction costs are low (Khanna and Rivkin 2001; Belenzon, S. and Tsolmon 2016), provision of mutual insurance (Khanna and Yafeh 2005) and increase in market power (Morck et al. 2005). Differently from previous research, we do not focus our attention on a single group affiliate and the advantages related to group membership. On the contrary, the goal of this paper is to understand the process of business group creation, and the relative advantages that an entrepreneur can have in adopting such organizational structure for his or her business. Indeed, while owning more than one business is also relatively common in the small business sector, we lack theoretical and empirical knowledge related to the entrepreneurial processes that lead to the formation of these groups (Iacobucci and Rosa 2010). The goal of this section is to introduce a simple theoretical model that highlights the main advantages of a business group growth over company growth, keeping the entrepreneur’s ownership of the overall business constant.

Growing a business is a complex management problem. Increasing the size of a company often involves important changes in the key routines and processes that make the company function.

Adopting these changes can be dangerous for the survival of the company itself. Consider the example of a successful manufacturing firm who wants to increase its capacity. In order to do so, the entrepreneur might consider to build a new factory in China and take advantage of the country low labour cost. Such investment, however, is very risky and the failure of this new initiative might have negative consequences on the entrepreneur's original business. We argue that a business group allows entrepreneurs to adopt a flexible growth strategy. Entrepreneurs can increase the size of their business minimizing the risk factors for their original company. In other words, they modularize the problem of creating and managing a big company breaking it down in different small pieces with low interdependence between them (Campagnolo and Camuffo 2010). The low interdependence between business units limits the negative effect that one unit can have on the others. For example, the legal independence of the group firms prevents that the bankruptcy of one company automatically propagates financial problems throughout the whole group (Bianco and Nicodano, 2006). By definition, the advantages of the modular configuration increase as the risk factors associated to organic growth increase. As a general set-up, let us assume that an entrepreneur wants to increase the size of its business from k to k^{Max}, where k^{Max} is the size of the company that maximizes profits. However, such expansion involves a risk factor p so that if a certain event occurs (e.g. the project of a Chinese plant by our imaginary entrepreneur fails), the survival of the whole business is at risk. In this case, the modularization of the business in two separate initiatives can be a legitimized growth strategy.

Business growth involves many risk factors. In this paper, we want to focus on a specific risk factor that is extremely important for early stage entrepreneurs, and can have a strong influence on their growth strategy: involving other people in the business.

Partners and External Resources

There are many reasons why small successful businesses do not want to grow (McKenna & Oritt, 1989). Many of them are linked to the entrepreneur's inability to delegate (Storey 1994) or, more in general, the inability/indisposition to involve other people in the business. Family businesses do not deal with external investors and partners because they do not want to lose control of their business and be accountable to others (McKenna & Oritt, 1981; O'Farrell & Hitchens 1988; Croci et al 2011). Some entrepreneurs lack the necessary skills to manage a large company but they are reluctant in hiring professional managers due to the lack of trust (Bloom et al. 2012; Hellmann et al. 2016).

We posit that a business group can be the optimal organizational form to mitigate the delegation problem and grow the business. Indeed, qualitative evidence shows that the involvement of external partners and the creation of a business group appear frequently together (Iacobucci and Rosa 2010). From a theoretical perspective, we argue that the creation of a business group facilitates the engagement of external partners/investors in the business. In this case, the creation of a group becomes an antecedent and facilitator of growth.

Business Group Structure: External Resource Provider's Benefits

Almeida & Wolfenzon (2006) develop a theoretical model showing that the transparency of a business group structure incentivizes external resource providers to invest in the business. The business group structure, indeed, reduces the entrepreneur's ability to divert assets/cash from the new initiative to the established one and the associated moral hazard. In addition, the creation of separate legal structures gives partners a realistic buy-out option for the future (Lechner and Leyronas 2009). In the words of an entrepreneur interviewed by Lechner and Leyronas (2009):

"*When I had an idea but not all the competences, I was looking for partners inside or outside the firm to develop the activity. So I decided to give them the activity upfront, invest in the company and take a stake in it…… You only can attract top people if you give them real responsibility, a stake in the project, and a buy-out option for the future* (Entrepreneur)."

The above benefits involve the investor/partner's side. Furthermore, we argue that an organizational separation can be advantageous also from an entrepreneur's perspective.

Business Group Structure: Entrepreneur's Benefits

Involving the wrong external partners in the business can have relevant negative effects for early-stage ventures. More people with decision power can slow down the decision-making process. Partners might require the entrepreneur to be more accountable and set-up effective control systems (Kazanjian 1988). Finally, external partners might behave in an opportunistic way and appropriate company resources for their own advantage. The business group structure allows the entrepreneur to access external resources and grow the business while reducing these risks. The legal and organizational separation between firms in the same group reduces the partners' influence on the original company and gives more flexibility to the entrepreneur. Indeed, in presence of a strong incompatibility between the entrepreneur and partner, the entrepreneur can simply exit from the new business and preserve his/her original one. Lechner and Leyronas (2009) found evidence of this behavior in their detailed case studies of business groups. In addition, to provide additional evidence about this theoretical mechanism, we conducted six in-depth interviews with business group entrepreneurs. The importance of the above theoretical mechanism was frequently highlighted by the entrepreneurs. In the words of an entrepreneur:

"*It is much better to have a partner in another company rather than a chief executive in your company. So, when you realize that is the right moment to go, you can go. In hindsight, I'm really happy I exited from that company. We had a lot of problems* (Entrepreneur)*".*

MODEL

Business group structure facilitates the agreement between an entrepreneur and external resource providers. Having access to more resources eases business growth. In the previous paragraphs we outlined the main benefits of this organizational form for the entrepreneur and external resource providers using qualitative evidence. In this section, we formalize the previous arguments with a highly stylized model to guide the empirical analysis. Our intent is not to develop a generally applicable model but rather to use it to formalize the previous qualitative intuition.

Model General Framework

A group of successful entrepreneurs introduce a new product in the market and enjoy a temporary monopoly. We assume that entrepreneurs are resource constrained in the short term and the capacity of their firms is limited to k. In order to maximize profits, the entrepreneurs can ask for external resources a to reach the optimal firm size $(k + a)^{Max}$. Equation (1) displays the generic profit function of an entrepreneur in the short term. The function is increasing in k and a, and can have either constant or diminishing returns:

$$(1)\ \pi \ = \pi\ (k, a)$$

Entrepreneurs can find external resources a involving external partners in the business. However, involving external resource providers can have negative consequences. As previously pointed out in the theory section, partners can slow down the decision making process or behave opportunistically. We model this issue in the following way. We assume that with probability *p* the partner is a good partner and the business runs smoothly. With probability (1-*p*) the partner turns out to be a bad partner. The entrepreneur and partner have opposing visions of the business, or the partner behaves opportunistically. As a result, the company makes zero profits. We generically define (1-*p*) as "partner risk". Entrepreneurs observe the *p* of their potential partners before the agreement and decide to accept external resources only if the expected benefit is higher than the expected cost. In this latter case, the investors/partners make a partnership agreement with the entrepreneur and become shareholders of the initial company. For simplicity reasons, we assume that in the short run our entrepreneurs interact with just few potential partner (entrepreneurs are time constrained and the search for a partner is costly) that are randomly extracted from a distribution *f(p)*. The entrepreneurs that do not find a suitable partner are resource constrained and obtain the following profits:

$$(2)\ \pi\_constrained = \pi\ (k)$$

The profits of the entrepreneur under the partnership agreement are:

$$(3)\ \pi\_partner = \ p\, \pi\ (k, a)$$

In our model, a partnership is a risky arrangement for the entrepreneur's original company. A bad partner may lead the business to failure (zero profits). Entrepreneurs can reduce this risk undertaking an organizational separation. The entrepreneur and partner invest in a separate company that is related to the original one but it is legally distinct. In this way, the entrepreneur creates a business group and concentrates the partner risk just on the second company: in case the entrepreneur realizes that the partner is a bad partner, he can exit from the second company and preserve his original one. In sum, the business group structure provides a flexible growth strategy: the entrepreneur access partner resources but reduces the risk for the original company. Following this intuition, we can represent the profit function of a business group as follows:

$$(4) \quad \pi\_group = \pi^g(k, \tilde{a}) \quad \textit{with} \;\; \tilde{a} = p * a$$

It is reasonable to assume that an organizational separation is not entirely free. A business group structure has higher coordination costs between activities and less economies of scale/scope. We can represent this disadvantage with the following generic assumption:

$$(5) \;\; \frac{d\pi}{da} > \frac{d\pi^g}{d\tilde{a}} \quad \textit{and} \quad \frac{d\pi}{dk} > \frac{d\pi^g}{dk}$$

Growth Strategies

Entrepreneurs are rational agents and choose the growth strategy that maximizes profits. They anticipate the amount of resources a needed to maximize the profit function in each option, and then choose the most convenient one. The parameters a^{*part}, a^{*group} represent the optimal amount of external resources in each option. The business size in the short term is determined by the total amount of resources collected.

Summary of Growth Strategies

Growth Modes	Expected Profits	Short-Term Business Size	Organizational Structure
Resource Constrained	$\pi\ (k)$	k	One Company
Partnership	$p\ \pi\ (k, a)$	$k + a^{*part}$	One Company
Business Group	$\pi^{g}(k, \tilde{a})$ $\tilde{a} =\ p * a$	$k + a^{*group}$	Business Group

Although the amount of resources *a* is endogenously determined by the entrepreneur, the choice of the best growth strategy is influenced by the exogenous parameter *p*. Entrepreneurs who face reliable partners (high *p*) choose to growth via partnership. Entrepreneurs who face partners with an intermediate *p* choose to grow though the creation of a business group. Finally entrepreneurs who face unreliable partners (low *p*) stay resource constrained.

Proposition 1- Business Group Size vs One-Company size

The aim of this section is to understand the determinants of business group and one-company entrepreneurs' *average business size* in the short-term. It is important to notice that the average business size among one-company entrepreneurs is the average of the two different groups reported in picture 1 (resource constrained and partnership). Thus, the relative size of one-company businesses, in comparison to business groups, depends on the size of a^{*part}, a^{*group} and their frequency $share^{part}, share^{constrain}$:

$$(7) \qquad Average\ Size\ OneCo =\ share^{part}(\ k + a^{*part}) + share^{constrain}(k)$$

$$Average\ Size\ Business\_Group =\ (\ k + a^{*group})$$

Thanks to assumption (4), we know that entrepreneurs who choose partnership over business group will ask for more external resources a:

$$(8)\quad \frac{d\pi\_partner}{da} = p\ \frac{d\pi}{da} > \frac{d\pi\_group}{da} = p\,\frac{d\pi^{g}}{d\tilde{a}}$$

The higher first derivative in case of partnership over business group implies that $a^{*part} > a^{*group}$. Thus, we can state that a partnership always leads to a greater size in comparison to business group. Conversely, a business group is always bigger than a resource constrained business. Indeed, the entrepreneurs who opt for group growth *strategically create a group to access external resources*. Without a business group structure, the risk of involving external partners (p) is too high for them. Considering these comparisons, we can state that the average size of business groups in short term is higher than the average size of one-company businesses if the share of resource constrained entrepreneurs is sufficiently high.

Proposition 1a: *There exist a distribution f(p) so that entrepreneurs who grow their business as a business group reach a bigger size in the short term than entrepreneurs who grow their business as one single big company*.

The key moderator of the above relationship is the parameter p (or more in general the distribution *f(p)*). Indeed, a reduction in p increases the number of one-company entrepreneurs who are capital constrained, and reduces the amount of external resources a requested by the entrepreneur more than proportionally in the case of partnership than in the case of business group. We can derive mathematically this last proposition by taking the derivative with respect to p of equation (8):

$$(9)\ \frac{d\pi\_partner}{dadp} = \frac{d\pi}{da} > \frac{d\pi\_group}{dadp} = \frac{d\pi^g}{d\tilde{a}} + ap\ \frac{d\pi^g}{d\tilde{a}d\tilde{a}}$$

(9) is always verified thanks to assumption (5) and the fact that $\frac{d\pi^g}{d\tilde{a}d\tilde{a}}$ is either zero or negative. This implies that a reduction in p generates a larger reduction in external resources for the partnership than the business group.

Proposition 1b: *In environments characterized by high partner risk (low p), entrepreneurs who grow their business as a business group reach a bigger size in the short term than entrepreneurs who grow their business as one single big company.*

Proposition 2- Exogenous decrease in credit supply

In our framework entrepreneurs seek external resources when their personal resources k are not enough to sustain business growth. However, in real life entrepreneurs can secure additional resources in the form of debt. We treat debt as additional resources available to entrepreneurs, and write $k = k_0 + D$. The variable k_0 represents the entrepreneur's personal resources and D the amount of debt the entrepreneur is able to secure. For simplicity reasons, we assume that D is exogenously determined by credit supply in the economy. In other words, the parameter D simply determines the initial level of resources *k* entrepreneurs start with. It is easy to understand that an exogenous increase in credit availability reduces the number of entrepreneurs who are looking for partner resources. Indeed, the first derivative of $\pi\_constrained$ with respect to *k* is greater than the derivative of $\pi\_partner$ and π_group. In other words, the option of staying resource constrained becomes more attractive as the amount of resources *k* increases (keeping all the other parameters constant):

$$(10) \qquad \frac{d\pi\_constrained}{dk} = \frac{d\pi}{dk} > \frac{d\pi\_partner}{dk} = p\frac{d\pi}{dk}$$

And

$$\frac{d\pi\_constrained}{dk} = \frac{d\pi}{dk} > \frac{d\pi\_group}{dk} = \frac{d\pi^{g}}{dk}$$

Equation (10) implies that an increase in credit supply increases the share of one-company entrepreneurs. Indeed, the one-company group is made by the sum of resource constrained and partnership entrepreneurs. A reallocation of entrepreneurs between these two groups does not have any effect on one-company entrepreneurs share. On the contrary, if just a few entrepreneurs move from business group to resource constrained, the share of business group decreases by definition. Conversely, we can state that a reduction in credit has the opposite effect:

Proposition 2: *An exogenous decrease in credit supply increases the share of entrepreneurs who opt for business group growth.*

Example with Standard Functional Forms

To clarify the rationale of the theoretical model, we provide an example with specified functional forms. In addition, appendix 2 provides a numerical solution to the model.

Let us assume that there is a group of N entrepreneurs with equal characteristics. They interact with a similar number of partners whose *ps* are uniformly distributed between 0 and *x*. The variable *x* represents the upper bound of the *p* distribution and is either lower of equal to 1. Each entrepreneur interacts with just one random partner. The entrepreneur profit functions in the 3 growth strategy cases are:

$$\pi\_constrained = \check{Z}k$$

$$\pi\_partner = p\,\check{Z}(a+k) - \frac{1}{2}a^2$$

$$\pi\_group = Z(ap+k) - \frac{1}{2}a^2$$

We use standard functions and assumptions to represent the profit functions. Internal and external resources are perfect substitute and have constant returns Ž. The cost of equity is increasing in *a*. Finally, we assume that a group structure provides a lower return $Z < \check{Z}$ due to the loss of economies of scope and higher coordination costs. For simplicity reasons we write $\check{Z} = bZ$ with b>1. We can find the optimal level of *a* maximizing the above functions:

$$\frac{d\pi\_partner}{da} = 0: \;\; pbZ = a$$

$$\frac{d\pi\_group}{da} = 0: \;\; pZ = a$$

Substituting the optimal level of external resources inside the initial functions we can determine the optimal level of profits:

$$\pi\_constrained^{*} = bZk$$

$$\pi\_partner^{*} = \frac{1}{2}(bZ)^2p^2 + bZkp$$

$$\pi\_group^* = \frac{1}{2}Z^2p^2 + Zk$$

Given the above functions, we can derive the threshold values for *p*:

$$\pi\_group^* > \pi\_constrained^* \quad if\ p > \sqrt{\frac{2(bk-k)}{Z}}$$

$$\pi\_partner^* > \pi\_group^* \quad if\ p > 1/b$$

Case $x > 1/b$

In case the upper bound *x* of the *p* distribution is greater than 1/b, the number of entrepreneurs who opt for partnership is greater than zero. This is the most interesting case to illustrate. For simplicity reasons, we define $\sqrt{\frac{2(\mathrm{bk-k})}{\mathrm{Z}}} = t$. Thus, the average size of one-company businesses is the following[1]:

$$Average\ Size\ OneCo\ = k + \frac{Z(b^2x^2-1)}{2(bt+bx-1)}$$

Conversely, the average size of business group is:

$$Average\ Size\ Group\ = k + \frac{btZ+Z}{2b}$$

The difference between $Average\ Size\ Group$ and $Average\ Size\ OneCo$ is the following function:

[1] Calculations to derive the average size of one-company and group businesses are reported in appendix 1.

$$Average\ Size\ Group - \ Average\ OneCo = \frac{1}{2}(\frac{Z - b^2x^2Z}{b(t+x)-1} - b(btZ + Z))$$

Proposition 1a states that there exist some parameters *k*, *b*, *Z* and *p* making the above difference greater than zero. Appendix 2, provides a numerical solution to proposition 1a.

Proposition 1b states that the difference between $Average\ Size\ Group$ and $Average\ Size\ OneCo$ is decreasing in *x*, the upper bound of the *p* distribution.

We can derive proposition 1b by taking the derivative, with respect to *x*, of the difference between $Average\ Size\ Group$ and $Average\ Size\ OneCo$. The derivative is always negative[2]:

$$\frac{d(Average\ Size\ Group - \ Average\ OneCo)}{dx} = -(\frac{bz\ (b^2x(2t+x) - 2bx + 1)}{b(t+x)-1})$$

Finally, we can represent the share of business group entrepreneurs in equilibrium with the following function:

$$Share\ Business\ Group = \ \frac{1}{b}\ - \sqrt{\frac{2(bk-k)}{z}}$$

Proposition 2 states that the above function is decreasing in *k*, the initial resources available:

2 Given b>1, the numerator is always positive. The denominator is positive if $x > \frac{1-bt}{b}$. This condition is always verified since $x > \frac{1}{b}$.

$$\frac{d(Share\ Business\ Group)}{dk} = -\left(\frac{\sqrt{\frac{(b-1)k}{z}}}{k\sqrt{2}}\right)$$

Given *b>1*, the derivative is always negative.

Case $x < 1/b$

In case the upper bound of the *p* distribution is lower than *1/b*, the number of entrepreneurs who opt for partnership is zero. This implies that the average size of business groups is always higher than the average size of resource constrained businesses, and there is no moderation.

EMPIRICAL ANALYSIS-PROPOSITION 1

We collected a sample of 4000 Italian entrepreneurs who founded their first business in 2003. We have data about all the businesses created by these entrepreneurs from 2003 to 2008 (6 years). Data comes from the business register of the Italian chambers of commerce: UnionCamere. The UnionCamere database is a publicly available database containing official data about all Italian companies and information about their founders. A European business intelligence company helped us in the process of data collection. Italy is an ideal setting for the study. The country has a low level of trust[3] among individuals (Guiso et al. 2006), companies tend to be small and family-owned (Economist 2011), and investor protection is relatively low (La Porta et al. 1998). These characteristics suggest that "partner risk" is an important issue for entrepreneurs: many Italian entrepreneurs do not expand their business because they are afraid to open their company

[3] Italians managers, for example, trust managers from other countries more than other Italian managers

to external resources (Croci et al 2011). In this context, the creation of business groups can be seen as a market-driven solution to a particular institutional environment. The following analysis focuses on the whole sample of Italian entrepreneurs without making any regional distinction. However, in the next section we exploit the regional variation between Italian regions to test proposition 1b.

Matching Variables

In order to test the predictions of our model, we matched our entrepreneurs on the demographic characteristics and the characteristics of their initial business at the time when they started their first company (2003). The characteristics of the business are extremely important since our predictions hold for constant levels of the key parameters (k, b and Z). We matched firms on the (log) amount of equity provided by the founder (*Initial Equity*), first-year (log) revenue (*Initial Revenue*), location[4], sector[5] and firm revenue growth rate in the first year (*First Year Growth*). We ended up with a sample of 1133 companies. These companies belong to similar sectors, are in similar locations, have similar initial size (revenue) and first-year growth rate. The owners of these businesses have similar age (*Entrepreneur Age*) and previous entrepreneurial experience (no one).

Independent variable- Business Group Growth

The goal of our empirical analysis is to estimate the effect of a business group structure on growth. For this reason, we adopt a very strict definition of business group to rule out possible

[4] The geographic location of the company. We used Italy's second NUTS administrative level (Region).
[5] The sector of the company. We use the 2 digits NACE classification. Sectors are reported in the appendix. This variable should take into account the fixed cost to start a new business F.

confounding factors. One of the most important factors is ownership structure. Ideally, we want the ownership structure to be the same in both business group and one-company entrepreneurs. Thus, we define an entrepreneur as the individual who owns the (relative) majority stake in the company, owns at least 50% shares in the business, and qualify as a founding member when the new firm is created. When a company in our sample changes ownership or the characteristics of the initial founder do not meet the above requirements, we drop the company from the sample. Consequently, we define a business group as a group of businesses owned and controlled by the same entrepreneur, according to the previous definition. Given the above definition of entrepreneur, we don't consider minority investments and acquisitions of established companies as determinants of business group growth. Our definition ensures that business group entrepreneurs have the ownership of all the companies in the group.

One second confounding factor could be diversification. Indeed, entrepreneurs might create two different companies simply because they perform totally different activities. Thus, we decided to exclude new companies belonging to sectors (2 digits NACE code) that are different from the sector of the original firm as part of the group. In other words, according to our definition, the only difference between group growth and company growth is the fact that the former involves the creation of a different organizational structure. All the companies in the group belong to the same sector[6]. Finally, it is worth to remark that we do not consider companies owned by other companies (subsidiaries) as part of the group. Indeed, the creation of a holding pyramid might be motivated by tax benefits or other "legal" issues (Bebchuk et al. 2000). Like in the case of

[6] As a robustness check, we run the analysis also without considering the above limitation. The key results do not change

diversification, we want to rule out these possible confounding factors. Business groups that do not fall in the defined category are not considered in the analysis.

In the end, we define Business Group Growth as a dichotomous variable 0-1. It has value 1 in case the entrepreneur decides to create a business group, according to the previous definition, at any point in time between 2003 and 2008. The variable has value zero otherwise.

Due to our matching procedure, the entrepreneurs who decide to grow their business as a single entity have the same initial characteristics of the entrepreneurs who opt for the group growth (*Business Group*). Likewise, their starting businesses in 2003 have the same size, first-year growth rate, sector and location. Due to the tight definition of business group, the number of business group entrepreneurs is relatively small: out of 1133 entrepreneurs only 4% opted for group growth. In the robustness checks section we relax our previous definition of business group to test the sensitivity of our results. Depending on the definition, the share of business group entrepreneurs ranges from 12% to 4%. In any case, the key results of the paper remain unchanged.

Dependent Variable 1- Business Equity and Revenue

Our dependent variable is the size of the business at the end of the 6^{th} year both in terms of *Equity* and *Revenue*. As anticipated, the equity and revenue of business groups is computed as the sum of equity and revenue of all the companies involved in the group. However, when a company in our sample changes ownership or the characteristics of the initial founder do not meet the above definitions of entrepreneur, we drop the company from the sample. We take the logarithm of both variables to reduce the skewness of the distribution and weaken the influence of the outliers.

Dependent Variable 2- Time to target size

Considering our theoretical framework, we develop also a dependent variable aimed at capturing the growth speed of the business. It represents the speed at which companies reach a target size. We set the target for hypothesis 1 equal to 1 million in equity and revenue. It is the 90th percentile of the size distribution (considering all the years from 2003 to 2008). As an additional robustness check, we tried different targets: 75th, 95th and 99th percentile. The key results do not differ.

Institutional variables as Moderators

Our key moderator is “partner risk” (1-*p*). Our theoretical model predicts that the size difference between business group and one-company entrepreneurs increases when *p* decreases. Borrowing from the literature on trust and social capital (OECD 2014), we develop a measure of the risk of partner opportunistic behavior at the community level- *Contentiousness*. The variable is simply the raw number of civil trials every 100,000 inhabitants in the city where our focal entrepreneur resides (Carmignani and Giacobelli 2009). We assume that entrepreneurs who live in cities characterized by high levels of *Contentiousness* have less trust in other individuals and perceive a higher partner risk (Guiso et al. 2006; Bottazzi et al. 2016). Consequently, we hypothesize that the benefit of a business group structure is higher in those cities. We test this hypothesis using *Contentiousness* as a moderator of the relationship between business group structure and growth. As an additional robustness check, we use the variable *Trials_Length* as a proxy of the institutional quality of a city. *Trials_Length* is the average length –in terms of days- of civil trials in the city where our focal entrepreneur resides (Carmignani and Giacobelli 2009). In cities characterized by high values of *Trials_Length* the enforceability of contracts and investor protection is relatively weaker. Without a reliable legal protection entrepreneurs and external resource providers are more vulnerable to opportunistic behaviors. Also in this context, the benefit of an organizational and legal separation between initiatives is more valuable.

Functional Specification

We test our hypotheses with an OLS and Cox Regression.

Descriptive Statistics and Matching

Table 1 displays the descriptive statistics.

****
Insert Table 1 about here
****

Table 2 reports the results of the matching process. The initial companies of one-company and business group entrepreneurs do not differ in terms of revenue, first-year growth rate, equity, region or sector in the initial year (2003). The same is true for entrepreneur’s demographic characteristics like age. Table 2 reports the comparison.

****
Insert Table 2 about here
****

RESULTS: PROPOSITION 1

Proposition 1a: Business Group Structure and Size.

Table 3 reports the results for proposition 1a. After 6 years from foundation, the average business size of entrepreneurs who grow their business as a group of separate companies instead of a unitary legal entity is larger both in terms of equity and revenue.

****
Insert Table 3 about here
****

Our results show that business groups are about 4 times bigger than standalone companies.

Table 4 and 5 provide the results of a cox duration model, while table 6 shows a visual representation of the results.

****
Insert Table 4 about here
****

****
Insert Table 5 about here
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****
Insert Table 6 about here
****

These results provide strong evidence that business group entrepreneurs raise more equity than one-company entrepreneurs and, as a consequence, grow faster. In each year, a business group entrepreneur is at least twice more likely (+100%) to hit the 1,000,000 revenue/equity threshold. In the next two paragraphs we rule out alternative explanations of the results.

Alternative Explanations- Different Growth Orientations

One alternative explanation of the above results could be the presence of entrepreneurs' heterogeneous growth orientations. Indeed, it might be that many one-company entrepreneurs simply do not want or are capable to grow. We try to address this issue matching our entrepreneurs on an additional variable: business size at the end of the 10^{th} year (2013). Keeping constant the size of the business at the end of the prolonged 10 years period, we can control for entrepreneur growth orientation and shift the focus of our analysis from size to growth speed. As presented in the theoretical section, the business group structure allows entrepreneurs to collect external resources more easily and grow faster in the short term. However, business group structure has no effect on the overall size of the business in the long term (k^{Max}). In theory, given enough time, even resource constrained entrepreneurs can reach k^{Max} reinvesting their profits over time. The faster growth of business groups in the early years is clearly visible in Table 7. This effect persist even if we control for business size at the end of the period.

****
Insert Table 7 about here
****

Thanks to the matching at the end of the period, the same share of one-company and group entrepreneurs reaches the target size, effectively controlling for heterogeneous growth orientations. However, even considering this additional constraint, business group entrepreneurs grow faster in the early years.

Alternative Explanations- Other Benefits of Business Group Organizational Structure

Our theory posits that a business group structure facilitates the involvement of external partners in the business. As a consequence of that, entrepreneurs who adopt a business group structure grow faster than one-company entrepreneurs. This reasoning implies that, without the involvement of external resource providers, the formation of a business group *per se* shouldn't have any effect on size or growth rate. We can test the above proposition focusing on business groups in which the entrepreneur owns 100% of the shares in the marginal company. In this case, by definition, the creation of a business group is not associated with the involvement of external resource providers. Table 8 reports the results of an OLS regression. In this table, business groups that are partially owned by the entrepreneur are not considered.

****
Insert Table 8 about here
****

The results of table 8 show that the creation of a business group does not have any effect on size as long as external partners are not involved. These findings provide evidence in favor of the theoretical mechanism outlined in the theory part, and rule out potential alternative explanations of why business groups grow faster than standalone firms.

Proposition 1b: Partner Risk as Moderator.

Table 9 and 10 provide evidence of the moderating role of *Contentiousness* and *Trials Length* on business group size.

****
Insert Table 9 and 10 about here
****

Contentiousness has no significant direct effect on the size of companies. However, it is a powerful moderator of the relationship between business group structure and size. The interaction term is significant even if we control for the city fixed effect (the third regression).

Trials Length has a negative direct effect on size. However, it positively moderates the relationship between business group structure and size. Also in this case, the interaction term is significant even if we control for the city fixed effect (the third regression). Table 9 and 10 provide support for proposition 1b.

EMPIRICAL ANALYSIS-PROPOSITION 2

In this second empirical part we want to shed light on the key mechanism in our theory, and try to solve potential endogeneity concerns. Our theory posits that business groups grow faster because they can access partner resources more easily. This suggests that entrepreneurs should select this mode of growth more often when their personal resources or alternative resources like debt are limited. We can test this proposition exploiting the 2007-2008 financial crisis as exogenous shock affecting credit availability.

Dependent Variable – Business Group Firms

Our dependent variable is a dummy variable with value 1 if an entrepreneur creates a new company at time *t* (with respect to the number of companies at time *t-1*). It is 0 otherwise. All the entrepreneurs start with *Business Group Firms* equal to 1. In order to remove from the analysis the serial entrepreneurs- entrepreneurs who create more companies sequentially- we drop from the sample any entrepreneur with 0 companies at any point in time.

Independent Variable – Credit Crunch

The key independent variable is the intensity of *Credit Crunch*. It measures the reduction in the number of loans provided by banks- at the sector, region and year level –from 2008 to 2013[7]. Credit crunch measures the reduction in credit supply in a specific region, industry and year. We

[7]Source: Bank of Italy

can confidently state that the variation in *Credit Crunch* is related to factors that are exogenous to entrepreneurs' skills and preferences.

Positive values of *Credit Crunch* mean a credit reduction. Conversely, negative values of the variable indicate a credit expansion. In case an entrepreneur owns more companies that are located in different regions, we take the average level of credit crunch experienced by all of them.

Controls and Moderators

We control for the lagged business growth rate and year dummies. The variable *Growth* has value 1 if the company/portfolio displays a positive growth rate in the previous period (logRevenue $_{t-1}$ – logRevenues $_{t-2}$). Otherwise, it has value zero.

Functional Specification

We run a fixed-effect OLS panel regression. Due to the presence of fixed effects, we don't use any time invariant control or matching technique (we use the full sample). The full regression is the following:

$$Business\ Group\ Firms\ it = \alpha + \beta 1\ Credit\ Crunch\ t + \beta 2\ Growth\ t - 1 +$$
$$\beta 2\ Credit\ Crunch\ t * Growth\ t - 1 +\ Year + \mu + \varepsilon\ it$$

Descriptive Statistics

Table 11 reports the descriptive statistics for all the variables.

****
Insert Table 11 about here
****

RESULTS: PROPOSITION 2

Results are presented in table 12.

****
Insert Table 12 about here
****

Just a small fraction of entrepreneurs (0.4%) create a new company at each point in time. However, an increase in credit crunch has a big effect on that probability. In addition, our theory predicts that the above effect is limited to those entrepreneurs who are growing their business but are resource constrained. For this reason, we introduce the lagged growth variable of the business/group as moderator of the relationship. As expected, successful entrepreneurs who are growing their business are more likely to create another company when the credit crunch is particularly strong. Credit crunch has no effect on businesses that are not growing (regression 2). As predicted by the theory, the entrepreneurs who opt for a group growth are mainly entrepreneurs who want to grow their business but face a resource constraint. These results provide additional evidence supporting the theoretical mechanisms illustrated in this paper.

ROBUSTNESS CHECKS

Business Groups and Tax Benefits

One possible confounding factor of the above analysis is the presence of shell corporations, designed primarily to lower or avoid taxes. We deal with this problem thanks to our purposive sampling. The related literature documented that the diffusion of this phenomenon is mainly linked to the creation of holding pyramids, in which one company is controlled by another company subject to a favorable taxation (Bebchuk et al. 2000). Tax benefits is a minor issue in case of companies directly controlled by a physical person and operating in the same country and industry[8]. Qualitative interviews with business group entrepreneurs confirm the minor role played by tax benefits in determining entrepreneurs' growth strategy (Iacobucci and Rosa 2010). Following this evidence, we selected our sample accordingly. We consider a company part of a business group only if it is owned and controlled by a physical person -the entrepreneur. We do not consider companies owned by other companies (subsidiaries) as part of the group. With such arrangement, the tax benefits entrepreneurs can achieve thanks to an organizational separation are minimal.

Replication

As a robustness check we repeated the analysis with a different cohort of 4,000 Italian companies. This time, all the companies were founded in 2008 instead of 2003. The key results of the above analysis can be perfectly replicated[9].

Diversified Groups

In this paper we adopted a very strict definition of business group in order to rule out potential confounding effects like business diversification. In the previous definition, we excluded businesses belonging to sectors that are different from the sector of the original firm. As a robustness check we repeated the above analysis relaxing this previous definition of business group. More specifically, we considered any new business founded by the same entrepreneur as

[8] In Italy the corporate income tax (IRES) is constant and does not depend on the income level.
[9] Authors can provide the results upon request.

part of the group independently of the sector. In a similar vein, we reduced the ownership stake needed to consider a business as part of a group from 50% to 20%. These modifications increase the number of business group entrepreneurs in the sample and slightly modify the magnitude of the regression coefficients. However, the key results of the paper (Proposition1a,b and Proposition 2) remain unchanged.

CONCLUSIONS AND DISCUSSION

There are many reasons why young albeit successful businesses do not grow. Previous literature shows that the lack of trust between the founder and external managers (Bloom et al. 2012), personal wishes regarding a certain life-style (Hurst and Pugsley 2011) or the disinclination to give control and/or be accountable to other parties (McKenna and Oritt, 1981; O'Farrell and Hitchens 1988) play an important role. The common element of these motivations is the entrepreneur's inability to delegate (Storey 1994) and open up the company to external resource providers. We posit that the creation of an organizational structure based on separate legal entities facilitates the involvement of external resource providers in the business, fueling its growth. In this framework, the business group structure becomes an antecedent and driver of growth.

We test our hypotheses using a sample of Italian entrepreneurs and found supportive evidence. Entrepreneurs who opt for group growth increase their business equity and revenue faster than the other entrepreneurs. This effect is stronger in cities characterized by a high "partner risk" and low institutional quality. In addition, we found evidence that this mode of growth is more common in periods characterized by a relatively low supply of credit.

The novelty of this study is the use of the entrepreneur as the unit of analysis rather than the company. Adopting this novel perspective (Sarasvathy et al. 2013; Scott et al. 1996), we are able to study a growth strategy - the creation of different organizational entities by the same entrepreneur -that has been overlooked by previous research (Sarasvathy et al. 2013). The main limitation of this paper is the focus on just one country: Italy. As outlined in the theoretical part, the results of this paper might not be generalizable to countries with different institutional/cultural characteristics. The literature on business groups, indeed, shows that this organizational form is more common in developing countries with weak institutions and less sophisticated financial systems (Belenzon and Tsolmon 2016; Chittoor et al. 2015). We think that a cross-country comparison could be an interesting new avenue of research.

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Table 1. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Business Group	1133	0.037	0.175	0	1
Initial Revenue	1133	8.673	4.867	0	17.097
First Year Growth	1133	2.518	4.227	-12.736	16.505
Initial Equity	1133	9.276	0.739	8.517	16.811
Entrepreneur age	1133	41	11.278	18	89
Manufacturing	1133	0.496	0.500	0	1
Time to 1Million equity	1133	4.680	0.287	0	5
Time to 1Million revenue	1133	3.421	1.056	0	5
Equity	741	12.56	1.942	7.130	42.153
Revenue	801	12.83	2.306	6.037	42.345
Contentiousness	806	790	206	507	1254
Trials Length	808	976	316	555	1599

Table 2. Entrepreneur's and Initial Business Characteristics at time zero (2003). OLS.

VARIABLES	(1) Business Group	(2) Business Group	(3) Business Group	(4) Business Group
Initial Revenue	0.000589	-8.62e-05	-0.000103	7.85e-05
	(0.000989)	(0.00139)	(0.00139)	(0.00142)
First Year Growth		-0.00111	-0.00118	-0.000964
		(0.00160)	(0.00160)	(0.00163)
Initial Equity			0.00384	0.00441
			(0.00654)	(0.00659)
Entrepreneur Age				-0.000223
				(0.000429)
Manufacturing				-0.00602
				(0.00993)
Constant	0.0266***	0.0352**	-4.39e-05	0.00474
	(0.00984)	(0.0159)	(0.0622)	(0.0638)
Observations	1,133	1,133	1,133	1,133
R-squared	0.000	0.001	0.001	0.001

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

Table 3. Business revenue and equity at the end of the 6th year (2008). OLS.

VARIABLES	(Matching) Equity	(Matching) Revenue	(No-matching) Equity	(No-matching) Revenue
Business Group	5.612***	3.965***	5.674***	4.818***
	(1.383)	(1.479)	(1.384)	(1.407)
Initial Revenue			0.0830***	0.189***
			(0.0181)	(0.0212)
First Year Growth			0.0947***	0.205***
			(0.0213)	(0.0237)
Initial Equity			0.567***	0.328***
			(0.0860)	(0.0596)
Entrepreneur Age			-0.00144	-0.00365
			(0.00409)	(0.00451)
Regional Dummies	No	No	Yes	Yes
Sector Dummies	No	No	Yes	Yes
Constant	12.35***	12.69***	6.783***	8.047***
	(0.0532)	(0.0557)	(0.857)	(0.911)
Observations	741	801	1,355	1,479
R-squared	0.224	0.107	0.336	0.348

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

Table 4. Time to 1 million equity. Cox Duration Model coefficients.

VARIABLES	(Matching) Time to 1 million equity	(No-matching) Time to 1 million equity
Business Group	2.060***	1.967***
	(0.248)	(0.268)
Initial Revenue		0.101***
		(0.035)
First Year Growth		0.131***
		(0.037)
Initial Equity		0.480***
		(0.094)
Entrepreneur Age		0.008
		(0.007)
Regional Dummies	No	Yes
Sector Dummies	No	Yes
Observations	1,085	1,991

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

Table 5. Time to 1 million revenue. Cox Duration Model coefficients.

VARIABLES	(Matching) Time to 1 million revenue	(No-matching) Time to 1 million revenue
Business Group	0.829***	0.857***
	(0.241)	(0.238)
Initial Revenue		0.647***
		(0.059)
First Year Growth		0.671***
		(0.059)
Initial Equity		0.283***
		(0.066)
Entrepreneur Age		-0.002
		(0.666)
Regional Dummies	No	Yes
Sector Dummies	No	Yes
Observations	1,085	1,991

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

Table 6. Time to 1 million revenue (2003-2008).

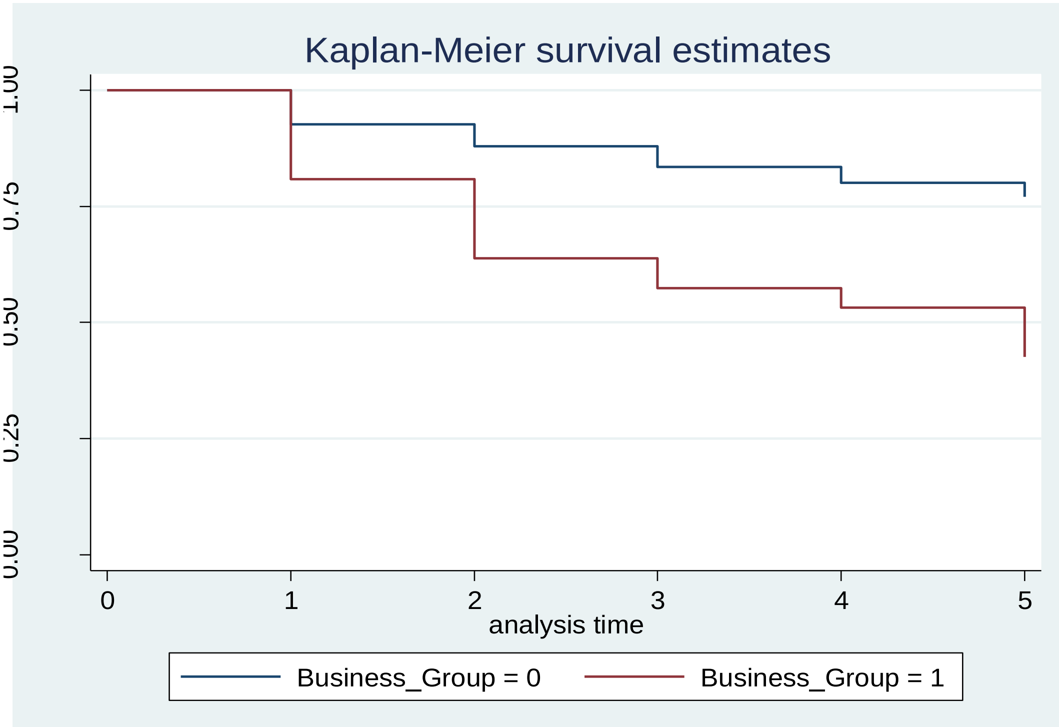

Table 7. Time to 1 million revenue (2003-2013). Matching on 2013 revenue.

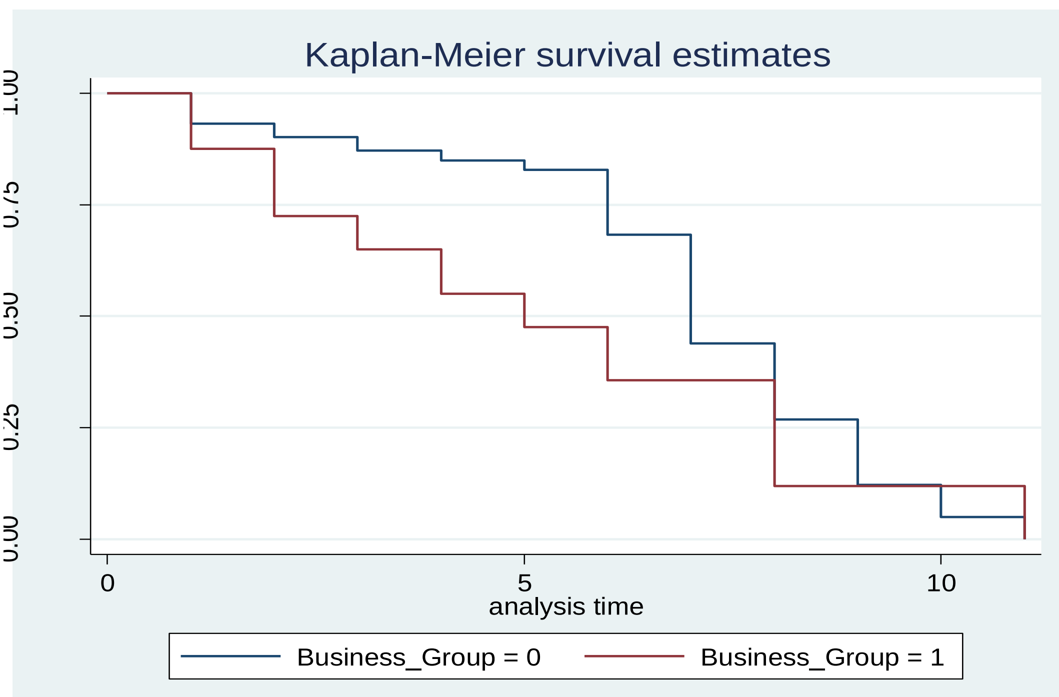

Table 8. Business revenue at the end of the 6th year. Business Groups with 100% ownership.

VARIABLES	(Matching) Revenue	(No-matching) Revenue
Business Group (100%)	-0.0989	-0.0371
	(0.550)	(0.329)
Initial Revenue		0.180***
		(0.0118)
First Year Growth		0.178***
		(0.0130)
Initial Equity		0.342***
		(0.0486)
Entrepreneur Age		-0.00407
		(0.00335)
Regional Dummies	No	Yes
Sector Dummies	No	Yes
Constant	12.69***	7.353***
	(0.0560)	(0.556)
Observations	771	1,449
R-squared	0.000	0.361

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

Table 9. Business revenue at the end of the 6th year (2008) and Contentiousness. OLS.

VARIABLES	(1) Revenue	(2) Revenue	(3) Revenue
Business Group	-0.791	-2.799	-2.738
	(4.819)	(3.715)	(3.736)
Contentiousness	0.000065	0.000294	
	(0.000173)	(0.000216)	
Business Group* Contentiousness	0.00734	0.00980**	0.00977**
	(0.00493)	(0.00360)	(0.00365)
Initial Revenue		0.154***	0.144***
		(0.0346)	(0.0405)
First Year Growth		0.167***	0.159***
		(0.0364)	(0.0403)
Initial Capital		0.339***	0.326**
		(0.114)	(0.118)
Entrepreneur age		0.000927	0.00340
		(0.00818)	(0.00760)
City Dummies	No	No	Yes
Sector Dummies	No	Yes	Yes
Constant	12.51***	8.282***	9.450***
	(0.265)	(1.104)	(1.159)
Observations	806	631	631
R-squared	0.152	0.389	0.410

Robust standard errors in parentheses. Errors clustered at the regional level.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 10. Business revenue at the end of the 6th year (2008) and Trials Length. OLS.

VARIABLES	(1) Revenue	(2) Revenue	(3) Revenue
Business Group	1.510	-9.264**	-9.170**
	(5.566)	(4.078)	(4.012)
Trials Length	-0.000269	-0.000458*	
	(0.000201)	(0.000242)	
Business Group* Trials Length	0.00438	0.0157***	0.0156***
	(0.00695)	(0.00475)	(0.00470)
Initial Revenue		0.149***	0.149***
		(0.0353)	(0.0394)
First Year Growth		0.165***	0.163***
		(0.0360)	(0.0392)
Initial Capital		0.356***	0.356***
		(0.1000)	(0.103)
Entrepreneur Age		-7.39e-05	0.00266
		(0.00719)	(0.00655)
City Dummies	No	No	Yes
Sector Dummies	No	Yes	Yes
Constant	12.81***	8.952***	9.052***
	(0.215)	(1.072)	(1.115)
Observations	808	633	633
R-squared	0.144	0.432	0.455

Robust standard errors in parentheses. Errors clustered at the regional level.
*** p<0.01, ** p<0.05, * p<0.1

Table 11. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Business Group Firms	20,132	0.008	0.093	0	1
Credit Crunch	20,132	0.101	0.120	-0.160	0.563
Growth (t-1)	20,132	0.546	0.497	0	1
Credit Crunch*Growth (t-1)	20,132	0.084	0.117	-0.160	0.563
Year	20,132	2010	1.707	2008	2013

Table 12. Credit Crunch and Group Growth. Fixed-Effect Panel regression.

VARIABLES	(1) Business Group Firms	(2) Business Group Firms
Credit Crunch	0.0446***	-0.00114
	(0.00690)	(0.0123)
Growth (t-1)		-0.0121***
		(0.00186)
Credit Crunch*Growth (t-1)		0.0657***
		(0.0186)
Year Dummies	Yes	Yes
Constant	0.00449***	0.0148***
	(0.000703)	(0.00491)
Observations	20,132	20,132
R-squared	0.005	0.009
Number of ID	3,549	3,549

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

Appendix 1

$$Average\ Size\ contrained = \left(\frac{1}{\sqrt{\frac{2(bk-k)}{z}}}\right) \int_0^{\sqrt{\frac{2(bk-k)}{z}}} (k)dp = k$$

$$Average\ Size\ partner = \left(\frac{1}{x - \frac{1}{b}}\right) \int_{\frac{1}{b}}^{x} (k + pbZ)dp = \frac{1}{2}\,(bZx{+}2k{+}Z)$$

$$Average\ Size\ OneCo = \left(\left(\frac{\sqrt{\frac{2(bk-k)}{z}})}{\sqrt{\frac{2(bk-k)}{z}}+x-\frac{1}{b}}\right) k + \left(\frac{x-\frac{1}{b}}{\sqrt{\frac{2(bk-k)}{z}}+x-\frac{1}{b}}\right)\left(k + \frac{1}{2}Z + \frac{1}{2}bZx\right)$$

$$Average\ Size\ OneCo = \left(\frac{t}{t + x - \frac{1}{b}}\right) k + \left(\frac{x-\frac{1}{b}}{t + x - \frac{1}{b}}\right)\left(k + \frac{1}{2}Z + \frac{1}{2}bZx\right)$$

$$Average\ Size\ OneCo = k + \frac{Z(b^2x^2 - 1)}{2(bt + bx - 1)}$$

$$Average\ Size\ Group = \left(\frac{1}{\frac{1}{b} - \sqrt{\frac{2(bk-k)}{z}}}\right) \int_{\sqrt{\frac{2(bk-k)}{z}}}^{\frac{1}{b}} (k + pZ)dp = \left(\frac{1}{\frac{1}{b} - t}\right)\left(\left(\frac{k}{b} + \frac{Z}{2b^2}\right) - \left(kt + \frac{t^2 Z}{2}\right)\right)$$

$$Average\ Size\ Group = k + \frac{btZ + Z}{2b}$$

Appendix 2

We assign some values to the parameters to find a numerical solution to proposition 1a: *k=1*, *b=8/7*, *z=3/4* and *x*=1.

$\pi\_group^{*} > \pi\_constrained^{*} \quad if\ p > 0.62$

$\pi\_partner^{*} > \pi\_group^{*} \quad if\ p > 0.875$

$Average\ Size\ contrained = \frac{1}{0.62}\int_{0}^{0.62}(\ 1)dp = \frac{1}{0.62}\int_{0}^{0.62}(1)dp = \frac{1}{0.62}(0.62) = 1$

$Average\ Size\ partner = \frac{1}{0.125}\int_{0.875}^{1}(\ pbZ + 1)dp = \frac{1}{0.125}(0.428 + 1 - 0.328 - 0.875) = 1.8$

$Average\ Size\ OneCo = 0.84(1) + 0.16(1.8) = 1.128$

$Average\ Size\ Group = \frac{1}{0.237}\int_{0.62}^{0.875}\left(\frac{p3}{4} + 1\right)dp = \frac{1}{0.237}(0.287+0.875-0.144-0.62) = 1.67$

$Average\ Size\ Group - Average\ Size\ OneCo = 0.54$

Appendix 3

Sector	Freq.	Percent
Manufacture of fabricated metal products	153	13.75
Administrative Management and General Management Consulting Services	140	12.58
Architectural and engineering activities	116	10.42
Packaging activities	76	6.83
Information service activities	70	6.29
Manufacture of machinery and equipment	65	5.84
Manufacture of food products	62	5.57
Professional and scientific activities	48	4.31
Financial services	42	3.77
Repair and installation of machinery and equipment	42	3.77
Manufacture of leather and related products	39	3.50
Other manufacturing	36	3.23
Manufacture of rubber and plastic products	36	3.23
Printing and reproduction of recorded media	36	3.23
Manufacture of wood and of products of wood	31	2.79
Agriculture and fishing	30	2.70
Manufacture of textiles	29	2.61
Waste collection, treatment and disposal activities	17	1.53
Manufacture of motor vehicles, trailers and semi-trailers	17	1.53
Telecommunications	13	1.17
Manufacture of other transport equipment	8	0.72
Electric power generation, transmission and distribution	7	0.63
Total	1,113	100.00

Chapter 2:
Portfolio Entrepreneurs' Behavior and Performance: An Intertemporal Economies of Scope Perspective

ABSTRACT

This article investigates the behavior and performance of entrepreneurs who run more than one business simultaneously, or portfolio entrepreneurs. Borrowing from literature on business groups and resource redeployment, the authors develop a model of portfolio entrepreneurship, in which the main advantage is these entrepreneurs' ability to redeploy resources across companies. This potential for redeployment then facilitates exit from poorly performing new ventures and increases the average quality of the surviving businesses. To test these ideas, a longitudinal data set covers a sample of more than 6,000 Italian entrepreneurs, spanning all the companies they created over their lifetimes. In support of the hypotheses, portfolio entrepreneurs redeploy resources across their portfolio businesses, in accordance with firm-related market feedback. The redeployment option helps them react quickly to negative market signals and shut down underperforming businesses early.

INTRODUCTION

In the expanding literature devoted to entrepreneurial performance, a common view confounds this type of performance with single-firm performance (Sarasvathy et al. 2013), though substantial fractions of entrepreneurs create and manage more than one company (Birley and Westhead 1993; Iacobucci and Rosa 2010). Entrepreneurs often create and manage new companies, either sequentially or simultaneously (Birley and Westhead 1993; Westhead and Wright 1998; Westhead et al. 2003), and the latter type, which we refer to as portfolio entrepreneurs, can obtain systematically superior performance (Baert et al. 2016; Lechner and Leyronas 2009; Westhead et al. 2005) due to their expanded learning, experience (Gottschalk et al. 2009; Westhead et al. 2005), and access to traditional economies of scope (Plehn-Dujowich 2008). Despite some recent insights into the performance of portfolio entrepreneurs, we still know relatively little about why they might attain superior performance, so in the current article, we elaborate on an overlooked aspect of portfolio entrepreneurship, namely, the possibility of benefiting from intertemporal economies of scope, i.e. the possibility to redeploy resources between businesses. Building on literature on resource redeployment (Helfat and Eisenhardt 2004; Lieberman et al. 2016), we argue that the main advantage of portfolio entrepreneurs is not a superior capability to select the best business opportunities ex ante but rather the option to redeploy resources across multiple businesses ex post, which reduces the *sunkenness* of their investments in new projects. This redeployment option facilitates their exit from new businesses that fail initial market tests and increases their responsiveness to negative market feedback.

Entrepreneurs often start projects with uncertainty about the potential outcomes (Gans et al. 2016; Kerr et al. 2014; Sarasvathy et al. 2013; Stern 2005). Creating a new business also requires sunk investments in plants and equipment, the recruitment of adequate personnel, and marketing, all of which would be difficult to recover following a market exit. These substantial sunk costs and commitments may discourage exits from ventures that prompt ambiguous but relatively negative early market feedback. Thus, many poor businesses survive for long periods of time (Gimeno et al. 1997). In such settings, we posit that the presence of intertemporal economies of scope, and thus the potential to redeploy resources, enables entrepreneurs who manage more than one business to exit faster from less profitable companies. Relative to prior literature on entrepreneurial opportunity costs and exits (Arora and Nandkumar 2016; Gimeno et al. 1997), we offer a novel focus on the entrepreneur's overall business portfolio, instead of a traditional entrepreneur–business dyad, to construct a more accurate measure of resource opportunity costs (Sarasvathy et al. 2013; Scott and Rosa 1996). In addition, we contribute theoretically to literature on portfolio entrepreneurship (Westhead and Wright 1998; Westhead et al. 2003, 2005), in that our framework helps reconcile some contradictory findings that suggest portfolio entrepreneurs' ownership exerts a positive effect on new firm performance (Westhead et al. 2005) but a negligible, and sometimes even negative, effect on survival (Gottschalk et al. 2009). Finally, as an empirical contribution, we extend strategy literature on resource redeployment. Portfolio entrepreneurship offers a novel, distinctive context in which to test theories of intertemporal economies of scope (Helfat and Eisenhardt 2004; Lieberman et al. 2016). Because different businesses in a portfolio are distinct legal entities, we can track resource movements across ventures and thereby estimate each entrepreneur's performance threshold. Previous research assumes the existence of such flows but never has observed them empirically (Gimeno et al. 1997; Lieberman et al. 2016).

To develop our hypotheses, we propose a model of resource redeployment, with a conceptualization based on Lieberman et al. (2016), translated to the context of entrepreneurial ventures. Then, to test these hypotheses, we employ a unique sample of 6,132 firms founded in 2006 in Italy. To classify business owners (as portfolio entrepreneurs or not), we collected data about all the companies in which the founders of our initial sample of firms have owned a majority of shares. Thus we can map the entire "entrepreneurial life" of our initial sample of founders. Portfolio entrepreneurs indicate a higher probability of exit and also exit earlier from poorly performing companies. In addition, in the presence of an external negative shock, their exit occurs following a relatively smaller performance decline, whereas single-business entrepreneurs wait to observe larger performance declines before exiting. This behavior entails a selection mechanism that in turn raises the relative quality of the surviving portfolio companies over time. Finally, we find positive evidence of the intertemporal redeployment of resources across companies in the same portfolio. Our results are consistent across several robustness analyses, a replication study, and the use of an instrumental variable for portfolio entrepreneurship.

THEORY AND LITERATURE

Portfolio Entrepreneurs

Business groups traditionally have been associated with large firms (Mahmood and Mitchell 2004; Manikandan et al. 2014), though owning more than one business is also relatively common in the small business sector (Iacobucci and Rosa 2010). Portfolio entrepreneurs own and manage multiple firms at the same time, often in an explicit attempt to seize additional entrepreneurial opportunities related to the original business idea (Iacobucci and Rosa 2010; Lechner and Leyronas 2009; Lynn and Reinsch 1990), which may require the involvement of other investors or partners (Almeida and Wolfenzon 2006). Westhead et al. (2005) show that new firms created by portfolio entrepreneurs perform systematically better than other firms, but they do not identify the mechanisms that lead to this performance gap. Portfolio entrepreneurship is included simply as one type of successful entrepreneurial experience (Gottschalk et al. 2009; Toft-Kehler et al. 2013), such that superior performance is presented as a byproduct of the founder's entrepreneurial skill or experience (Westhead et al. 2005).

We acknowledge the importance of this framework, but we argue that looking at portfolio entrepreneurship using only an experience framework may be limiting. The inconclusive prior results regarding on the link between a founder's entrepreneurial experience and business success also suggest the need for an alternative framework (Birley and Westhead 1993; Schaper et al. 2007; Schror 2006; Westhead and Wright 1998). Gottschalk et al. (2009) could not replicate Westhead et al.'s (2005) results when they consider the survival of new firms as performance variable. Instead, they find that firms owned by portfolio entrepreneurs do not achieve a better survival rate; with some definitions of portfolio entrepreneurship, these companies even appear more likely to die. No theory of portfolio entrepreneurship has addressed this puzzle.

In an attempt to establish one, we argue that the key advantage of portfolio entrepreneurs when launching new businesses is not their ability to select better business opportunities ex ante due to their superior entrepreneurial experience or skill but rather their option to redeploy resources across businesses ex post. This flexibility should have important consequences for portfolio entrepreneurs' behavior and performance.

Resource Redeployment

The creation of a new business involves substantial sunk investments, such as renting office or factory space, purchasing machinery, and searching for and training qualified personnel. These resources have little value outside the business context and thus represent risky investments. Entrepreneurs often exit the market, usually followed by the liquidation of the business resources and a transition into the salaried workforce. According to Manso (2014), 52% of self-employment periods last fewer than two years, and 28% of salaried workers older than 25 years of age have experienced at least one self-employment spell. Following their divestment, entrepreneurs cannot recover the full value of their sunk investments, for various reasons. Inefficiencies in the factor market (e.g., low competition) reduce the entrepreneur's bargaining power (Chittoor et al. 2015), and the very fact that the entrepreneur wants to sell the business represents a negative signal (Lieberman et al. 2016). We posit that the option to redeploy resources across businesses within the same portfolio reduces the "sunkenness" of the entrepreneur's investments in a new business. Business group research documents the intense exchange of capital, labor, and other inputs or factors of production among companies that are members of the same group (Belenzon and Tsolmon 2015; Carney et al. 2011; Chittoor et al. 2015; Manikandan et al. 2014). In this framework, the group functions like an internal factor market, facilitating resource exchanges that are more efficient than they would be in an external factor market. Similarly, we argue that because portfolio entrepreneurs can easily redeploy resources among their companies, without using the external factor market, they can recover a larger fraction of business-related sunk investments (Lieberman et al. 2016). Some qualitative evidence supports this idea (Baert et al. 2016): In-depth case studies show that even if portfolio businesses belong to different sectors (Lynn and Reinsch 1990), they share their common resources (Baert et al. 2016; Iacobucci and Rosa 2010), which facilitates activity divestment (Lechner and Leyronas 2009). This redeployment option has important consequences for the entrepreneur's entry and exit decisions, but these factors have been overlooked in previous literature.

Redeployment, Exit Timing, and Performance

Entrepreneurs make decisions in a context of extreme uncertainty when they launch a new venture (Sarasvathy et al. 2013). According to Kerr et al. (2014), entrepreneurship is fundamentally about experimentation, because the knowledge required to be successful cannot be identified in advance or deduced from some set of initial principles. Therefore, the most successful entrepreneurs (and investors) are those who respond effectively and quickly to ex post market signals. They are not necessarily the most skilled entrepreneurs or those who started with the best business ideas.

In line with these considerations, we posit that a key decision following the creation of a new venture is the exit decision. There likely is little heterogeneity in how people respond to a successful outcome, but recognizing and responding to failure is much more difficult. People differ strongly in their ability and willingness to terminate underperforming ventures (Baptista et al. 2014; Block and Sandner 2009). In many cases, survival is a sign of stubbornness or a lack of better options, rather than an indicator of success. Gimeno et al. (1997) find that the entrepreneur's opportunity cost is fundamental for estimating a business-specific performance threshold. Entrepreneurs with high human capital in innovation-based industries for example often prefer to fail quickly rather than merely survive for an extended period, while running a poorly profitable business (Arora et al. 2016). But the flexibility provided by resource redeployment may reduce portfolio entrepreneurs' commitment to any specific business, such that they exit faster from underperforming ventures than single-business entrepreneurs do.

Furthermore, the faster reaction of portfolio entrepreneurs should influence the average performance of the portfolio firms. Because portfolio entrepreneurs shut down their underperforming companies earlier, their surviving companies may perform better than companies owned by single-business entrepreneurs, over time. We formalize these predictions in our proposed model.

MODEL AND HYPOTHESES

We assume that an entrepreneurial opportunity (Eckhardt and Shane 2003; Kirzner 1973; Short et al. 2010) is a random variable x with mean E(x) and distribution $f(x)$, where x represents the cash flow generated by the business. In each period t, K opportunities arise and are randomly distributed across people. For simplicity, we assume that people draw their opportunities from the same distribution $f(x)$ and cannot predict when a new opportunity will arise. This latter assumption implies that entrepreneurs cannot freely decide when to start a new business; it is conditional on finding a business opportunity (Baert et al. 2016; Lechner and Leyronas 2009). If all the businesses of a given entrepreneur fail at time t, he or she must join the salaried workforce and earn a fixed salary w, which we normalize to $w = 0$.

Resource Redeployment

Following Lieberman et al. (2016), we divide the process of launching a new business into three phases. In phase 1, entrepreneurs make a sunk investment F, required to enter the business. In phase 2, they observe cash flows x, and then in phase 3, they decide whether to stay or exit. If an entrepreneur chooses to continue, he or she earns the same return as in the prior period forever ($Z = x\frac{1}{\rho}$[10].). If the entrepreneur chooses to exit, he or she can shut down the business and recover

[10] Here, ρ represents the interest rate.

a fraction *A* of the original investment *F* by selling "business-generic" resources in the external market.

Entrepreneurs running a business at time *t* who decide to seize a new business opportunity at time *t + 1* then become portfolio entrepreneurs, who can redeploy resources from one business to another. Following Lieberman et al. (2016), we model resource redeployability as the ability to recover a higher fraction *R* of the sunk investment *F* in case of exit. The transaction costs associated with internal redeployment are lower than those of external factor markets (Chittoor et al. 2015), so *R* > *A*. In other words, the potential for internal redeployment of resources reduces the "sunkenness" of the entrepreneur's investment in the new business (Lieberman et al. 2016). The degree of relatedness among these resources also should facilitate their redeployment (Lee and Lieberman 2010).

Key Assumption (a): *Portfolio entrepreneurs can redeploy resources across businesses.*

Key Assumption (b): *When resources are related, portfolio entrepreneurs can redeploy an even greater share of them.*

Entry and Exit Decisions

Following Kerr et al. (2014) we argue that entrepreneurship is fundamentally about experimentation, because it is almost impossible to predict the success of a new venture ex ante. Thus, people do not know the exact distribution $f(x)$, but they have some prior distribution in mind $f_i(x)$ and use it to estimate the expected $E_i(x)$. Therefore, a would-be entrepreneur seizes a business opportunity if

$$-F + E_i(x) + \text{Max } E_i(x\frac{1-\rho}{\rho}, \text{AF}) > 0.$$

A portfolio entrepreneur seizes an additional business opportunity if

$$-F + E_i(x) + \text{Max } E_i(x\frac{1-\rho}{\rho}, \text{RF}, \text{AF}) > 0.$$

Thus, entrepreneurs with a company already in place seize an opportunity in response to a lower expectation of the cash flow $E_i(x)$, relative to other people, because of their potential ability to recover more of the fixed costs in the case of failure. The entrepreneur's exit decision is similar to the entry decision: Given an observed cash flow x, entrepreneurs compute the total value of their business, $Z = x\frac{1}{\rho}$. If they realize that the current expected value is lower than their alternative investment, they exit. The exit decision for single-business entrepreneurs thus is

$$Z \leq AF,$$

whereas that for portfolio entrepreneurs is

$$Z \leq RF.$$

Assuming that single-business and portfolio entrepreneurs draw business opportunities from the same distribution $f(x)$, Probability $(x\frac{1}{\rho} < AF) <$ Probability $(x\frac{1}{\rho} < RF)$. In addition, if portfolio entrepreneurs anticipate the benefit of redeployment they seize opportunities with a relatively lower $E_i(x)$, increasing the probability of an early exit. Accordingly:

Hypothesis 1a: *New companies created by portfolio entrepreneurs are more likely to exit than companies founded by single-business entrepreneurs, and at a higher level of performance than the threshold for single-business firms.*

The difference between the two probabilities increases as F increases.[11] As long as the fixed costs needed to start a new business are low, there is no big difference in the behaviors of

[11] A numerical example might help explain this logic. Assume that *f(x)* is a uniform distribution that ranges from 0 to 100 = *u*(0,100), and F = 10, A = 0.1, and R = 0.2. The probability of exit for a single-business entrepreneur is 0.01, but it is 0.02 for a portfolio entrepreneur. The difference between the two probabilities is 0.01. Now assume F = 100, A = 0.1, and R = 0.2. The probability of exit for a single-business (portfolio) entrepreneur is 0.1 (0.2), so the

single-business and portfolio entrepreneurs. The advantage of redeployment increases with high sunk costs. In this sense, we predict

Hypothesis 1b: *Start-up fixed costs positively moderate the relationship between portfolio and exit probability.*

The effect of resource similarity on exit probability is ambiguous though, due to the potential for synergies (Liebermann et al. 2016).

Exit Timing

The preceding model is extremely simple. Entrepreneurs observe cash flow x generated by their business and immediately decide whether to exit. In real life though, the signal in phase 2 is ambiguous and incorporates factors that are exogenous to business quality. Therefore, we assume that in each period, our entrepreneurs observe not x but rather $xt = x + \varepsilon(t)$, where x represents the "true value" of the business, and $\varepsilon(t)$ is a performance component unrelated to the quality of the business.[12] It reflects external factors (e.g., positive/negative business cycles), and entrepreneurs do not know its size or distribution. In each period t, the entrepreneur observes xt and develops expectations after incorporating the new signal. We assume entrepreneurs adopt a simple Bayesian updating process, in which future expected cash flows are the average value of previous realizations (Lieberman et al. 2016):

$$\bar{x}_t = \frac{1}{t}\sum_{i=0}^{t} x_i.$$

At each point in time t, entrepreneurs decide to stay in business or exit. They exit only if $Z_t = \bar{x}_t \frac{1}{\rho} \leq$ opportunity cost. Over time, the error component $\varepsilon(t)$ becomes a less important

difference in probability is 0.10. As F increases (from 10 to 100), the difference between the two probabilities increases too.

[12] For simplicity, we assume $\varepsilon(t) \sim N(0,\sigma)$.

determinant of exit,[13] consistent with the idea that the early years of the business feature more noise, hiding the "real" performance of a company, but the entrepreneur gains a better understanding of the business potential over time, such that $\lim_{t\to\infty} \bar{x}_t \frac{1}{\rho} = x\frac{1}{\rho}$. This situation is similar to the case without ambiguity in the previous section.

Following this framework, we estimate the minimum cash flow *xt* that triggers the exit decision at a generic time *t*. It is represented by the parameter Ʈ. If an entrepreneur observes a cash flow equal to or lower than Ʈ, at a generic time *t*, he or she immediately exits. The threshold Ʈ depends on the opportunity costs, such that entrepreneurs exit if $Z_t \leq AF\ or\ RF$. We can rewrite Z_t as follows:

$$Z_t = \frac{1}{t}\left(\sum_{i=0}^{t-1} \mathrm{x}_i + Ʈ\right)\frac{1}{\rho} \leq AF\ if\ Single - Business$$

$$Z_t = \frac{1}{t}\left(\sum_{i=0}^{t-1} \mathrm{x}_i + Ʈ\right)\frac{1}{\rho} \leq\ RF\ if\ Portfolio$$

For simplicity, assume that all the previous realizations of *x* prior to time *t – 1* are the same: $\mathrm{x}_1 = \mathrm{x}_2 = \mathrm{x}_3 \ldots = \mathrm{x}_{t-1} = \mathrm{x}_i$ Thus:

$$Z_t = \frac{1}{t}(\mathrm{x}_i(t-1) + Ʈ)\frac{1}{\rho} \leq AF\ if\ Single - Business$$

$$Z_t = \frac{1}{t}(\mathrm{x}_i(t-1) + Ʈ)\frac{1}{\rho} \leq RF\ if\ Portfolio$$

Rearranging this equation, we can isolate the single-business threshold value:

$$Ʈ\mathrm{s(t)} \leq t\ (AF\rho) - \mathrm{x}_i(t-1),$$

whereas the threshold value for portfolio entrepreneurs is

$$Ʈ\mathrm{p(t)} \leq\ t\ (RF\rho) - \mathrm{x}_i(t-1).$$

[13] Because we assume *ε(t)~N(0,σ)*, $\sum_{i=0}^{t} \varepsilon(i)/t$ approaches 0 as t increases.

Ultimately, the Ʈ$(.)$ formula depends on the current period *t*, previous realizations x_i, and the opportunity cost AF or RF. Keeping x_i constant for every entrepreneur, it is clear that Probability ($\mathrm{x}_t <$ Ʈp(t)) is greater than Probability ($\mathrm{x}_t <$ Ʈs(t)) for every *t*. Portfolio entrepreneurs thus exhibit a greater probability of exit in each period *t*. In other words, the *exit rate* of portfolio entrepreneurs is higher than that of single-business entrepreneurs. Formally,

Hypothesis 2a: *New companies created by portfolio entrepreneurs exit at a higher rate than companies created by single-business entrepreneurs.*

Hypothesis 2b: *The start-up fixed costs positively moderate this relationship.*

Responsiveness

The threshold values Ʈs(t) and Ʈp(t) represent the lower bounds of the performance distribution that single-business and portfolio entrepreneurs, respectively, consider acceptable. An entrepreneur exits if the current market signal x_t (at time *t*) is lower than the threshold value. Assuming that the business is still in existence at time *t – 1*, a portfolio entrepreneur exits at time *t* if he or she experiences a performance decline $(x_t - x_{t-1}) =$ (Ʈp(t) $- x_{t-1}$). Single-business entrepreneurs need a decline $=$ (Ʈs(t) $- x_{t-1}$). Assuming that the initial realization x_{t-1} is the same for everyone, because Ʈp(t) > Ʈs(t), we predict that portfolio entrepreneurs need to experience a relatively weaker performance decline to be "convinced" to shut down their business.

Hypothesis 3: *Keeping the initial performance x_{t-1} constant for every entrepreneur, portfolio entrepreneurs must experience a relatively weaker performance drop $(x_t - x_{t-1})$ at a generic time t to trigger their exit decision.*

****
Insert Figure 1 about here
****

It is important to note that the performance drop can be explained either by the bad quality of a firm (x) or a temporary negative shock $\varepsilon(t)$. However, entrepreneurs do not know which explanation is the correct one. Given what they observe in the market, they decide whether to keep the company alive for an additional period or not. Because the cost of keeping alive a bad business is higher for portfolio entrepreneurs, they are more sensitive to negative market signals.

Selection and Performance

Portfolio entrepreneurs keep their businesses alive only if they provide sufficiently large cash flows $x_t > \Upsilon\mathrm{p}(t) > \Upsilon s(t)$; they close all others. Their higher performance threshold generates a selection effect, such that portfolio entrepreneurs maintain better businesses than single-business entrepreneurs over time. The difference becomes more significant over time as the effect of the noise $\varepsilon(t)$ disappears.

Hypothesis 4*: Portfolio entrepreneurs' surviving companies are more successful than single-business entrepreneurs' companies in the long run.*

From a theoretical perspective, we observe this selection because portfolio entrepreneurs make fewer type II errors, i.e. it is less likely that they keep alive a company with a low quality x. However, because of the higher threshold, they are also more likely to shut down moderately good companies (type I error).

DATA AND MEASURES

Data Collection

To test our hypotheses, we use a sample of 6,132 Italian firms and data collected from the business register of Italian chambers of commerce, UnionCamere. This UnionCamere database is publicly available and contains official data about all Italian companies. A European business intelligence company helped us with the data collection process. First, we selected an arbitrary year (2006) and extracted, from the UnionCamere database, a sample of firms founded in Italy that year. They represent our focal firms. Second, we collected balance sheet data about these firms for 2006–2011, along with personal information about their founders. For each founder, we collected data about all the firms in which he or she currently owns or previously owned majority stakes. Italy is an appropriate setting to test these propositions, because of its high level of entrepreneurial activity and business ownership compared with other developed countries (Ernst & Young 2013).

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Insert Figure 2 about here
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Our unit of analysis is *new companies* created in 2006. We seek to compare focal companies founded by single-business entrepreneurs with those founded by portfolio entrepreneurs. Because all the focal firms were created the same year, it is easy to make comparisons in terms of their survival rate, exit timing, and performance. We use different dependent variables for each hypothesis, but we employ the same independent and control variables. That is, the key independent variable is the status of the business owner: portfolio or single business. We also use controls at the focal business, entrepreneur, and portfolio levels. At the focal business level, we control for sector, location, and size at entry (revenue in 2007). At the entrepreneur level, we control for previous entrepreneurial experience, the entrepreneur's role in the company, and his or her age. Finally, at the portfolio level, we control for portfolio age, diversification, and performance (revenue).

Dependent Variables

All the dependent variables relate to the *focal company* (new company founded in 2006). Data about all other companies are detailed in the section "Controls at the portfolio level."

The *Active* dummy variable takes a value of 1 if the focal firm survives for the entire five-year period of observation, and 0 otherwise. A firm ceases to exist in the case of voluntary dissolution or bankruptcy. We make no distinction between these two cases. The *Survival_time* variable reflects the number of years the focal firm survived. If the firm is still active at the end of the five-year period (2006–2011), it takes a value of 5. Finally, for *Revenue*, we take the log(revenue + 1) of the focal firm for a given year t.

Controls at the Focal Firm Level

We control for several characteristics of the focal firm. For *Revenues_t0*, we measure the size of the company one year after entry (i.e., log(revenue + 1) in 2007[14]), in line with prior literature that suggests initial size is a good proxy for startup quality (Arora and Nandkumar 2016). We also include *Regional dummies* to indicate the geographic location of the company, according to Italy's second NUTS administrative level (Region). The list of regions is in Appendix B. For the *Sector dummies*, we use the two-digit NACE classification (see Appendix B).

Finally, for *Entry_Costs*, we use two proxies to measure the costs required to start a business. The first measure is the average asset value of all companies entering a given sector,

[14] 347 companies exited before 2007. We do not have information about their revenue.

reflecting the resources (F) needed to start a business in that sector. This measure is exogenous to the entrepreneur's decision and represents a structural characteristic of the industry (Folta et al. 2006). As a robustness check, a second measure pertains to the asset value of the company at its entry. This second measure is not industry specific but instead reflects the entrepreneur's personal commitment to the business. The results are consistent in both cases, so we report the results using the second measure only.

Controls at the Entrepreneur Level

We use the term "entrepreneur" as synonymous with the founder and main shareholder. These actors founded their company in 2006 and keep control of it by owning a majority of equity (51% shares) or serving as its CEO. All the companies in our sample are owned by individuals, not other companies, such that we exclude any subsidiaries of established companies. For each founder, we control for the following variables:

CEO, equal to 1 if the entrepreneur who controls the company (51% shares) is also the CEO of the company and 0 otherwise.

Age of the entrepreneur, according to five classes. Members of Class 1 are 20 to 30 years of age; Class 2 is between 30 and 40 years; Class 3 is between 40 and 50 years; Class 4 is 50 to 60 years; and Class 5 indicates entrepreneurs who are older than 60 years.

Experience, or the number of companies owned by the entrepreneur from which he or she exited (whether closed or sold) before 2006.

Key Independent Variable: Portfolio

Entrepreneurs are either *portfolio* entrepreneurs, who own or are the CEOs of more than one firm at the same time, or single-business entrepreneurs, who own or are the CEOs of only one firm.

We use a dichotomous classification (0 or 1) for portfolio entrepreneurship, as has been used in previous literature (Westhead et al. 2005). The average portfolio is quite small in number (90% of entrepreneurs own three or fewer firms, and the average number of firms per entrepreneur is two). The status of an entrepreneur, in our conceptualization, also is dynamic and may vary over time. A single-business entrepreneur in 2006 might found a new company in 2008 and become a portfolio entrepreneur, which raises some classification concerns. We decided to classify entrepreneurs according to their status at the moment of the founding of the focal firm in 2006, which represents a conservative approach, because just a small fraction of entrepreneurs (4%–5%) changed their status during our 2006–2011 study period. For clarity, we removed these entrepreneurs from the sample, though to check the robustness of the findings, we also ran the analysis with the full sample and a time-varying classification of entrepreneurs. The key results did not change. Finally, to address other issues that might distort this classification, we removed all holding and management companies, as well as alleged shell corporations, as we detail in Appendix A. After these efforts, out of 6,132 entrepreneurs, 83% are classified as single-business entrepreneurs and 17% are classified as portfolio entrepreneurs. Among the single-business entrepreneurs, about half had previous entrepreneurial experience (i.e., serial entrepreneurs). It is worth noting again that our analysis focuses on portfolio entrepreneurs, rather than large business groups, such that most firms in our sample are small or medium enterprises, with an average number of employees per business of just 23.

Controls at the Portfolio Level

To isolate the effect of having a portfolio of businesses, from that of the specific characteristics of the portfolio, we adopt some control variables at the portfolio level. For each entrepreneur, we have data about all other firms owned (51% stake) or in which he or she served as CEO, creating a sample of more than 12,200 firms. For simplicity, we combine all the companies owned by the same entrepreneur, with the exception of the focal 2006 firm, into a unique variable: the portfolio of businesses owned by the entrepreneur. At the portfolio level, we thus control for *Portfolio_age*, or the difference between 2006 and the year of founding of the entrepreneur's first firm in the portfolio, as well as *Portfolio_size*, which is the sum of log(Revenue + 1) of all the firms (except the focal company) owned by the same entrepreneur in 2006. This variable offers a measure of both the past performance of the companies created by the entrepreneur and the resources available to this entrepreneur. It also might serve as a proxy of the entrepreneur's wealth. The *Portfolio_C2* variable is the sum of the shares of the two largest sectors (in terms of assets) in the portfolio, which offers a measure of the portfolio's sectoral concentration for 2006 as the reference year. By definition, all these measures apply only to portfolio entrepreneurs. A single-business entrepreneur's *Portfolio_size* would be 0, and the *Portfolio_C2* would be 1. We summarize the descriptive statistics in Table 1.

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Insert Table 1 about here
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EMPIRICAL ANALYSIS

Hypotheses 1 and 2: Exit Probability and Timing

The econometric specification[15] to test Hypotheses 1 and 2 is:

$$\begin{aligned} Active_{ij} = & \propto + \beta_1 Portfolio_j + \beta_2 Entry\_Cost_i + \beta_3 Portfolio_j * Entry\_Cost_i + \beta_4 Age_j \\ & + \beta_5 Experience_j + \beta_6 CEO_j + \beta_7 Revenue\_t0_i + \beta_8 Portfolio\_size_i \\ & + \beta_9 Portfolio\_C2_i + \beta_{10} Portfolio\_age_i + \beta_{11} Region_i + \beta_{12} Sector_i + \varepsilon_{ij} \end{aligned}$$

[15] The subscript *i* denotes variables at the focal firm level, and *j* denotes variables at the entrepreneur/portfolio level.

$$
\begin{aligned}
Time\_to\_exit_{ij} = \\
&\propto + \beta_1 Portfolio_j + \beta_2 Entry\_Cost_i + \beta_3 Portfolio_j * Entry\_Cost_i \\
&+ \beta_4 Age_j + \beta_5 Experience_j + \beta_6 CEO_j + \beta_7 Revenue\_t0_i \\
&+ \beta_8 Portfolio\_size_i + \beta_9 Portfolio\_C2_i + \beta_{10} Portfolio\_age_i + \beta_{11} Region_i \\
&+ \beta_{12} Sector_i + \varepsilon_{ij}
\end{aligned}
$$

We estimate the first model using ordinary least squares and Probit and Logit regressions; for the second model, we use a Cox survival analysis. The results are consistent across different functional specifications. Table 2 and 3 contain the results of the first and second regressions, respectively. Figure 3 provides a visual representation of the survival analysis results.

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Insert Table 2 and 3 about here
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Insert Figure 3 about here
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Portfolio entrepreneurs' new firms have 5%–12% higher probability of exit in the 2006–2011 period, and their exit (hazard) rate is 0.20 points higher. The variable Entry_Cost moderates this relationship. As expected, the survival difference between portfolio and single-business entrepreneurs' new companies increases as the amount of resources needed to start the business (F) increase. These results are consistent across different functional specifications and support Hypotheses 1 and 2: Portfolio companies are more likely to exit than single-business companies. By next investigating the mechanism explaining this higher exit rate, we test our theoretical predictions regarding the different performance thresholds for single-business and portfolio entrepreneurs.

Hypothesis 3: Portfolio Entrepreneurs and Responsiveness

Due to the positive business cycle in 2006 and 2007, most of the companies in our sample experienced moderate growth in their early years. However, the difficult business climate in 2008 and 2009 (i.e., the global financial crisis) generated a generalized drop in sales. Italian (real) gross domestic product (GDP)[16] grew 1.5% in 2006 and 2% in 2007, then dropped –1.1% in 2008 and –5.5% in 2009. Similar to Aghion et al. (2017) and Delgado et al. (2015), we consider the crisis a negative economic shock for all companies in the sample. It can be modeled as negative or low *ε(t)* in the model framework. We are interested in the intensity of the performance drop at the firm level that triggers the exit decisions of different entrepreneurs. To be consistent with our theoretical model, we measure the performance drop as the difference between the value of the company the year before exit and the initial value (2007) before the crisis. Thus, our dependent variable is $Revenue_{(\mathrm{exit\ t-1})} - Revenue\_t0$, or the company loss (or increase) in value before exit. We find no significant difference in revenues between single-business and portfolio companies in 2007, the year before the crisis. Thus, the variation in the dependent variable is mostly driven by the first term of the difference, $Revenue_{(\mathrm{exit\ t-1})}$, which represents the lower bound on the entrepreneur's performance. Table 4 contains the revenues in 2007, and a t-test confirms that there is no statistically significant difference between the two types of entrepreneurs.

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Insert Table 4 about here
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[16] These data came from IMF DataMapper.

By construction, we focus on the sample of firms created in 2006 that later exited, reducing the analysis sample to 780 firms. We control for the Exit_Year of each firm.17 Thus:

$$Revenue\_Exit_{ij} - Revenue\_t0_{ij}|Exit =$$

$$\propto + \beta_1 Portfolio_j + \beta_2 Age_j + \beta_5 Experience_j + \beta_3 CEO_j + \beta_4 Revenue\_t0_i$$
$$+ \ \beta_5 Portfolio\_size_i + \beta_6 Portfolio\_C2_i + \beta_7 Portfolio\_age_i + \beta_8 Region_i$$
$$+ \beta_9 Sector_i + \beta_{10} Exit\_Year_i + \varepsilon_{ij}$$

As the results of this analysis in Table 5 show, most of the failing companies experienced a decline in their value before ultimately exiting (the intercept of Model (1) is –0.52, so the average company experienced a performance drop of about 52% before exit18). However, the average drop in revenue of single-business entrepreneurs' companies is systematically higher than that of portfolio entrepreneurs'. In the theoretical model specification, the intercept of the regression is at $(x_{t-1} - Ꚍs(t))$, whereas the intercept plus the Portfolio coefficient is $(x_{t-1} - Ꚍp(t))$, capturing how much value is lost before exit. Figure 4 provides a visual representation of the two values for companies that exited in 2012.

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Insert Table 5 about here
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Insert Figure 4 about here
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[17] The baseline is 2010. We cannot consider companies that exited in 2009, because their $\text{Revenue}_{(\text{exit } t-1)}$= Revenue_t0.
[18] The dummy variables Exit_year_2011 and Exit_year_2012 indicate the year in which the company exited. The baseline year is 2010. The negative coefficients of both Exit_year_2011 and Exit_year_2012 indicate that the more time the entrepreneur waits to shut down the business, the more he or she loses.

These findings are consistent with our theory: Single-business entrepreneurs need to experience a stronger shock (i.e., performance decline) than portfolio entrepreneurs to trigger their exit. In other words, portfolio entrepreneurs exit at a higher level of firm performance.

Hypothesis 4: Portfolio Entrepreneurship, Selection, and Performance

The econometric specification to test Hypotheses 4 is:

$$Revenue_{ij} = \propto + \beta_1 Portfolio_j + \beta_2 Age_j + \beta_5 Experience_j + \beta_3 CEO_j$$
$$+ \beta_4 Portfolio\_size_i + \beta_5 Portfolio\_C2_i + \beta_6 Portfolio\_age_i + \beta_7 Region_i$$
$$+ \beta_8 Sector_i + \varepsilon_{ij}$$

We estimate this regression five times, one for each year. Table 6 summarizes the results; each column reports the regression in a different year (2007 to 2012).

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Insert Table 6 about here
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The results clearly show that portfolio companies do not start off as better companies. Their revenues in 2007 and 2008 are not significantly different from those of single-business entrepreneurs' companies. A performance difference only emerges over time, as the number of companies in the sample decreases, suggesting a selection effect over time. During the 2008–2009 negative business cycle, entrepreneurs shut down all the companies below the performance threshold, as presented in the previous section. However, portfolio entrepreneurs' higher performance threshold, due to their redeployment option, increased the average performance of their surviving businesses over time.

Resource Redeployment

A crucial assumption of our model is that portfolio entrepreneurs can redeploy resources across businesses, such that we anticipate resource flows from the portfolio's closing firms to surviving ones. It is difficult to observe such exchanges directly, so we propose an indirect test. Whenever a portfolio entrepreneur closes a firm, his or her remaining portfolio of businesses should experience an increase in (asset) value, due to the reallocation of resources. For this prediction, the dependent variable pertains not to the 2006 firm but rather to the portfolio, namely, *Portfolio_Asset*, which is the sum of the (log) assets of all firms owned by the entrepreneur i at time *t*, with the exception of those founded in 2006. This variable represents the resources (assets) in the entrepreneur's portfolio at any given moment of time, minus the resources allocated to the new firm (founded in 2006). By definition, single-business entrepreneurs are excluded from this analysis, because their *Portfolio_Asset* is a missing value. The dependent variable $Close\ it$ is a dummy variable with a value of 1 if entrepreneur *i* closes the 2006 firm at time *t* and 0 otherwise. Finally, we introduce a measure of resource relatedness (*Relatedness*) across firm sectors, measured by comparing the 2006 firm sector and the most representative sector (in terms of revenue) in the portfolio, according to a pairwise similarity index developed by Lee and Lieberman (2010) and Aghion et al. (2013) to define relatedness on a range from 0 to 1. It equals 1 if two sectors *i* and *j* have identical patterns of joint occurrence across all portfolios. It is 0 if the two sectors do not co-occur at all. The higher the index, the more similar (in terms of resources) the two sectors are. These descriptive statistics are summarized in Table 7.

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Insert Table 7 about here

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Finally, we run the following regression:

$$Portfolio\_Asset_{it} = \propto + \beta_1 Close_{it} + \beta_2 Relatedness_i + \beta_3 Relatedness_i * Close_{it} + \beta_4 Year_t + \beta_5 Portfolio\_Revenue_t + u_i + \varepsilon_{it}$$

In the fixed-effect panel regression, $Year$ dummies capture the year's fixed effects, and u_i is the portfolio (entrepreneur) fixed effect. Finally, we control for portfolio revenue.

As we report in Table 8, the analysis indicates that the portfolio of businesses whose proprietor closed a firm in a given year experienced an increase in asset value that same year. There is no such correlation one year before exit. Although we cannot directly observe the flow of resources from the closing firms to the portfolio, our results strongly suggest that such reinvestment exists, which provides positive evidence of redeployment. Finally, *Relatedness* increases the amount of the resources that are redeployed.

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Insert Table 8 about here

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Redeployment and Exit

The results of Hypothesis 2 and 3 show that portfolio entrepreneurs are more likely to exit, and exit faster. The results of the previous section show that portfolio entrepreneurs redeploy resources when they exit. In this section we want to investigate whether the *amount* of resources that are redeployment is related to exit. As we explained in the theoretical model, the larger the share of resources that can be redeployed, the faster (and more probable) the exit is.

The analysis involves two steps. First, we estimate the amount of resources that are redeployed from the focal company to the portfolio. Following the analysis in table 8, *Resources_Redeployed* is calculated as the difference (%) between the value of the portfolio the year in which the focal company closes and the average value of the portfolio over time. Entrepreneurs that didn't close their focal company have a *Resources_Redeployed* equal to zero. Second, we introduced the variable *Resources_Redeployed* in the original regression in table 2 and 3. The results of analysis are reported in table 9. Like in table 8, the analysis is limited to portfolio entrepreneurs.

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Insert Table 9 about here
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As expected, we found a strong and positive relationship between the amount of *Resources_Redeployed* and exit probability and speed.

ROBUSTNESS CHECKS

We performed a series of additional analyses to verify the robustness of our results. One concern is the endogeneity of the *Portfolio* variable, which we try to address in two ways. First, we use an instrumental variable (IV) for *Portfolio*. Second, we exploit the change in status (from single business to portfolio or vice versa) of some entrepreneurs over time and run a fixed-effect panel regression. In addition, to identify the mechanism that leads to the better performance of portfolio entrepreneurs over time (Hypothesis 4), we craft an artificial counterfactual to rule out alternative explanations. Finally, to support the external validity of our study, we replicate our results using a different cohort of companies and entrepreneurs.

Endogeneity of Portfolios

The possible endogeneity of our explanatory variable represents a limitation on our results. Selection into the *Portfolio* category could be driven by personal characteristics like the entrepreneur's skill, wealth, or experience (Hvide and Møen 2010), such that these variables might provide alternative explanations for our results. We take these variables partially into account with our controls for the past entrepreneurial experience of the founder and with

Portfolio_size, which reflects resources available to the entrepreneur and the past performance of his or her companies. To check for robustness, we try to address the issue of endogeneity by using an IV approach; to identify appropriate instrumental variables, we conducted three in-depth interviews with portfolio entrepreneurs. We combined this information with existing literature on portfolio entrepreneurship motivation (Iacobucci and Rosa 2010; Plehn-Dujowich 2010) to specify all possible variables that might correlate with the choice of becoming a portfolio entrepreneur but not with variables like skill, wealth, or experience. Through this process, we derived a single IV.

That is, the interviews revealed that managing a portfolio of small businesses provides some advantages over managing a single, large firm. For example, labor unions tend to be weaker if employees are scattered across several small organizations rather than concentrated in a single large company. Italian laws (e.g., Law 300/1997) even provide additional protection against firing for employees of large companies (more than 15 employees). These benefits may be relatively minor, but they can influence entrepreneurs' decisions in labor-intensive sectors located in regions with strongly unionized workforces. All else being equal, these entrepreneurs may prefer to invest in a portfolio of different businesses, instead of expanding their original firm. In this case, entrepreneurs decide to create a portfolio of businesses for reasons that are exogenous to their specific characteristics (e.g., skill). With this reasoning, we constructed our IV. First, we identified the region of origin of the *first company* created by each entrepreneur and computed the share of the population belonging to the Italian union CGIL.[19] This measure offers

[19] The Italian General Confederation of Labor (CGIL) is widely recognized as the most radical and important national trade union. It has a membership of over 5.5 million people and is currently the biggest trade union in Europe.

a proxy of the workforce unionization in that region, *Unions*. We use unionization data from 1997[20] to minimize any possible direct effect of this variable on current firm performance. Second, we combined *Unions* with another variable, *Sector_Labor*, that captures the labor intensity of the sector of the first firm founded by each entrepreneur. Labor intensity is the average number of employees over the average (log) revenues in the sector.[21] The interaction between *Unions* and *Sector_Labor* is our IV. In the first-stage regression, we control for the GDP of the first company's region,[22] to better isolate the effect of *Unions* and *Sector_Labor* on the probability of becoming a *Portfolio* entrepreneur.

This IV should correlate with the likelihood of becoming a portfolio entrepreneur, because higher workforce unionization in the region and labor intensity in the sector should give entrepreneurs stronger incentives to create a portfolio of businesses instead of one large company. We also believe this IV satisfies the exclusion restriction assumption. Because it captures variables related to the prior businesses of the entrepreneur, the unit of analysis is the first company founded, which should not have any direct effect on the focal firm's performance/survival. In other words, the IV influences the growth strategy of the entrepreneur (i.e., the decision to grow the first company or invest in different companies) without affecting the performance/survival of a focal company created in 2006. For portfolio and serial entrepreneurs, the location of the first firm often differs from the location of the 2006 focal firm; a similar difference arises in the sectors. The location/sector of the first firm coincides with the location/sector of the focal firm only among novice entrepreneurs without previous experience.

[20] Unfortunately, it is relatively hard to find unionization data at the regional level in Italy before 1997.
[21] We use data on employees and revenues to compute this variable.
[22] The regional GDP, in millions of euro, comes from the Italian National Institute of Statistics (Istat).

Therefore, we can control for the focal firm's location and sector in the main (second-stage) regression without ruling out an IV effect. Table 9 contains the IV descriptive statistics; Table 10 replicates the results for Hypotheses 2 and 3 with the IV. The analyses related to the other hypotheses are available on request.

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Insert Table 10 and 11 about here

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Consistent with our previous findings, the results of the IV regressions support Hypotheses 2 and 3. Our instrument is strongly correlated with *Portfolio*. A weak identification test (Stock-Yogo) indicates that the instrument is particularly strong (F > 11). In addition, taking the separate components of our IV (*Unions* and *Sector_Labor*) as distinct instruments, we can test for their validity using a Sargan test of overidentifying restrictions. According to these test results, we cannot reject the null hypothesis that both instruments are valid and uncorrelated with the error term.

Time-Variant Classification of Entrepreneurs

We can exploit changes in the status of some entrepreneurs to run a fixed-effect panel regression of Hypotheses 2 and 3. Only 5% of our entrepreneurs changed their status from single business to portfolio during 2006–2011, and 4% of portfolio entrepreneurs closed enough businesses to be considered single-business entrepreneurs at the end of the period. Overall, the share of entrepreneurs who changed status is small, yet even in this small sample, our finding that portfolio entrepreneurs are more likely to exit continues to receive support[23].

[23] The results of this analysis are available on request.

Counterfactuals

With another analysis, we attempt to show that the selection effect explains the performance differences between portfolio and single-business entrepreneurs (Hypothesis 4). Single-business entrepreneurs continue to operate companies with cash flow $Ʈs(t) \leq x_t \leq\ Ʈp(t) - Ʈs(t)$, but portfolio entrepreneurs do not. If portfolio and single-business entrepreneurs were to adopt the same threshold $Ʈ(\mathrm{t})$, we anticipate no performance difference between their companies. To reproduce this notion in the counterfactual, we force all entrepreneurs to exit when they accumulate a loss in value equal to or lower than the portfolio threshold $Ʈ\mathrm{p}(\mathrm{t})$. To define this threshold, we use the results from Table 5. The intercept α of the model offers a proxy of $(x_{t-1} - Ʈ\mathrm{s}(\mathrm{t}))$, and the intercept plus the coefficient *Portfolio* is a proxy of $(x_{t-1} - Ʈ\mathrm{p}(\mathrm{t}))$. Remember that $(x_{t-1} - Ʈ(\mathrm{t}))$ represents the cumulative drop in performance needed to trigger the exit decision. To develop a common exit rule for everyone, we replace the revenue of a company with a missing value if that company experienced a loss equal to or greater than $(x_{t-1} - Ʈ\mathrm{p}(\mathrm{t}))$ in the previous year. Thus, we force the single-business entrepreneurs to behave like portfolio entrepreneurs. Figure 5 provides a visual representation of the new threshold value.

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Insert Figure 5 about here
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Finally, we run a regression identical to the one used to test Hypothesis 4, with a different dependent variable, $HRevenue$, that represents the hypothetical value of the company in the counterfactual. It is equal to the actual value of the firm’s revenue ($Revenue$) if the firm did not experience a drop in value in the previous year equal to or higher than $(x_{t-1} - Ʈ\mathrm{p}(\mathrm{t}))$, our common threshold. Otherwise, $HRevenue$ is equal to a missing value (due to exit). As a baseline model, we used the estimates of $(x_{t-1} - \text{Ꚍp}(t))$ in the first regression of Table 4,[24] which are average values and represent simply an approximation of $(x_{t-1} - \text{Ꚍp}(t))$. As a robustness check, we also tried different threshold values.[25] We report the results in Table 12.

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Insert Table 12 about here
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The findings suggest that the different reactions of entrepreneurs to negative market signals explain much of the performance difference observed over time. If we exclude extremely underperforming businesses that single-business entrepreneurs "refuse" to close (in the counterfactual, we force them to exit), we find barely any performance difference between portfolio and single-business companies over time.

Replication

Finally, our study relies on a cohort of firms founded in Italy in 2006. To check the robustness of the results, we replicated our analysis using a different cohort of 7,000 firms founded in Italy in 2003. The key results are perfectly replicated with this different sample.[26]

CONCLUSION AND DISCUSSION

The key advantage of portfolio entrepreneurs appears to be their ability to reinvest resources across businesses, which facilitates exit and triggers a faster reaction to negative market signals. This faster reaction can explain why portfolio entrepreneurs' surviving firms perform better than

[24] That is, every company is forced to exit if it experiences a performance drop equal to +0.20 in 2010, –0.30 in 2011, and –0.70 in 2012
[25] Minus or plus one standard deviation.
[26] The results of this analysis are available on request.

other companies, though only after the (ex post) selection occurs. We find support for all our hypotheses, and our results are robust to different functional specifications, methodologies, and measures. We also apply an IV approach to resolve potential problems of endogeneity. The outcomes of these exercises show that our results are robust even when we take into account the idiosyncratic characteristics of our entrepreneurs.

This article accordingly contributes to entrepreneurship literature in several respects. First, we show that the potential to redeploy resources crucially shapes an entrepreneur's business continuation decision and reaction to negative market feedback. The survival of a firm thus relates strictly to the entrepreneur-specific performance threshold (Gimeno et al. 1997). This finding might suggest the need for a change in the perspective used to design public policies to encourage entrepreneurship. Policy makers traditionally worry about low survival rates (Cader and Leatherman 2009; Westhead et al. 2003), so researchers tend to seek proposed solutions to reduce them. Our results suggest that an equally important problem is the survival of systematically underperforming businesses (mostly owned by single-business entrepreneurs). Instead of simply trying to increase the survival of new firms, policy makers should implement efforts to facilitate exit for poorly performing companies (e.g., reducing damage due to failure).

Second, we seek to address some crucial determinants of new firm survival and success. Previous literature indicates that entrepreneurs who run more businesses at the same time produce better performing companies (Westhead et al. 2005) but has not specified the sources of this performance gap. Whereas most literature highlights entrepreneurs' experience as a main explanatory variable (Gottschalk et al. 2009; Sarasvathy et al. 2013), we suggest that a substantial part of the gap can be explained by their different performance thresholds, which result from their capacity to redeploy resources.

Third, we extend intertemporal economies of scope theory in this article (Helfat and Eisenhardt 2004; Lieberman et al. 2016). Our results show that this theory can serve to explain exit decisions by portfolio entrepreneurs.

It also is pertinent to acknowledge some limitations of the current study. We define entrepreneurs as people who own the majority stake in a company or are its CEO. We do not know whether or to what extent these entrepreneurs own minority shares in other companies. Similarly, we identify only companies that are controlled directly by the entrepreneurs in our sample, without determining whether those entrepreneurs control companies indirectly. Our focus on direct control reflects the complexity of doing otherwise. Ultimately though, we believe these limitations do not challenge the validity of our results, and we hope continued research will address them.

Figure 1. Performance Lower Bound (Theoretical Prediction)

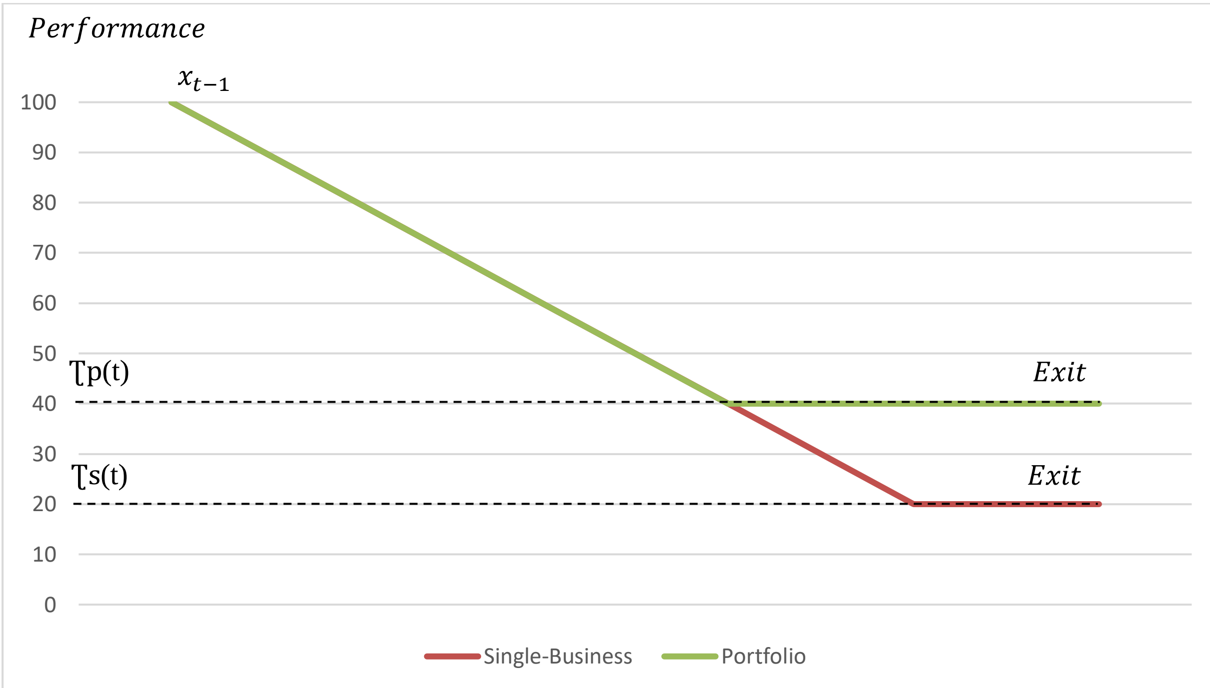

Figure 2. Data Gathering Process

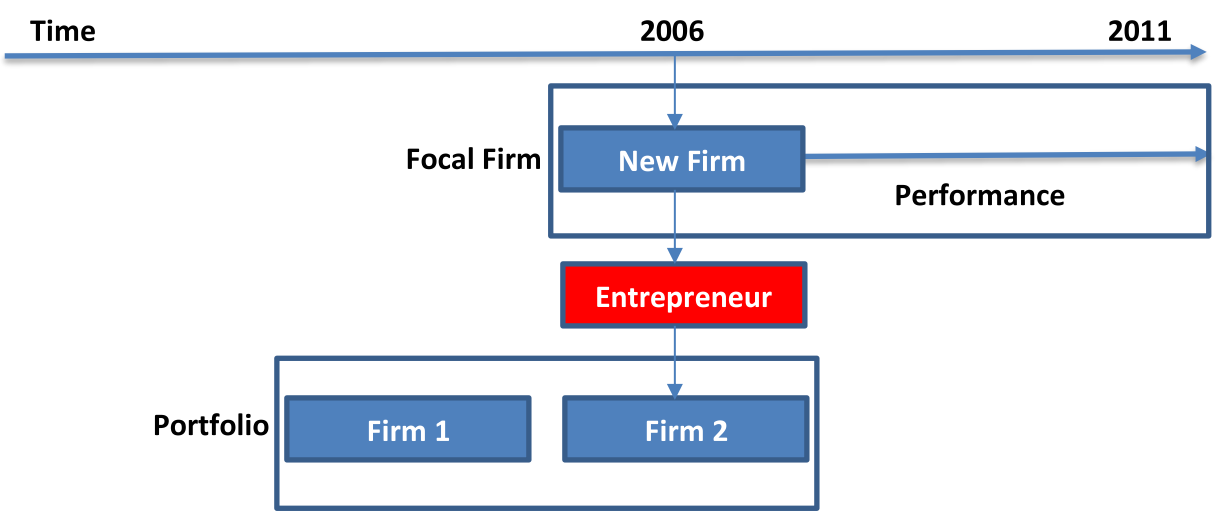

Figure 3. Survival Curves by Entrepreneur Type

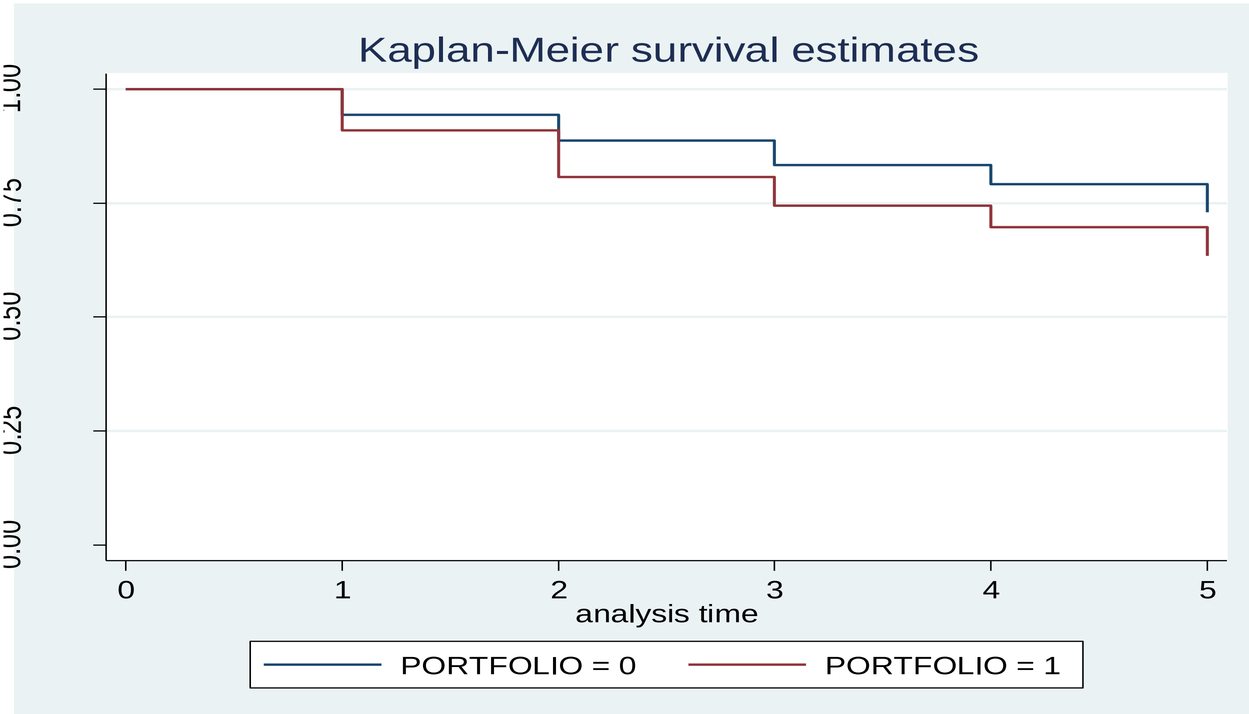

Figure 4. Average Cumulative Decline in Performance (exits in 2012)

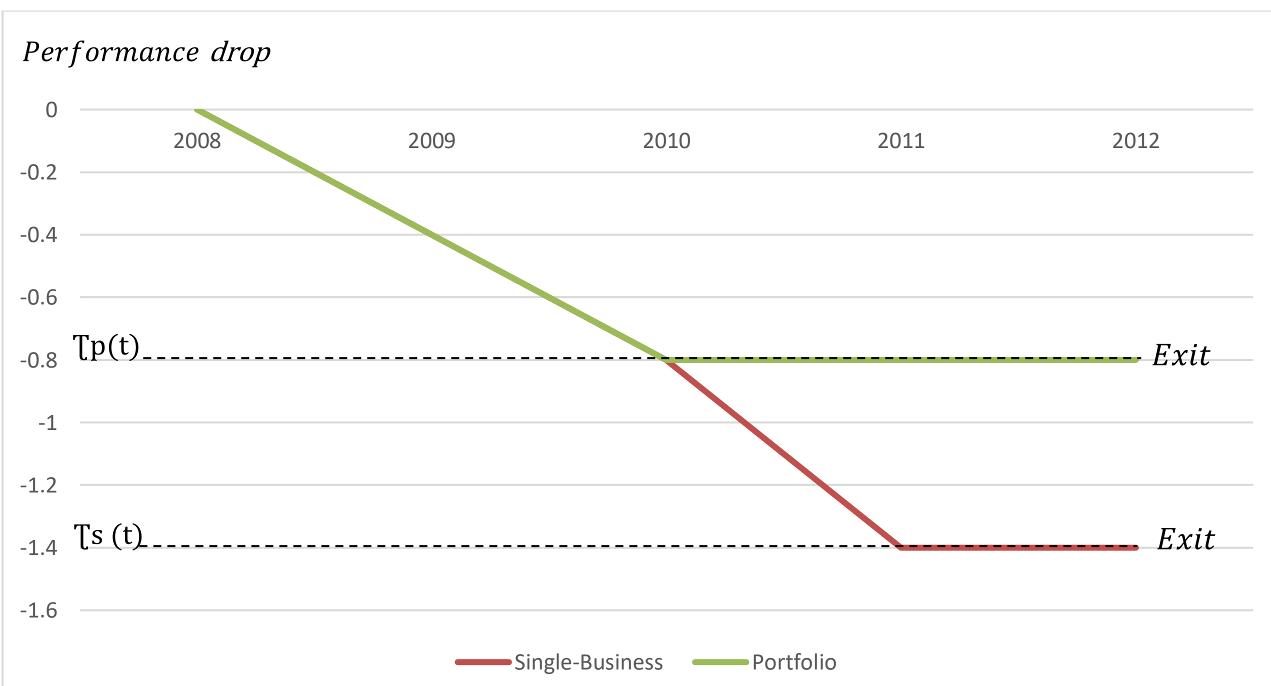

Figure 5. Common Threshold in the Counterfactual (exits in 2012)

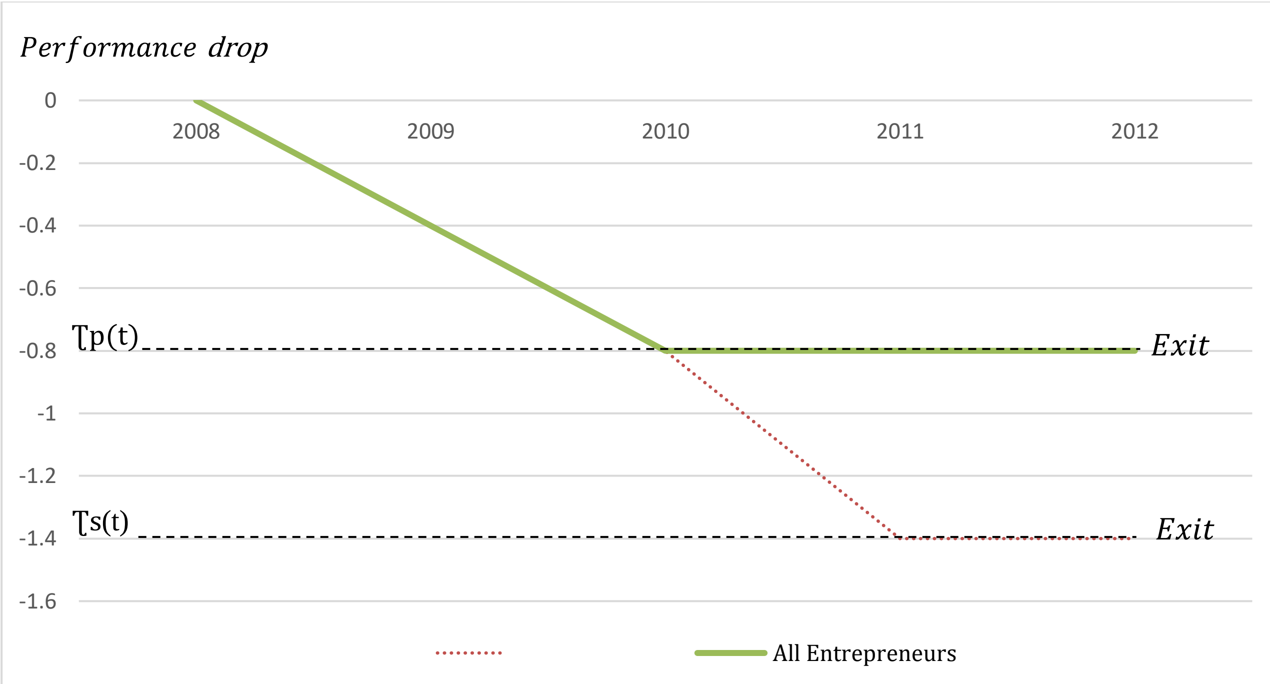

Table 1. Descriptive Statistics and Correlation Matrix

	Unit of Analysis	Mean	Std.Dev.
Revenue	Focal Company	11.75	3.768
Entry_Cost	Focal Company	12.28	0.590
Active	Focal Company	0.682	0.465
Lifetime	Focal Company	4.024	1.581
Age	Entrepreneur	3.531	1.193
Experience	Entrepreneur	0.670	2.056
CEO	Entrepreneur	0.605	0.488
Portfolio	Entrepreneur	0.172	0.378
Portfolio_age	Portfolio	4.113	9.852
Portfolio_size	Portfolio	4.151	13.81
Portfolio_C2	Portfolio	0.930	0.176

	1	2	3	4	5	6	7	8	9	10	11
Revenue	1										
Entry_Cost	0.6106	1									
Active	0.0878	0.0770	1								
Lifetime	0.1548	0.1183	0.6853	1							
Age	0.0231	0.0846	0.0001	0.0629	1						
Experience	0.0040	0.1434	-0.0738	-0.0890	0.0878	1					
CEO	-0.0188	-0.0581	0.0332	-0.0271	-0.3396	-0.0810	1				
Portfolio	0.0006	0.1450	-0.0877	-0.1072	0.0613	0.3438	-0.0771	1			
Portfolio_age	0.0202	0.1957	-0.0941	-0.0971	0.1626	0.5343	-0.0896	0.4516	1		
Portfolio_size	0.0406	0.2290	-0.0837	-0.1035	0.0664	0.6314	-0.0804	0.6339	0.5489	1	
Portfolio_C2	-0.0001	-0.1409	0.0863	0.1026	-0.0475	-0.5261	0.0767	-0.6237	-0.4582	-0.7783	1

Table 2. Focal Firm Survival Probability (ordinary least squares regression coefficients)

VARIABLES	(1) Active	(2) Active	(3) Active
Portfolio	-0.0978***	-0.0472*	0.299**
	(0.0163)	(0.0256)	(0.128)
Entry_Cost			0.0374***
			(0.00573)
Portfolio*Entry_Cost			-0.0287***
			(0.0102)
Age		0.00388	0.00176
		(0.00521)	(0.00519)
Experience		-0.00916**	-0.0103**
		(0.00440)	(0.00444)
CEO		0.0210	0.0209
		(0.0129)	(0.0129)
Revenue_t0		0.0134***	0.00455*
		(0.00202)	(0.00253)
Portfolio_size		0.00140	0.00157
		(0.00101)	(0.00100)
Portfolio_age		-0.00123	-0.00109
		(0.00102)	(0.00103)
Portfolio_C2		0.0829	0.101
		(0.0667)	(0.0669)
Constant	0.711***	0.969***	0.638***
	(0.00636)	(0.109)	(0.192)
Region Dummies	No	Yes	Yes
Sector Dummies	No	Yes	Yes
Observations	6,132	5,785	5,785
R-squared	0.012	0.053	0.070

Notes: Robust standard errors are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3. Focal Firm Time_to_Exit (Cox survival model coefficients)

VARIABLES	(1) t	(2) t	(3) t
Portfolio	0.386***	0.218**	-1.382***
	(0.0560)	(0.0948)	(0.463)
Entry_Cost			-0.186***
			(0.0248)
Portfolio*Entry_Cost			0.135***
			(0.0372)
Age		-0.0366	-0.0189
		(0.0225)	(0.0225)
Experience		0.0316**	0.0291**
		(0.0133)	(0.0138)
CEO		-0.0810	-0.0718
		(0.0553)	(0.0559)
Revenue_t0		-0.0543***	-0.0195**
		(0.00676)	(0.00947)
Portfolio_size		-0.00524	-0.00708**
		(0.00323)	(0.00334)
Portfolio_age		0.00356	0.00442
		(0.00365)	(0.00376)
Portfolio_C2		-0.290	-0.450*
		(0.237)	(0.239)
Region Dummies	No	Yes	Yes
Sector Dummies	No	Yes	Yes
Observations	6,132	5,785	5,785

Notes: Robust standard errors are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4. Two-Sample t-Test for Portfolio and Single Business Entrepreneurs' Company Revenues in 2007

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
Single-Business	4,844	11.827	.0445894	3.103097	11.74006	11.9149
Portfolio	941	11.893	.1223393	3.752847	11.65291	12.1330
Difference		-.0655	.1146369		-.2902517	.159210

Ha: diff != 0 Pr(|T| > |t|) = 0.5677

Table 5. Focal Firm Performance Drop and Exit (OLS regression coefficients)

VARIABLES	(1) Revenue_(exit- t0)	(2) Revenue_(exit- t0)	(4) Revenue_(exit- t0)
Portfolio	0.753**	1.269***	1.382***
	(0.307)	(0.365)	(0.352)
Age		-0.172*	-0.205**
		(0.0867)	(0.0787)
Experience		0.150**	0.198***
		(0.0557)	(0.0440)
CEO		0.627**	0.737***
		(0.250)	(0.204)
Revenue_t0		-0.337***	-0.371***
		(0.0490)	(0.0657)
Portfolio_size		-0.0165	-0.0289**
		(0.0124)	(0.0132)
Portfolio_age		-0.350	-0.241
		(0.895)	(0.975)
Portfolio_C2		-0.0158**	-0.0118*
		(0.00713)	(0.00656)
Exit_year_2011	-0.506*	-0.547*	-0.537**
	(0.263)	(0.277)	(0.192)
Exit_year_2012	-0.903***	-0.944***	-0.920***
	(0.260)	(0.236)	(0.226)
Constant	-0.520***	4.040***	2.411*
	(0.188)	(0.783)	(1.376)
Region Dummies	No	No	Yes
Sector Dummies	No	No	Yes
Observations	780	780	780
R-squared	0.019	0.134	0.212

Notes: Robust standard errors are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6. Focal Firm Performance over Time (OLS)

	(1)	(2)	(3)	(4)
VARIABLE	Revenue_2008	Revenue_2009	Revenue_2010	Revenue_2011
Portfolio	0.0663	0.588***	0.548**	0.624**
	(0.192)	(0.197)	(0.227)	(0.248)
Age	-0.0168	-0.120***	-0.207***	-0.269***
	(0.0392)	(0.0447)	(0.0508)	(0.0567)
Experience	0.0676*	0.0719*	0.0774*	0.123**
	(0.0390)	(0.0386)	(0.0448)	(0.0538)
CEO	0.0544	0.0735	0.191	0.205
	(0.0952)	(0.108)	(0.120)	(0.136)
Portfolio_size	0.00515	0.0134*	0.0164*	0.0234**
	(0.00696)	(0.00807)	(0.00878)	(0.00988)
Portfolio_age	-0.159	-0.292	-0.411	0.301
	(0.515)	(0.528)	(0.571)	(0.685)
Portfolio_C2	3.39e-05	-0.0144*	-0.00962	-0.0133
	(0.00705)	(0.00827)	(0.00869)	(0.0101)
Constant	14.55***	14.99***	15.69***	15.28***
	(0.994)	(0.878)	(0.827)	(0.918)
Region Dummies	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes
Observations	5,399	4,995	4,610	4,237
R-squared	0.074	0.068	0.077	0.081

Notes: Robust standard errors are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Portfolio_Asset_t	4,009	33.868	33.908	2.708	369.878
Portfolio_Revenue_t	4,009	23.028	22.345	0	219
Close_t	4,009	0.1489	0.3560	0	1
Relatedness*Close_t	4,009	0.00053	0.0083	0	0.5

Table 8. Resource Redeployment (fixed-effect panel regression coefficients)

VARIABLES	(1) Portfolio_Asset	(2) Portfolio_Asset	(3) Portfolio_Asset
Close	2.624***	2.320***	1.932**
	(0.851)	(0.845)	(0.839)
Relatedness*Close			91.53***
			(13.40)
Portfolio_Revenue		0.727***	0.783***
		(0.0967)	(0.0957)
Constant	33.48***	17.75***	16.85***
	(0.127)	(2.277)	(2.164)
Year Dummies	No	Yes	Yes
Portfolio Fixed effect	Yes	Yes	Yes
Observations	4,009	4,009	4,009
R-squared	0.003	0.142	0.151
Number of E_id	1,035	1,035	1,035

Notes: Robust standard errors are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9. Redeployment and Exit (OLS and Cox survival model coefficients)

VARIABLES	(1) Active	(2) t
Resources_Redeployed	-0.191**	0.620**
	(0.0821)	(0.293)
Age	0.0109	-0.0441
	(0.0159)	(0.0587)
Experience	0.00406	-0.0103
	(0.00557)	(0.0187)
CEO	0.0415	-0.103
	(0.0334)	(0.125)
Revenue_t0	0.00641	-0.0254*
	(0.00441)	(0.0152)
Portfolio_size	0.000355	-0.00378
	(0.000963)	(0.00364)
Portfolio_age	-0.000531	0.00341
	(0.00119)	(0.00450)
Portfolio_C2	0.0976	-0.426
	(0.0744)	(0.273)
Constant	0.821**	
	(0.365)	
Region Dummies	Yes	Yes
Sector Dummies	Yes	Yes
Observations	941	941
R-squared	0.117	

Notes: Robust standard errors are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 10. Instrumental Variable Descriptive Statistics

Variable	Unit of Analysis	Obs	Mean	Std. Dev.	Min	Max
Unions	First Firm	6132	0.090	0.038	0.051	0.182
Sector_Labor	First Firm	6132	1.129	1.223	0	9.034
IV (interaction)	First Firm	6132	0.102	0.128	0	1.408
Region_GDP	First Firm	6132	114,620	73,637	3,000	246,000

Table 11. Focal Firm Survival Probability (2SLS regression coefficients)

VARIABLES	(1) Active	(2) Portfolio	(3) Lifetime	(4) Portfolio
Portfolio	-0.209***		-0.750***	
	(0.0653)		(0.1836)	
Age	0.00360		0.0602***	
	(0.00516)		(0.0145)	
Experience	-0.00851**		-0.0370***	
	(0.00400)		(0.0112)	
CEO	0.0179		-0.0576	
	(0.0129)		(0.0362)	
Revenue_t0	0.0138***		0.0615***	
	(0.00189)		(0.00531)	
Region_GDP	6.15e-06*		2.20e-05**	
	(3.32e-06)		(9.33e-06)	
IV		4.089***		4.089***
		(0.159)		(0.159)
Constant	0.779***	-1.150***	4.483***	-1.150***
	(0.139)	(0.0249)	(0.734)	(0.0249)
Region Dummies	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes
Observations	5,785	5,785	5,785	5,785

Notes: Robust standard errors are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 12. Counterfactual (ordinary least squares regression coefficients)

VARIABLES	(1) HRevenue_2007	(2) HRevenue_2008	(3) HRevenue_2009	(4) HRevenue_2010	(5) HRevenue_2011
Portfolio	-0.0233	0.0411	0.197	0.0398	0.0266
	(0.185)	(0.185)	(0.155)	(0.190)	(0.223)
Age	0.0563	-0.0365	-0.0329	-0.0436	-0.0194
	(0.0359)	(0.0392)	(0.0353)	(0.0405)	(0.0482)
Experience	-0.0569	0.0559	0.0577	0.0164	0.0265
	(0.0599)	(0.0374)	(0.0403)	(0.0464)	(0.0755)
CEO	0.0741	0.0533	-0.0382	-0.0523	-0.0338
	(0.0893)	(0.0945)	(0.0791)	(0.0906)	(0.103)
Portfolio_size	0.0149**	0.00150	0.00422	0.00799	0.00796
	(0.00722)	(0.00652)	(0.00603)	(0.00800)	(0.00985)
Portfolio_age	-0.276	-0.312	-0.557	-0.750	-0.690
	(0.562)	(0.470)	(0.414)	(0.480)	(0.468)
Portfolio_C2	0.00249	0.00293	-0.00639	-0.00475	-0.0115
	(0.00680)	(0.00652)	(0.00481)	(0.00778)	(0.00887)
Constant	4.344	12.92***	14.73***	15.46***	15.85***
	(3.872)	(1.112)	(1.118)	(1.157)	(1.130)
Region Dummies	Yes	Yes	Yes	Yes	Yes
Sector Dummies	Yes	Yes	Yes	Yes	Yes
Observations	5,785	5,722	3,100	2,070	1,511
R-squared	0.107	0.072	0.115	0.132	0.140

Notes: Robust standard errors are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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Appendix A

In some cases, entrepreneurs create different companies (legal entities) for strategic goals that have nothing to do with seizing a new business opportunity. First, different ventures do not necessarily imply different businesses. Therefore, we remove from the analysis all the 2006 firms that are in the same sector as any other active firm owned by the same entrepreneur, such that we exclude undifferentiated portfolios. Second, though by definition the companies in the portfolio are in different sectors, some might have been designed to run "unproductive" activities, like managing the resources of other companies (e.g., holding companies). We accordingly removed all companies belonging to the following sectors: Business Administration, Real Estate, Financial Services, and all generic service companies. Third, some companies might be shell corporations, designed primarily to lower or avoid taxes. We followed the guidelines provided by the Italian financial police (Guardia di Finanza), which identify a company as a "shell company" (Società di Comodo) if its "expected operating revenues," estimated using the assets available, are much lower than its actual ones. The rules to compute the expected operating revenues of a company given its assets are detailed, based on the intuition that companies with an extremely low level of revenue in comparison with their available assets are more likely to be non-operating or shell corporations. We adopt these criteria and remove any alleged shell companies. The main results are robust to alternative definitions of portfolio entrepreneurs though; they do not change even if we ignore all these modifications and define a portfolio entrepreneur simply as someone who owns more than one company. The results of this alternative analysis are available on request.

Appendix B

Italian Region	Frequency	Percentage
ABRUZZO	141	2.30
BASILICATA	39	0.64
CALABRIA	62	1.01
CAMPANIA	487	7.94
EMILIA ROMAGNA	587	9.57
VENEZIA GIULIA	125	2.04
LAZIO	702	11.45
LIGURIA	109	1.78
LOMBARDIA	1260	20.55
MARCHE	239	3.90
MOLISE	18	0.29
PIEMONTE	423	6.90
PUGLIA	325	5.30
SARDEGNA	89	1.45
SICILIA	233	3.80
TOSCANA	490	7.99
TRENTINO ALTO ADIGE	77	1.26
UMBRIA	92	1.50
VALLE D'AOSTA	6	0.10
VENETO	628	10.24
Total	6,132	100.00

Sector	Freq.	Percent
Agriculture and fishing		
Agriculture and fishing	170	0.028
Mining and quarrying	5	0.008
Total	**175**	**0.029**
Manufacturing		
Manufacture of fabricated metal products	879	0.143
Manufacture of machinery and equipment	352	0.057
Manufacture of food products	254	0.041
Manufacture of other chemical products	226	0.037
Manufacture of furniture	184	0.030
Manufacture of leather and related products	171	0.028
Manufacture of electrical equipment	170	0.028
Manufacture of wood and of products of wood	160	0.026
Manufacture of rubber and plastic products	153	0.025
Manufacture of computer, electronic and optical products	138	0.023
Manufacture of textiles	120	0.020
Other manufacturing	113	0.018
Manufacture of other transport equipment	108	0.018
Manufacture of motor vehicles, trailers and semi-trailers	50	0.008
Manufacture of paper and paper products	37	0.006
Manufacture of machinery for metallurgy	34	0.006
Manufacture of beverages	26	0.004
Manufacture of chemicals and chemical products	13	0.002
Manufacture of basic pharmaceutical products	12	0.002
Manufacture of coke and refined petroleum products	3	0.000
Manufacture of tobacco products	2	0.000
Total	**3205**	**0.523**
Services		
Architectural and engineering activities	736	0.120
Advertising and market research	411	0.067
Other professional and scientific activities	345	0.056
Repair and installation of machinery and equipment	291	0.047
Packaging activities	171	0.028
Printing and reproduction of recorded media	162	0.026
Legal and accounting activities	138	0.023
Scientific research and development	103	0.017
Retail trade (except of motor vehicles)	67	0.011
Construction	56	0.009
Other services	47	0.008
Wholesale trade (except of motor vehicles)	31	0.005
Business support service activities	23	0.004
Electric power generation, transmission and distribution	18	0.003
Specialized construction activities	17	0.003

Information service activities	17	0.003
Software publishing	12	0.002
Transporting and storage	12	0.002
Sports activities and amusement and recreation activities	12	0.002
Pre-press and pre-media services	12	0.002
Human health activities	11	0.002
Wholesale and retail trade; repair of motor vehicles and motorcycles	10	0.002
Veterinary activities	8	0.001
Civil engineering	7	0.001
Education	5	0.001
Telecommunications	5	0.001
Travel agency activities	5	0.001
Hotels and similar accommodation	4	0.001
Waste collection, treatment and disposal activities	4	0.001
Motion picture, video and television programming activities	3	0.000
Waste treatment and disposal	2	0.000
Employment activities	2	0.000
Services to buildings and landscape activities	2	0.000
Gambling and betting activities	2	0.000
Repair of computers and personal and household goods	1	0.000
Security and investigation activities	1	0.000
Total	**2752**	**0.448**
Grand Total	**6132**	**1.000**

Chapter 3:

Demand-Side Disruption: Evidence from the US Mobile Dating Application Industry[27]

ABSTRACT

The theory of disruption has made a profound effect on innovation management literature and practice. Disruption process initiates by newcomers that introduce improvements in performance dimensions that are not relevant for the mainstream market. This process, if is successful, can result in a shift in the consumption behavior of the mass market and eventually in displacement of incumbents by new entrants. While prior research has enhanced our understanding of the disruption process, it tends to focus on improvements in more visible performance dimensions –e.g., change in the size of the disk drive or shift from film to digital pictures. More recent development of the theory of disruption, however, has pointed to disruptive forces that emerge from latent performance dimension –e.g., social aspect of consuming a product in addition to its observable benefit. The aim of this paper is to empirically explore the latent performance dimensions that can drive consumption and result in disruption. Drawing on the context of the U.S dating app industry from 2011 to 2015, our paper explores why incumbents tend to overlook a potentially large market segment and how newcomers can disrupt the industry through improving the product along overlooked dimensions. Our empirical analysis is based on the text analysis of user-generated app reviews as a novel way to capture latent product dimensions that are crucially important for demand-side.

[27] This chapter represents a paper coauthored with Niloofar Abolfathi.

The most exciting phrase to hear in science, the one that heralds new discoveries, is not "Eureka!" [I found it] but "That's funny …"

–Isaac Asimov

Introduction

In November 2004, Guinness World Records recognized Match.com as the largest online dating site in the world. At the time, more than 42 million singles globally had registered on Match.com since its launch in 1995. Because of its first-mover advantage as well as its strong network externalities, the company made a successful transition from the desktop to the phone screen and launched its first mobile application in March 2010, retaining its leading position in the mobile dating application market. At the end of 2012, however, a new startup –namely Tinder– entered the market, and after a few months became the undisputed market leader. After more than ten years of dominance, Match.com's market share plummeted to the level of an also-ran.

The topic of incumbents' displacement by new entrants has an important place in the innovation management literature (Christensen and Bower 1996). Prior research documented how new technologies can be competence-destroying (Dosi 1982, Tushman and Anderson 1986) or require substantial organizational rearrangements for incumbents to survive (Henderson and Clark 1990). While extant research has enhanced our understanding on how markets are disrupted, it has been mainly dominated with a resource-based perspective in studying firm superior performance in disruption events. Recent studies, instead, show that newcomers can exploit customer heterogeneity to achieve competitive advantage (Priem et al., 2013; Ye, Priem, and Alshwer, 2012, Adner 2002). Despite its unprecedented importance in the innovation management literature, we know less how a demand-side approach can contribute to explaining the incumbents' displacement. The goal of this paper is to take a demand-side perspective in exploring the fundamental drivers of disruption.

A demand-side approach to innovation management, entrepreneurship, and strategic management (Priem, Li, and Carr 2012) emphasizes the importance of firm's knowledge about customers (Yli-Renko, Autio and Sapienza 2001), instead of its resources and capabilities, as one of the main sources of sustainable competitive advantage. According to this view, "opportunity-rich, resource-poor" entrepreneurs (Priem et al. 2012) can displace large incumbents thanks to a better understanding of "unmet" customer needs. Christensen's theory of disruption is built on similar premises about the role of demand environment in disruption events (Christensen and Bower 1996; Christensen, Raynor, and McDonald 2015). The main theoretical mechanism behind industry shakeout based on Christensen's theory is that disruptive innovation can reveal previously unknown customer heterogeneity inherent in market segments (Adner 2002; Adner and Snow 2010). Such customer heterogeneity has been also documented in prior research on formalizing a demand-side perspective to disruptive innovation.

In this paper, we set out to unpack the driving forces behind disruptive innovation by showing how an improvement in performance dimensions that are extremely important for demand-side can result in the displacement of incumbents. We show that disruptive innovations are not radical because they are generally superior to previous technologies –they are better technologies only along some performance dimensions that are important for some customers. The art of a successful disruptor is to identify performance dimensions that are crucial for potential customers and improve such dimensions to transform consumption behavior. Emerging theories in the innovation management literature highlight entrepreneur's ability to understand and address "user problems" that were neglected by incumbents as key drivers of success (Christensen, Dillon, Hall, and Duncan 2016).

We undertake an in-depth analysis of the mobile dating application market to illustrate the importance of including the demand-side elements of firm positioning in explaining industry evolution. In this setting, the main "user problem" was the embarrassment in spreading information on a socially stigmatized product (Hudson and Okhuysen 2009; Vergne 2012). Even if companies could manage to acquire new users, it was hard to reach a critical mass, as users were hesitant to share any ideas about their experience with others. Such social stigma was particularly relevant for people interested in using apps designed for casual dating –chatting with or meeting other people without a serious intention to find a lifetime partner. Popularizing dating as a social game with a focus on the *fun* and *entertaining* aspects of the experience, new entrants like Tinder substantially reduced the social stigma associated with short-term dating and ignite word of mouth in a previously poorly attracting market segment. Through improving the product along an overlooked performance dimension –i.e., *fun/entertaining*– newcomers found a way to benefit from the inherent heterogeneity in the demand environment and eventually disrupt the dating industry.

To provide empirical evidence of the underlying mechanisms behind the disruption in the mobile dating industry, we collected a unique database of dating apps released on the Apple Store from 2007 to 2015. One of the main novelties of this paper is to build on the text analysis (Kaplan and Vakili 2015; Büschken and Allenby 2016) of customers' reviews to classify the key performance dimensions of each app in the market. In this way, we are able to empirically test the demand-side elements that contribute to a disruption event.

Our paper provides several contributions to the literature on innovation and technology management. The text analysis of customer reviews allows us to empirically test the theoretical mechanisms behind the macro phenomenon we observe –disruption in the dating industry. Our analysis reveals three important aspects of the theory of disruption that have gained little attention by previous studies. First, new entrants can improve the product's performance along dimensions that are not necessarily technological, but provide customers with new *experiences*. Prior research has been mainly theorizing on disruption with a focus on technical dimensions or "technology" more in general (Christensen and Bower 1996; Adner 2002; Adner and Zemsky 2006). In this study, we theorize and elaborate on overlooked product dimensions that can drive consumption and eventually result in disruption of markets.

Second, our study also contributes to the literature on incumbents' failure to respond to disruption. In particular, this paper provides additional evidence on why incumbents ignore some market segments in which disruption could take place. The theory of disruption argues that incumbents do not pay much attention to where disruption initially happens, –i.e., in the low-end of the market or insignificant segments that are less profitable. Our findings, instead, shows that small market size is not the only reason that incumbents ignore such market segments. In the context of the online dating market, for instance, the main barrier to serve the short-term market was not the fringe of few customers in this market, but the social stigma associated with that. Indeed, new entrants that overcame the social stigma could access a profitable, underexploited market.

Third, our analysis shows that revealing customer heterogeneity is the key disruption driver (Adner 2002). A fundamental question for each firm is how to position itself within an industry (Porter 1980, 1996; Levinthal 2016). Important in this regard is that the choices of product configurations and market segments are extremely interrelated (Adner et al. 2014). Incumbents might ignore a potentially large segment simply because people in that segment are not consuming the product at all, given the current product configuration. A substantial improvement along a new performance dimension is necessary to bring these people into the consumption zone. In this regard, close managerial attention is required to make improvements in performance dimensions that despite being latent can drive consumption. Finally, building on the literature on social stigma (Hudson and Okhuysen 2009; Vergne 2012), our study suggests successful strategies to reduce stigma in affected markets. The wave of new players in the mobile dating industry was successful to mitigate the social stigma associated with the short-term dating market and to effectively transform many non-customers into users.

This paper is structured as follows. First, we review the relevant literature. Second, we take an inductive approach and explain the evolution of the dating industry from 2007 to 2015, with particular attention to the 2013-2014 period where disruption started to take place. Third, we derive hypotheses concerning the theoretical mechanisms behind the industry shakeout. Next, we introduce our database that is used to empirically test the hypotheses. Finally, we discuss our results and their theoretical and managerial implications.

Theoretical Background

The resource-focused approaches to firm competitive advantage and performance have attracted significant scholarly attention in the strategic management literature. A nascent body of literature, however, has emphasized how a demand-side perspective to the firm's value system, in addition to the dominant resource-based view, can explain firm superior performance (Priem, Li, and Carr 2012). This stream of literature points to "downstream from the focal firm, toward product markets and consumers" (Priem, Li, and Carr, 2012: 346) elaborating on value creation for (or with) customers before value capture for upstream companies (Priem 2007) to guarantee the firm's very survival. In this regard, failing to perceive or inability to address heterogeneous customer needs can result in firm's displacement. This demand-side perspective to competition is at the core of the theory of disruption introduced by Christensen (1996; 2015). Disruption refers to a process through which a smaller company with limited resources successfully challenges large incumbents that are focused on their existing and most profitable customers. Incumbents tend to improve their products and services along performance dimensions that are appealing to the mainstream market and overlook dimensions relevant for some other market segments (or consider them as secondary). Disruption typically occurs when the mainstream market starts appreciating the dimension offered by a new entrant and changes its consumption behavior. The pharmaceutical giant, Eli Lilly, for example, significantly lost its dominant position in the worldwide insulin market to a more convenient type of insulin treatment introduced by Novo Nordisk. The new insulin pen introduced by the competitor was well-received by the market as it was a remarkable improvement in a performance dimension that was critical for customers who take insulin, yet overlooked by Eli Lilly –the convenience of injection (Christensen 2004).

Studies on disruption following Christensen's initial work explores incumbents' optimal reaction to disruptive new entrants. Adner and Snow (2010), for example, identify a "retreat strategy" through which incumbents can turn the threat of disruptive technologies into opportunities building on the demand environment. This retreat strategy can include retrenchment through targeting a new niche market with the old technology or applying the old technology in a new use. The crux of this demand perspective to innovation management is that firms facing disruptive innovation can benefit from the heterogeneity in customers' preferences, and therefore, apply the existing technology in a different demand setting. Seamans and Zhu suggest that the nature of incumbents' reaction to disruption depends on the demand structure. In their paper, they show that after the entry of Craigslist in the US, a newspaper is more likely to engage in repositioning strategies –through changing its content– when reader preferences are heterogeneous. On the contrary, when reader preferences are homogeneous, newspapers are more likely to respond to the new entrant threat through implementing cost-cutting strategies (Seamans and Zhu 2017). Our paper contributes to this literature on demand-side approaches to disruption through two important aspects.

First, the theory of disruption argues that incumbents (usually targeting mass market) might not always react to new entrants as these new players only target small market niches. This argument, however, might not be always true. In this regard, incumbents are not always able to serve important and sometimes large market segments as a result of potential risks companies face from operating in these markets. Social legitimacy, for instance, is an important consideration for firm's prosperity and its lack can put the very survival of the firm at risk (Hudson and Okhuysen 2009). If the firm's offerings require engagement in a core-stigmatized activity, users tend to reduce the word-of-mouth or outright avoid such activity if other less stigmatized options are available (Hudson and Okhuysen 2009; Vergne 2012). These obstacles can severely reduce the profitability of a company operating in the core-stigmatized sector. Therefore, it is likely to expect that incumbents overlook serving a large market segment if it is associated with social stigma. In the setting of online dating industry, for example, incumbents avoid serving the short-term relationships market since it is highly stigmatized. However, if some companies are able to find an effective way to reduce social stigma in the short-term segment, they can benefit from a large, unexplored market.

Second, a brief foray into the extant research on disruptive innovation reveals that the literature is mainly focused on disruption through improving product dimensions that are easy to observe. Christensen and Bower (1997), for example, emphasize the miniaturization of the disk drive, in opposition to disk capacity, as a disruptive technological trajectory. Another common example is the cell phone GPS in the I-phone. While the traditional handheld GPS had the advantages of a longer battery and smaller dimension, the bundling between the phone and GPS can provide customers extremely valuable services like data integration with other mobile applications, such as restaurant reviews and reservation systems (Christensen and Wessel 2012). The recent development of the theory of disruption, however, points to disruptive forces that emerge from less visible (latent) product characteristics (Christensen and Wessel 2012; Christensen et al. 2016). In his last updates of his theory, Christensen pointed out that the key success driver of disruption is understanding overlooked “jobs people need done”. A case of such latent characteristics is the social aspect of consuming a product or service. For instance, if most college students value the social interaction with their peers more than the educational benefits they receive from attending the courses, e-learning institutions can hardly disrupt the traditional universities. Even if these institutions dramatically improve the quality of online lectures offered, they cannot outcompete conventional schools as the educational aspect is not the dimension that mainly drives consumption. Since, by definition, these “latent” product dimensions are hard to grasp and measure, there has been less scholarly attention to disruption cases occurred through such demand-side elements. This paper addresses this gap in the literature drawing on users’ feedback (reviews) on products to identify latent product aspects that are determinant of user consumption. This approach was pioneered in marketing literature (Büschken and Allenby 2016).

Empirical Context: Disruption in the Mobile Dating App Market

Mobile dating applications are mobile applications created to ease access, communication and matching with a potential partner (Finkel et al. 2012). This form of online dating represents an important social phenomenon as it fundamentally changed the way people meet and connect with others. According to a recent study, at least 15% of Americans have used a dating application or a dating website, with a triple increase in the use of dating apps since 2013 (Duguay 2017). Such evident changes in people's social life have spurred the interest of scholars, particularly in the psychology and sociology studies, to examine the dating app sector more carefully (Finkel et al. 2012; Sumter et al. 2017; Duguay 2017). This study sets out to draw on the mobile dating app sector, as it provides us with an excellent setting to study the evolution of an industry in which incumbents are disrupted by new entrants.

The mobile dating app market was somehow born with the introduction of the first iPhone in January 2007. The basis of this market, however, can be traced back to the dot.com era that enabled desktop-based dating websites. Match.com was the pioneering website which launched its interface in 1995 (Finkel et al. 2012). The era of desktop dating websites can be explained through two generations. The very first generation of dating websites operated simply as personal online advertisement pages, providing the opportunity of posting one's profile as well as browsing other users' profiles. Following Match.com, many other companies, like OkCupid and PlentyOfFish introduced dating website with similar functions in the next few years. The second generation of dating websites emerged in 2000 when eHarmony launched a new online dating service based on "science" rather than "intuition". This newer generation of dating websites worked as online matching systems based on sophisticated algorithms. Such algorithms helped to process users' self-reported preferences, collected as extensive lists, and eventually to suggest suitable dates. This new approach was so successful that the first generation websites had to adopt sophisticated algorithms too.

The release of the iPhone I in January 2007, which fostered the widespread development and use of mobile applications, resulted in the first technological shift. Not so concerned with this technological change, incumbents –those companies with desktop dating websites– could make a successful transition to the new interface –i.e., phone screen. Websites such as Match.com, OkCupid, PlentyOfFish, and eHarmony launched their mobile application and dominated the industry in the early years after the introduction of iPhone I. An important advantage incumbents could benefit from was network externalities. As these companies were the first movers in the desktop-era online dating, they enjoyed from having an already large customer base. Like any other network-based service, the probability of finding a suitable partner on a given platform increases as the number of platform users grows.

In addition to having a large customer base, incumbents in this new era continued to draw further on their core capability, i.e., matching algorithms, to promote their services. Thanks to an enormous amount of personal data that they have collected over the first years of the industry emergence, they were able to refine their matching algorithms. From a strategic point of view, these advantages –i.e., strong network externalities and fined-tuned matching algorithms, seemed quite insurmountable for new entrants. With a small customer base and little historical data available on users, new entrants struggled to gain a slight share of the market in the first couple of years. In this way, the mobile dating apps industry was dominated by the desktop-era legacy brands between 2007 and 2013. The industry landscape, however, changed drastically in 2013. A small new player –Tinder– entered the market and, a few months later, became the most popular dating app in the U.S., dispatching all the established players. Figure 1 represents the market share of top four dating apps in the U.S. from January 2013, when Tinder was just released, to November 2014, when the app made it to the top of the US market. Confirming a similar pattern for the market evolution, Figure 2 provides a graphical representation of the number of worldwide Google searches for the industry top players from 2010 to 2016.

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Insert Figures 1 and 2 about here
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The trends illustrated in Figure 1 and Figure 2 suggest that while legacy brands like OKCupid and Match.com dominated the industry in the early years, they were disrupted by the new player –Tinder, after 2012. This disruption is quite surprising as Tinder did not introduce a cutting-edge matching algorithm to suggest more promising dates to its users nor an advanced technology –ironically, the application was initially quite poor and subject to frequent crashes. Considering this, the case of Tinder's takeover represents one of the most important moments of the industry evolution and resembles other cases of industry disruption (Christensen and Bower 1996; Christensen et al. 2015). Next section is to investigate the underlying strategy that Tinder applied to take over the U.S. dating app industry. We investigate the theoretical mechanisms behind this market evolution and propose several hypotheses. The core of our argument is to show how the new entrant was able to go beyond the boundaries of the existing market, target a new demand segment through improving firm offerings along one overlooked dimension.

Hypothesis Development

A Demand-Side Perspective to Online Dating: Long-term vs. Short-term Dating Segments

Our interest is to explain how incumbents in the mobile dating industry are disrupted. To better understand the market structure, we adopt a demand-side perspective to the dating industry and explore the heterogeneity in the demand environment (Priem et al. 2012). Drawing on this perspective, we explicate why incumbents did not address the heterogeneous customer preferences in the online dating market. While customer needs might seem quite identical with every user looking for a suitable partner to date, our in-depth study on the context revealed a different pattern consisting of people who are looking for long-term relationships and those that are searching for short-term relationships. The customer segments which incumbents targeted from the very beginning were those conventional users that were looking for an ideal, lifetime long relationships. Building on their key advantage, the early incumbents provided this group of customers with sophisticated matching algorithms. Going through an extensive list of preferences, OkCupid or Match.com could match users to find their “soul mate”. eHarmony, for example, represents the most iconic example of this “scientific” matching approach to dating. The company was founded by Neil C. Warren, a clinical psychologist and the author of eight books on love, marriage, and emotional health. The application that Warren and his team released to the market applied 29 dimensions to match users. These dimensions were identified to be critical for matching people through extensive research the company had done on thousands of married couples[28]. The long-term relationships segment appeared to be a market well addressed by established players.

Instead of competing for segments served by incumbents, Tinder drew on demand heterogeneity addressing the needs of people that were interested in “short-term” or “casual” relationships. The market for short-term relationships was largely ignored or underexplored by major brands as their sophisticated algorithms, were not designed for users who were simply looking for meeting new people to have a quick chat or a casual date. The interesting aspect about this overlooked market is that Tinder was not the first or the only company releasing an app for short-term relationships. Most of the companies that aimed to serve the short-term market were not particularly successful before 2012. One of the main problems that many companies faced in the short-term market was the “social stigma” attached to it.

[28] www.eharmony.com

Online dating, overall, is an industry that suffers from social stigma. People who work in the industry are well aware of the stigma that "hangs high on the tree of matchmaking". The stigma is quite notable even now that the industry is becoming more mature. As an employee puts it: "[a]s someone who is the marketing director for a dating app startup, the stigma is not easy to erase no matter how niche or sophisticated these apps are getting" (Tudda 2016). There are several reasons behind the stigma associated with online dating, however, "there's a consensus on at least one: People associate it with desperation" (Treleaven 2013). In this sense, people who use specialized companies and their sophisticated algorithms might admit that they are incapable of looking for the love of their life themselves, maybe because they are not desirable enough.

This stigma associated with online dating is even stronger for apps that choose to position themselves as short-term dating apps. The reason for an augmented stigma in the short-term dating can be traced back to people's perceptions and beliefs about finding the right partner. In psychology literature, for instance, it is well established that most people, regardless of their gender, prefer their partners to be non-promiscuous. Many people, women in particular, intentionally limit their number of partners because they worry having several partners could hurt their chances of finding long-term monogamous love once they are ready to settle down (Vrangalova 2016). Popular press articles reflect a higher social stigma attached to short-term dating:

> *"So nobody—or rather, nobody important—is judging you for joining eHarmony or browsing OkCupid. But online dating apps are a slightly different story. The swipe-right-for-sex mechanism almost seems too easy, and as a result these apps still have a rep for promoting hookup culture over real relationships" (*Purewal 2017*).*

Based on our arguments that are rooted in the social stigma literature, we posit:

Hypothesis 1a: Companies that target highly stigmatized market segments underperform those that target slightly stigmatized segments.

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Insert Figures 3 about here
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It is interesting to know that while the market for short-term relationships was larger than the one for long-term relationships, because of the high level of social stigma associated with casual dating, very few companies succeeded in it. Figure 3 gives a visual illustration of the mobile dating market segmentation. Being among the few to thrive in this market, Tinder did not choose to compete with the established players. Instead, it could come up with improvements in firm offerings along overlooked dimensions. As elaborated in the next section, Tinder strategically positions its application to look like a "game" and introduced "game-like" features that reduced the stigma associated with online dating.

Improving the product along one dimension: The gamification strategy as a remedy for short-term dating stigma

Tinder was one of the few apps that could successfully overcome the social stigma attached to the short-term relationships and penetrate this market (Figure 2). The app was founded on September 1st, 2012, and launched the following October out of Hatch Labs, an internet start-ups incubator company. One year later, the app boasted more than ten million users and was downloaded more than 40 million times[29]. According to industry analysts, the app has been a pioneer of new techniques to optimize mobile user experience, with the introduction of the *swiping paradigm*. Swiping feature refers to the way that users go through different Tinder profiles to select their potential dates. To create a personal profile, Tinder relies on

[29] growthhackers.com

information provided by one's Facebook account to extract age, gender, friends, and interests. Contrary to apps like Match.com with a wide list of personal preferences, the personal information that is available on a Tinder profile is very limited. The platform, instead, focuses on one's appearance using personal pictures. Users can show their interest in someone else by swiping right (i.e., like) or left (i.e., pass). When two users mutually like each other, the app shows that it is a 'match' meaning that users can chat with each other on Tinder's platform (Sumter, Vandenbosch, and Ligtenberg, 2017).

One distinctive feature of Tinder, according to its founders and industry analysts, is the game-like experience provided to its users. Liking or dismissing users in browsing mode resembles earlier online games, such as "Hot or Not", which were created over the past decade as a user rating game. In a similar way, Tinder can be compared with the first iteration of Facebook, i.e., Facemash, that was designed for Harvard students to rank each other based on attractiveness (Stampler, 2014). Related to this, Sean Rad, Tinder co-founder and CEO stated that: "We always saw Tinder, the interface, as a game" (Stampler, 2014; Duguay, 2017). The very first online interface of the app release on July 2012 also stresses the idea of a social game (Figure 4).

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Insert Figure 4 about here
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Tinder's focus on the game-like features is also reflected in users' reviews in which words such as "fun" and "entertaining" appear on top. Users tend to highlight in the reviews the dimension of the experience that attracted their attention the most (Büschken and Allenby 2016). Figure 5 shows a comparison of the top five words that commonly appear on users' reviews of Tinder and two main incumbents (match.com and eHarmony). This analysis has been implemented through taking all users reviews of these three apps in 2012 and 2013 on the apple store.

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Insert Figure 5 about here
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The results of this preliminary analysis suggest that all reviews of the three apps share a common word: “people”. This implies having a large customer base is important for users. The importance of the number of users is revealed through reviews like “Good for meeting people” or “Cool way to meet new people” in all three apps. Despite this similarity, the results point to important differences between Tinder and the other two apps. In the reviews of Match.com and eHarmony, it is quite common to see reviews centered on the word “Match”. This is because both apps are well-known for having sophisticated matching algorithms. Note that both companies entered the market as dating websites and later launched their mobile application. The synergy between the website and the mobile application represents an important competitive advantage for them. The key word that distinguishes Tinder from Match.com and eHarmony is “fun”. While it is quite common to find reviews like “It's a fun way to meet new people” or “Fun game” on Tinder, they are almost absent on Match.com or eHarmony.

The introduction of game-design elements and principles in non-game contexts to maximize the “fun” aspect of an activity is often called *gamification* (Goasduff and Pettey 2011). Gamification has quickly become a legitimized digital marketing strategy for companies in different sectors. Some consulting companies started providing specific services related to gamification[30] (Goasduff and Pettey 2011). While it is an important strategic tool, the usefulness of gamification strategy crucially depends on the context in which it is applied.

We argue that one of the main benefits of gamification is the reduction of social stigma associated with a given activity. The literature on social stigma provided evidence that organizations operating in a stigmatized industry (e.g., short-term dating market) can reduce or dilute this effect through creating a cognitive link with a non-stigmatized category (e.g., playing games). In addition, games do not belong to a random category, they are associated with happy moments of one's childhood. Applications that are able to evoke such pleasant experiences are less likely to be damaged by moral censorship (Keller, 1993). As long as a user is playing a game, stigmatized activities, like violence, are easier to be tolerated. Building on these arguments, we propose:

Hypothesis 1b: Companies in highly stigmatized market segments that improve their products along the "fun"/"entertaining" dimension overperform those in the same segments that do not make such improvement.

Tinder has been one of the pioneering apps in the gamification of dating services, known as "the ultimate gamification of romance" and "Pokémon GO for the heart" (Robinson and Brooker 2016). Following Tinder's success, many other apps quickly imitated the gamification strategy adopted by Tinder. In this sense, many other companies entered and succeeded in the stigmatized segment of short-term relationships using a similar strategy (Lee, 2014). A brief foray into the industry literature reveals this imitation trend:

> *"While creating a more expansive taste profiling of an individual is sophisticated, the new method in which we go seeking for it in quick snap judgments*

[30] As an example, visit www.bunchball.com

and flicks of the wrist could potentially seem immature. In fact, it seems like dating apps are borrowing from our favorite childhood past time: games." (Hakala, 2013).

"Dating apps like Kahnoodle and Tinder are riding the tide of what's been called the gamification of dating apps. As Susie Neilson points out in The Atlantic, "Consumers respond very well to gamification in other sectors; businesses report increases in "engagement" by hundreds of percentage points when they gamify." (Neilson, 2013)

Testing the theoretical mechanism: Word of mouth in a stigmatized industry

The goal of this part is to unpack the reasons behind why companies that target highly stigmatized market segments perform worse in comparison to those that target less stigmatized market segments. Prior research suggests that word of mouth is an important driver of firm performance. Customer reviews on a product can have a positive impact on boosting sales and revenues (Chevalier and Mayzlin 2006). While online dating companies hope to expand their customer base through the effective use of word of mouth, the social stigma attached to this sector avoids attracting more users. Even if companies manage to gain users, it is hard to reach critical mass as people who downloaded the app are hesitant or embarrassed to spread some information and write a review of the app. There is ample evidence of this stigma in the form an unwillingness to reveal one's experience in finding her partner online. Here is an example retracted from a social forum:

"I have never been ashamed about anything in my life or anything about me until I met my partner online. Even with people who openly have told me they met their partner online I just cannot admit that's where I met my partner and I end up lying that we met at work as we work with partner companies but I don't elaborate... I just

find it terribly embarrassing as I would think bad of a girl who was looking for love online. It screams desperation and loneliness and that you can't find anyone else normally."[31]

Or,

"When it comes to an adorable meet-cute and a 'how we met' story that your children will swoon over, 'he swiped right' typically doesn't come to mind. In fact, a lot of women have a good deal of anxiety about using dating apps for that very reason. They don't want to have to tell people if they do end up meeting someone serious" (Marshall 2016).

Such insufficient word of mouth is not good news for companies. Because of the stigmatized nature of their service, traditional marketing channels, such as TV advertising, are not always the best marketing strategies (Hudson and Okhuysen 2009). Based on these arguments, we propose:

Hypothesis 2a: Companies in highly stigmatized market segments benefit less from word of mouth comparing to companies in slightly stigmatized market segments.

As anticipated in H1b, gamification can be used to reduce the social stigma attached to the short-term market. We argue that gamification helps companies to activate word of mouth in highly stigmatized market segments. For instance, the early interviews about Tinder document an association between using such short-term oriented apps and being able to talk about this activity with friends through having the perception of engaging in a gaming activity:

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[31] mumsnet.com

> "*With every match, I could send a message or keep playing. Though I honestly started with the intent of finding true love, after a few weeks, I realized that the app at its core just wasn't set up for seriousness. Lunch break with coworkers? Let's play Tinder. Bored on a Friday night but too lazy to go out? Let's play Tinder. It became a way to pass the time, to look at guys' pictures and judge them without consequences. It was a game, not a tool for real-life dating" (Lee 2014).*

In this way, gamification provides users with legitimacy to spreading the words about a product that its consumption previously was perceived highly stigmatized. Thus, we posit:

Hypothesis 2b: Companies in highly stigmatized market segments that improve their products along the "fun"/"entertaining" dimension mitigate the negative effect of stigma on word of mouth.

Data and Methods

Data Sources

To test our hypotheses, we collected data about all dating apps on the Apple store between 2012 and 2015. We use a search strategy[32] on websites that provide information about apps, such as App Annie, to identify available dating apps. We then verified the outcomes of our search strategy based on the description of apps. Additionally, we used several press articles on mobile online dating to double-check the validity of our search results. The final sample includes 151 apps which represent both larger apps such as "Match.com" and smaller ones such as "Christian American Singles Dating". In the next step, we downloaded all user-generated reviews of the apps in our sample between January 2012 and March 2014. In case the application entered in the market after March 2014, we collected all the user-generated reviews posted during the first year of life. We excluded all apps with less than 5 reviews in total for two reasons. First, these apps are irrelevant from an industry evolution perspective since they could not reach the critical mass. Second, we need a sufficiently high number of reviews to use our methodology to identify firm positioning in the market. Thus, we ended up with a sample of 131 apps and more than half a million reviews in total. Our empirical analysis is divided into two parts. In the first part, we focus on the financial performance of our applications at the end of the 2011-2015 period using a cross-sectional design to test H1a and H1b. In the second part aiming to test H2a and H2b, we employ a longitudinal analysis to better understand the industry dynamics leading to the end-of-period outcome.

Part 1. Hypotheses 1a and 1b

Dependent variables

We construct two variables to measure an app's performance, *Downloads* and *Revenue*. Our first dependent variable, *Downloads,* is the average logged number of monthly downloads in 2016. We use the logarithm to reduce the skewness of the distribution and weaken the influence of the outliers. Apps that exited from the apple store or have a number of monthly downloads lower than 5000 have a value equal to log(5000) since there is no data on the exact number of downloads for such apps.

Our second dependent variable, *Revenue*, is measured as the average monthly logged revenue. Apps that exited from the apple store or have revenues lower than $5000 have value a value equal to log(5000). The market entry in our sample takes place between 2011- 2015 and our data is focused on the performance outcomes at the end of this period (2016). Unfortunately, we do not have data on the apps' financial performance for the whole period, therefore, we need to apply a cross-sectional analysis.

Independent variables

One of our key independent variables is *short-term* which reflects an app's target market segment. Dating apps, generally speaking, are designed to serve either the long-term or short-term market, and signal their target market through the information released to the public. To classify an app's orientation, we used the app's name and the description released on its website and/or in its description section on the Apple store in the first year in which the app is released. The process is as follows. First, based on a complete review of the apps in our sample and all relevant websites, we identified the most common words in an app's name and its description that point to a short-term orientation. The list of these words is presented in Appendix 1. Second, we classified an app as short-term if at least one of such common words appear in its name or description. Conversely, we classified an app as long-term if the common words never appeared in the name or description. This measure of short-term orientation can capture how explicit a company is in attracting users who are interested in short-term or casual dating. As a robustness check, we asked some students to classify the sample into short-term or long-term dating apps. The results were consistent with our initial classification. This variable is a dummy equal to 1 if an app has short-term orientation and 0 otherwise.

Our next independent variable captures firm positioning reflected by its outstanding performance dimensions in users' opinion. In this way, positioning can be explained as the location of firms on a multi-dimensional landscape in which firms can master in one or several performance dimensions (Adner et al. 2014). In this paper, we are interested to illustrate firm positioning building on user reviews. The reason is that users' reviews incorporate product attributes that impressed them (negatively or positively) in their reviews. In order to identify dimensions that are important for users, we performed an exploratory topic modeling analysis (Kaplan and Vakili, 2015). The process of this analysis is described in details in Appendix 2. Topic modeling analysis of reviews enabled us to identify 6 key performance dimensions critical for users. The list of emerged dimensions and their associated group of keywords are as follows.

(1) *User quantity*. This performance dimension refers to having a large user base. A dating app with many users can exploit strong network externalities to attract even more users. The keywords relevant to this performance dimension include *people, meet,* and *friend.* Examples of reviews containing these keywords are: *"Not a bad app for meeting people"* or *"You meet lots of people".*

(2) *Matching quality*. Dating apps can use several techniques to improve the probability of matching users. eHarmony, for example, uses complex matching algorithms based on user-generated personality and interest data. The keywords related to this dimension are *match, rate,* and *love.* Examples of reviews containing these keywords are: "*This is the best dating app on iTunes store, u can find ur match"*, or "*The ultimate app to find love".*

(3) *Fun*. As explained earlier, some applications are focused on the entertaining aspect of the dating experience. Keywords relevant for this dimension include: *fun, entertain,* and *bore*. Examples of reviews containing these keywords are: *"This is fun when you are bored"* or *"Okay this is literally so much fun! I love it! Definitely what I'm doing during class haha"* or *"The app is great and super entertaining but it is extremely glitchy at this stage"*.

(4) *Poor technology*. Contrary to other dimensions that refer to the presence of a certain quality in performance dimensions of an app, this variable reflects the lack of a performance quality. Related keywords in this dimension include: *crash, fix,* and *glitch.* Examples of reviews containing these keywords are: "*fix the bugs that are making it crash or*

not even open!", or *"I really enjoyed this app and was meeting a lot of people until it started crashing".*

(5) *Social network*. Some dating apps rely on social network websites, such as Facebook or LinkedIn to verify the identity of users. In some cases, users cannot even use the app without having a social network profile. Using social networks might help apps to reduce the number of fake profiles and in turn improve their performance. In addition, integration with a social network can improve the messaging function of apps. Keywords that represent this performance dimension include *Facebook*[33]*, social,* and *messag.* Examples of reviews containing these keywords are: *"Had to go to Facebook to change my age!!! Shouldn't have to be 17...",* or *"I have literally met 15 girls since January 1 and I opened my account in December. MeetMe is truly a revolution social media and social networking! To be able to combine app technology with social online matchmaking is nothing short of genius*".

(6) *Advanced features*. Some dating apps use special features to connect and match people. An app called "Dates near me", for example, draw on GPS technology to find people located close to the user. Another app, "Bumble", allows only girls to pick their potential match by sending the first message. We included all special features in a common performance dimension and labeled it as advanced features. The keywords identifying the dimension are *cool, feature*, and *option*. Examples of reviews containing these keywords are: "*Very nice app! It is easy to use, has cool features. You can request dates, which make things much easier for you and others on the app to meet", "Feature-wise Bumble is exactly like Tinder, except girls start the conversations".*

[33] Facebook is just the name of the most popular social network. We include in the keywords all the social network names like Google+ or LinkedIn

To summarize, we used the keywords emerged from our topic modeling analysis to classify the position of each app on a multi-dimensional space of different performance dimensions. In this way, each company can choose to excel its app along one or more performance dimensions. For each dimension, we assigned a score to each app based on how frequently the identified keywords appear in the reviews. Because we are mainly interested in understanding the shift in the industry leadership, we focus only on the reviews posted between January 2012 and March 2014 to identify the keywords and performance dimensions. In case the app entered the industry after March 2014, we use the reviews posted during the first year of its activity. The following formula is used to compute app *i* performance along a specific dimension *j*:

$$Perfomance\ Dimension\ Score_{ij} = \frac{Count\ of\ total\ keywords_{ij}}{Count\ of\ total\ words_{i}}$$

Figure 6 provides a visual representation of the scores given to each performance dimension for Tinder and eHarmony. In this figure, to obtain a relative value the performance dimension scores of each app are divided by the average performance dimension scores in the sample.

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Insert Figure 6 about here
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As expected, Tinder performs well in the *Fun* dimension and rather poorly in terms of technology. According to the figure, Tinder is more than twice (2.5) as Fun as the average dating application. On the contrary, eHarmony is one of the least fun applications, but is extremely good at matching people with similar characteristics. According to this figure, the Matching Quality of *eHarmony* is twice as good as the average dating application.

As a robustness check, we introduced an alternative dichotomous variable (dummy) for each dimension. The dimension dummy is coded equal to 1 if the keywords identified by the topic modeling analysis appear among the top 5 most frequent words[34] in an app's body of reviews, and 0 otherwise. This measurement is a raw proxy of how important each dimension is in the app's reviews.

Control variables

We controlled for several variables to account for an app's characteristics. The year in which an app is released on the apple store, *Year First Version,* accounts for the app's incumbency in the sector. The next control variable, *Specialized,* captures whether a dating app targets a particular category of people, for example, a specific race or age range. Targeting a segment of the population can help to the app's matching strategy, therefore, might affect its performance. To control for specialization, we introduced a dummy variable equal to 1 if the app focuses on a subcategory of users and 0 otherwise. Through another control, *Paid,* we measured the pricing models of apps. Most of the dating apps adopt a freemium pricing model. This pricing model means that apps are free to download and use but could ask for additional payments (in-app purchases) to benefit from premium features (e.g., who has liked/viewed one's profile). There are few dating apps that do not use a fermium model. We controlled for the pricing model that an app deploys through creating a dummy variable equal to 0 if the app is free to download and 1 otherwise. Our control variables are coded based on information provided by Apple Store.

Part 2. Hypotheses 2a and 2b

[34] We tried alternative thresholds of 5, 7 and 10 top keywords. The results are robust to different cutoff points.

The aim of hypotheses 2a and 2b is to test the theoretical mechanism using a longitudinal analysis. For this reason, we constructed a new dependent variable:

Dependent variable

In the second part of our analysis, we use the number of *Monthly Reviews* as the dependent variable. The number of monthly reviews is not only a good indicator of the number of new customers but also a measure of customer engagement. Since we are mainly interested in understanding the shift in the industry leadership, we focus only on the reviews posted between January 2012 and March 2014. This shorter timeframe reduces the number of dating apps from 131 to 87.

Independent variable

Building on the literature on Industrial Organization, we use the app's installed base of customers as the key independent variable to estimate word of mouth (Grajek and Kretschmer 2009). Since we do not have access to the exact number of users for each app, we use the *Cumulated Number of Reviews* as the best available proxy. Similarly to the previous section, we use the performance dimensions identified with the LDA to compute the monthly score for each dimension of each app. In this analysis, we compute a score for app *i's* performance along a specific dimension *j* for each month *t*:

$$Performance\ Dimension\ Score_{ijt} = \frac{Count\ of\ total\ keywords_{ijt}}{Count\ of\ total\ words_{it}}$$

The descriptive statistics for all the variables are presented in Tables 1 and 2.

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Insert Table 1 and 2 about here

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Results

Part 1. Hypotheses 1a and 1b

We initially tested hypotheses 1a and 1b using the OLS regression. Since the dependent variables *Downloads* and *Revenue* are censored, we tested our propositions using a Tobit regression with a threshold at log(5000) for *Downloads* and *Revenue*. Results are consistent with all the different functional specifications. The results presented in table 3 and 4 support hypotheses 1a and 1b. Dating apps that are explicit in their orientation towards short-term relationships underperform both in terms of the number of downloads as well as revenue. Dating apps that exploit the "fun" performance dimension, however, overcome the social stigma associated with short-term dating and benefit from a considerable market. The interaction between *Fun* and *Short-Term* is positive and statistically significant in all regressions except[35] the full model in table 4. The coefficients of the other dimensions are generally not statistically significant as well as the interaction between *Matching Quality* and *Short-Term.*

These results support our propositions on the industry evolution. In the 2011-2012 period, the dating app market somehow reached an equilibrium in which the long-term market was considered the most profitable. Tinder and its many imitators after 2012, on the other hand, improved the product along a dimension that was previously neglected: *Fun.* This strategy allowed them to enter and succeed in a much larger market –i.e., short-term dating. The key finding is that the majority of dating apps that targeted the short-term market with an emphasis on *Fun* overperformed those in the same market that did not apply the gamification strategy.

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[35] The insignificant results could be due to multicollinearity (the score measures are strongly correlated because they share the same denominator). However, the results suggest that the hypothesized effect is stronger in generating downloads rather than revenues.

Insert Tables 3 and 4 about here
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Table 5 replicates the previous analysis using the dichotomous dimension scores (dummy). The results reported in Table 5 provide evidence for the robustness of our findings.

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Insert Table 5 about here
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Part 2. Hypotheses 2a and 2b

In order to estimate the effect of the performance dimensions on word of mouth, we ran a panel OLS regression using the user generated reviews for each app on a monthly basis from January 2012 to March 2014. Table 6 reports the estimate of word of mouth for both the long-term and short-term market segments. The results show that word of mouth is much weaker in the short-term market. The word of mouth effect is twice as strong in the long-term segment. The two coefficients are statistically significant (5% confidence interval). These findings lend support to hypothesis 2a (word of mouth spreads at a slower pace in the short-term segment than in the long-term segment).

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Insert Table 6 about here
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Table 7 reports the moderating effect of performance dimension scores on word of mouth for both long-term and short-term market segments. The results show that Fun has a positive effect on word of mouth only in the short-term segment. The results are robust to a fixed effect model specification, and the elimination of Tinder from the sample. This suggests that the effect we are measuring is not app specific, or inflated by a specific outlier (Tinder).

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Insert Table 7 about here
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Robustness Checks

Bass diffusion model

The results in table 7 assume a linear diffusion process. However, traditional studies on innovation diffusion suggest that diffusion curves of new products follow more complex dynamics (Chatterjee and Eliashberg 1990). In order to check the robustness of our results, we allow for a non-linear relationship introducing in the regression the squared term of *Cumulated Reviews*. Such specification allows us to estimate the three key parameters of a Bass model of diffusion (Bass 1969). Since its introduction in the 1960s, the Bass model and its revised forms have been widely influential in marketing and management science (Satoh 2001). According to this model, the diffusion process of a new product depends on three parameters: *p*, *q* and *M*. P represents the coefficient of innovation- how many customers spontaneously decide to adopt the new product. Q represents the coefficient of imitation-how many customers decide to adopt because they interact with other adopters. Finally, M is the market size. Provided that *F(t)* indicates the cumulative number of adopters at time t, the number of new adopters in every given period is derived from the formula:

$$\frac{dF(t)}{dt} = (p + qF(t))(1 - F(t))$$

In this framework, the parameter *q* represents the effectiveness of word of mouth. It can be easily estimated using the coefficients of an OLS regression (Satoh 2001). Table 8 reports the coefficients of the regression with the squared term of *Cumulated Reviews* while table 9 reports the estimates of *q* for the two subsamples: short-term and long-term relationship market.

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Insert Table 8 and 9 about here
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As expected, the word of mouth coefficient *q* in the short-term segment is lower than that in the long-term segment. However, an increase in *Fun* score has a considerable effect on word of mouth in short-term market. As reported in table 9, a standard deviation increase in *Fun* produces a word of mouth coefficient that is much stronger than that in the long-term market.

Simulation and Counterfactual

In order to give a better understanding of the economic relevance of the results outlined in the previous paragraph, we crafted an artificial counterfactual of industry evolution. Using the parameter estimates of the previous analysis we simulated the diffusion curves of the long-term and short-term dating markets manipulating the *Fun* dimension. Results are reported in figures 7 and 8. Our simulation lasts for 27 months (from January 2012 to March 2014) mirroring the time frame of our study, and uses the (observed) total number of reviews on January 2012 as a measure of initial market size for both the long-term and short-term segment. Finally, we assume that there is no entry in the industry.

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Insert Figure 7 and 8 about here

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Figure 7 simulates industry evolution in absence of the *Fun* dimension. In this instance, the long-term market remains a more attractive segment for companies and there is no disruption in the industry. Figure 8 simulates the effect of a standard deviation increase in *Fun* for all the short-term apps. The resulting increase in word of mouth triggers a faster expansion of the short-term segment that, at some point in time, displaces the long-term one. This final result resembles the actual industry evolution we observe in the data.

It is important to acknowledge that this final exercise has several limitations. In this simulation, we assume no entry in the industry. In the real market, the expansion of the short-term segment is due to the entry of new companies like Tinder. In addition, the simulation assumes all the applications in the short-term market to increase *Fun* by the same amount (one standard deviation). Actually, applications are more heterogeneous in adopting a gamification strategy. Overall, despite these limitations, we believe that this simulation provides additional evidence about the theoretical mechanisms behind the disruption event.

Discussion and Conclusion

The disruption theory introduced by Christensen (1996) had a profound impact on innovation literature and practice. Despite this significant effect, there are still many open questions related to the generalizability (King and Baatartogtokh 2015) and theoretical underpinnings of the disruption theory (Adner 2002). Building on the evolution of the mobile dating app industry, in this paper we explore the pattern of incumbent replacement by newcomers as described in the disruption theory. Our study illustrates how a group of new entrants disrupt established firms by targeting a poorly-served market segment and improving the product along a latent dimension (i.e., fun).

This paper remarks three important, yet overlooked aspects of the disruption. First, prior research on disruption has focused on improvements through technical dimensions (Christensen and Bower 1996) or “technology” more in general (Adner et al. 2010). Our findings, instead, suggest that new entrants can improve a product along dimensions that are not merely technological but produce new “experiences” to customers. Such dimensions are not easy to observe as in many cases they are latent in the demand environment. Second, there could be other reasons that incumbents ignore the niche market (where disruption happens) rather than market size and profitability. In our context, for example, the short-term dating market was extremely large but plagued by social stigma. The new entrants were able to successfully penetrate the short-term market thanks to stigma dilution improvements. Third, the choice of target market segments and product dimensions are highly interrelated.

Incumbents might ignore a potentially large segment for the simple reason that people are not consuming at all, given the current product configuration (Adner et al. 2014).

Our findings contribute to the studies on demand-side innovation suggesting how strategies based on customer heterogeneity can result in a competitive advantage, even when a firm holds only “obsolete or mundane resources” (Priem 2007; Ye et al., 2012). Finally, this paper contributes to the literature on social stigma through proposing strategies that companies in highly stigmatized industries can apply to reduce the negative effects (Hudson and Okhuysen 2009; Vergne 2012). A promising avenue for further research is to test the psychological and sociological effects of gamification on social stigma in a laboratory setting.

Our findings have managerial implications as well. Echoing the work of Christensen (2012; 2016), we believe that managers and entrepreneurs should focus their attention not only on the current customers and what they like but also on understanding the *main reasons that some people do not consume their offerings.* Substantial product improvements along unexplored, usually latent dimensions can suddenly reveal new markets.

Appendix 1

Words related to a short-term attitude of dating: *adult, fling, hookup, flirt, hot, speed date, sexy, any word related explicitly to sex.*

Appendix 2

First, we extracted a random sample of reviews, weighted for popularity, for each app. This process resulted in a total of more than 17,000 reviews. Second, we cleaned the resulting dataset following the standard practices (Büschken and Allenby 2016). Cleaning involved the following steps:

1. Splitting text into sentences identified through ".", ",", "!", or "?"; after the sentence split, all punctuation is removed.

2. Removing stop words using a standard vocabulary of stop words in the English language

3. Adopting Porter stemming algorithm for removing the commoner morphological and inflexional endings from words in English

After the cleaning process, we utilized a Latent Dirichlet Allocation (LDA) to identify the latent topics in the text (Kaplan and Vakili 2015). We started the analysis with 20 topics and subsequently reduced the number to obtain clusters with a clear linguistic focus. In the end, we stopped the analysis at 10 topics. They identify the 10 major topics people mention in their reviews. For each cluster, we estimated the probability that each of the words appeared in it, and made a list of the 6 words with the highest probability.

Topic (1): **App's technical problems**. The most 6 most common words related to the topic are: *Update, crash, fix, work, time, still.*

Topic (2): **Found my love**. The most 6 most common words related to the topic are: *Love, rate, match, realli, start, year.*

Topic (3): **Fun and Entertaining App**. The most 6 most common words related to the topic are: *fun, entertain, funni, bore, help, wai*

Topic (4): **Nice people**. The most 6 most common words related to the topic are: *Nice, best, ever, ppl, date, probab*

Topic (5): **Messaging**. The most 6 most common words related to the topic are: *Messag, send, profile, super, view, fake*

Topic (6): **App's advanced features**. The most 6 most common words related to the topic are: *Cool, feature, need, option, search, version*

Topic (7): **Finding potential dates**. The most 6 most common words related to the topic are: *Site, people, date, want, find, someone*

Topic (8): **Social networks**. The most 6 most common words related to the topic are: *Time, Facebook, delete, photo, log, social*

Topic (9): **Nice idea but bad design**. The most 6 most common words related to the topic are: *work, great, idea, realli, glitch, design*

Topic (10): **Great way to meet people**. The most 6 most common words related to the topic are: *People, meet, new, friend, wai, great*

We utilized these 10 topics to define the main competitive dimensions. Some topics are redundant and identify similar aspects (e.g. topics 7 and 10). Thus, we merged these topics together to define 6 key competitive dimensions: *User Quantity* (topics 7 and 10), *Matching Quality* (topics 2 and 4), *Fun* (topic 3), *Poor Technology (*topics 1 and 9), *Social Network (*topics 8 and 5*)* and *Advanced Features* (topic 6).

Finally, to reduce the probability of type 2 errors, we selected only the 3 most distinctive keywords for each dimension and excluded the keywords that appear in multiple topics. A final list of the keywords for each competitive dimension is reported on page 19.

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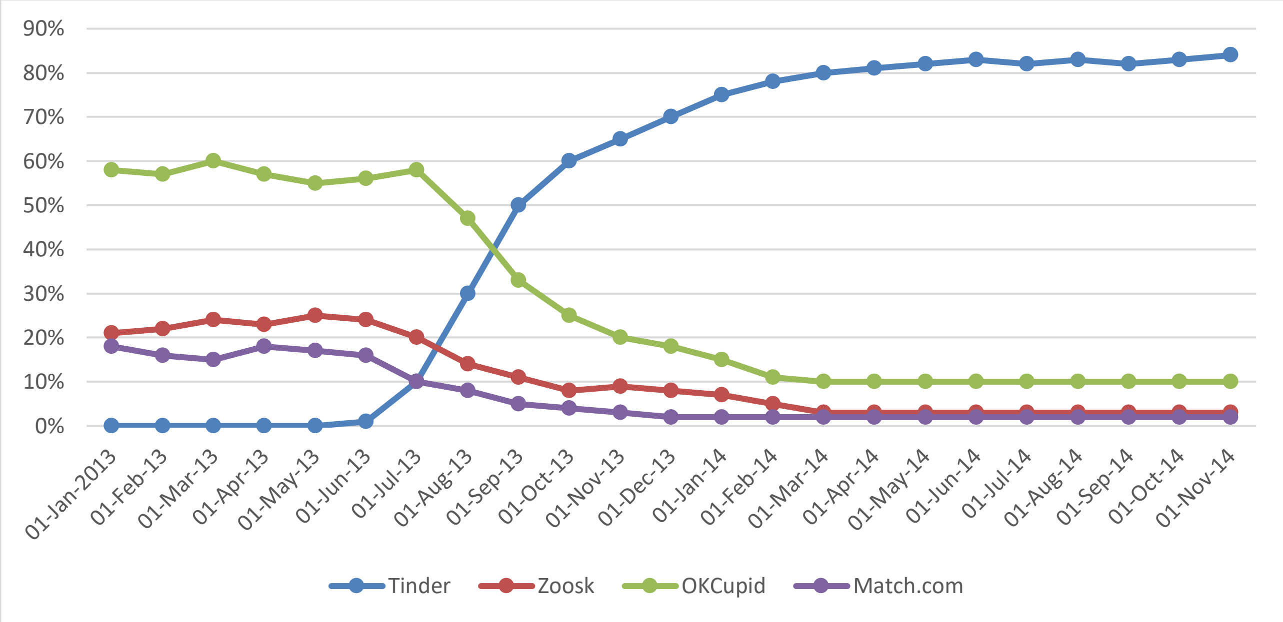
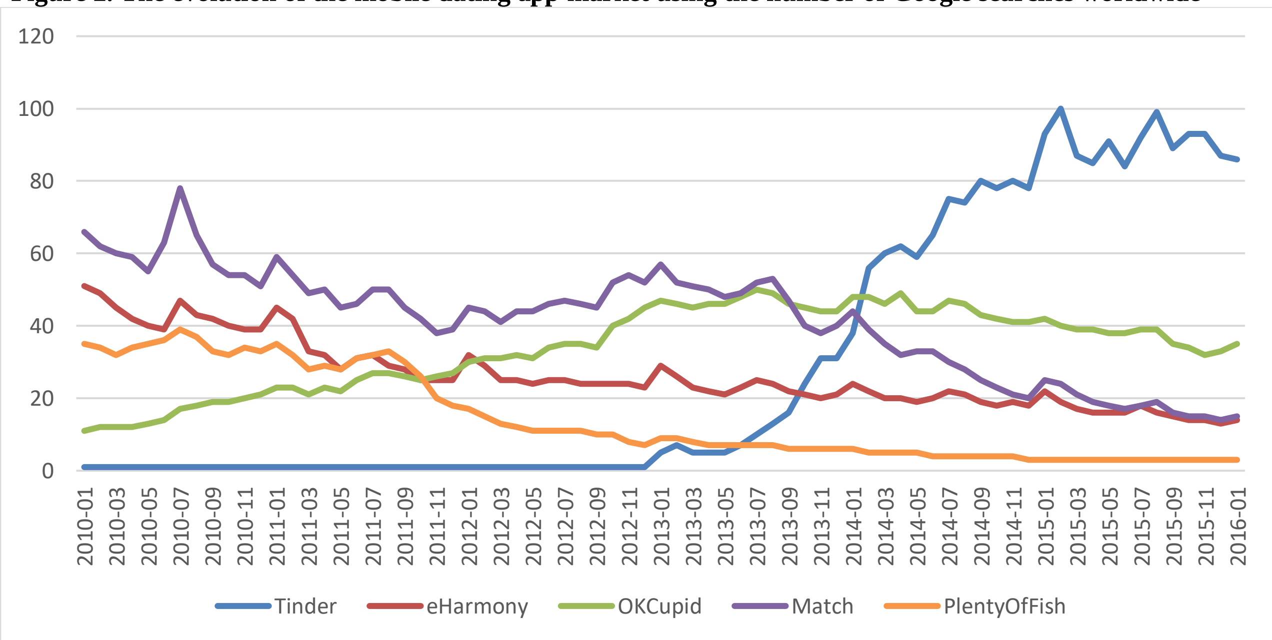
Figure 1. Market share[a] of mobile dating apps in the US market.



[a]Aggregate market share as a percentage of total app sessions across an anonymous panel of millions of the US users

Source: www.7parkdata.com

Figure 2. The evolution of the mobile dating app market using the number of Google searches worldwide



Source: https://trends.google.com/trends/

**Figure 3. Mobile dating application market:
Comparing the size of segments and the relative level of social stigma**

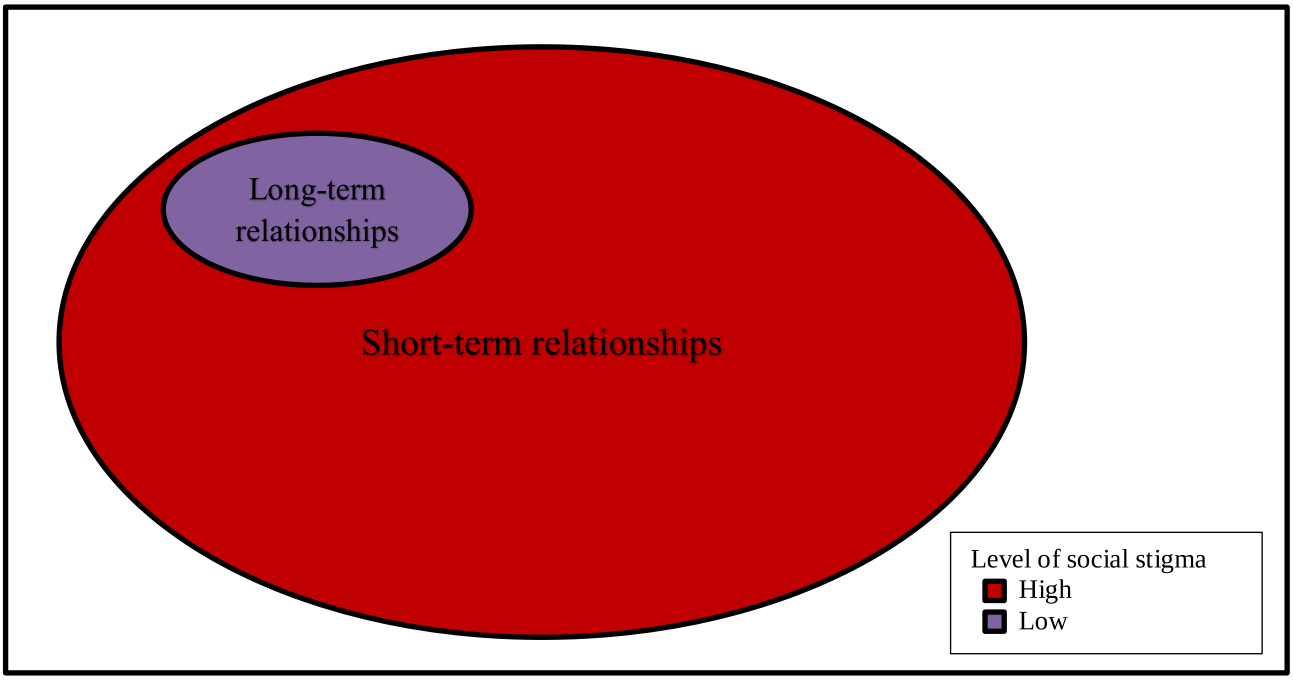
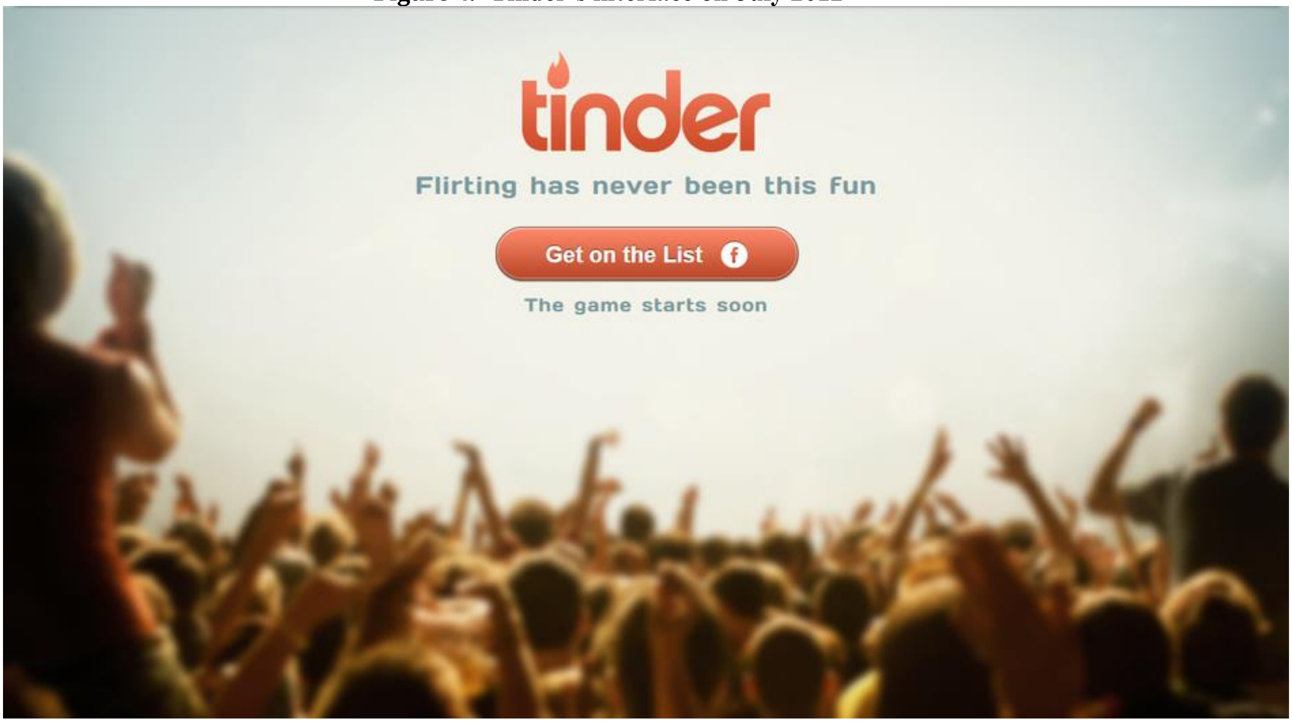


Figure 4. Tinder's interface on July 2012



Source: www.gotinder.com

Figure 5. The five top words appearing in Tinder, Match.com, and eHarmony reviews

Tinder	Match.com	eHarmony
1. people	1. match	1. match
2. fun	2. use	2. time
3. Facebook	3. site	3. website
4. work	4. people	4. people
5. fix	5. easy	5. money

Figure 6. Dimension scores for selected apps

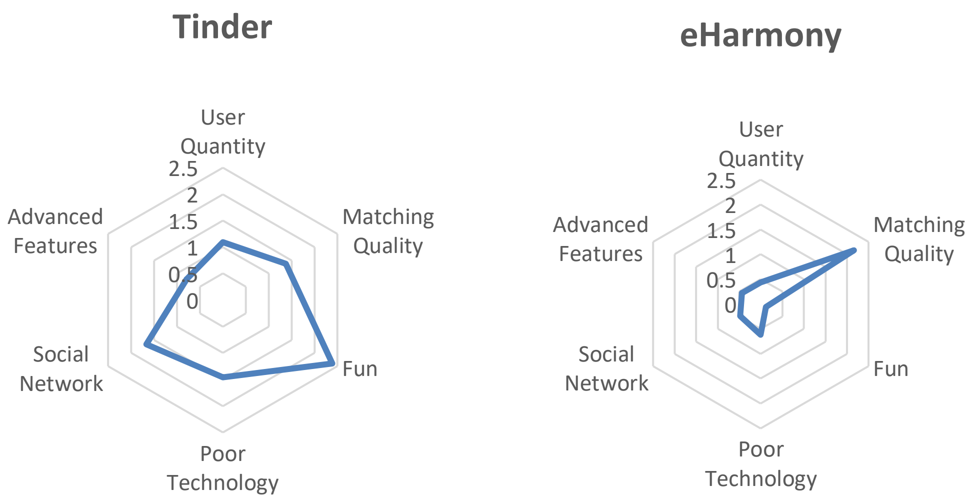
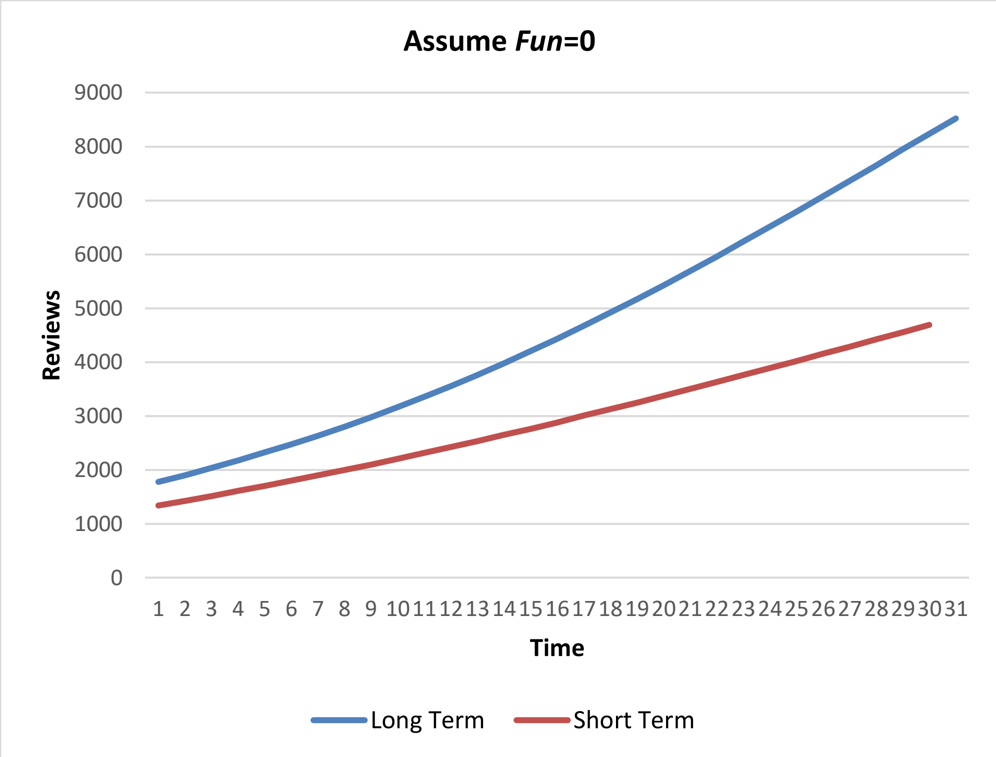
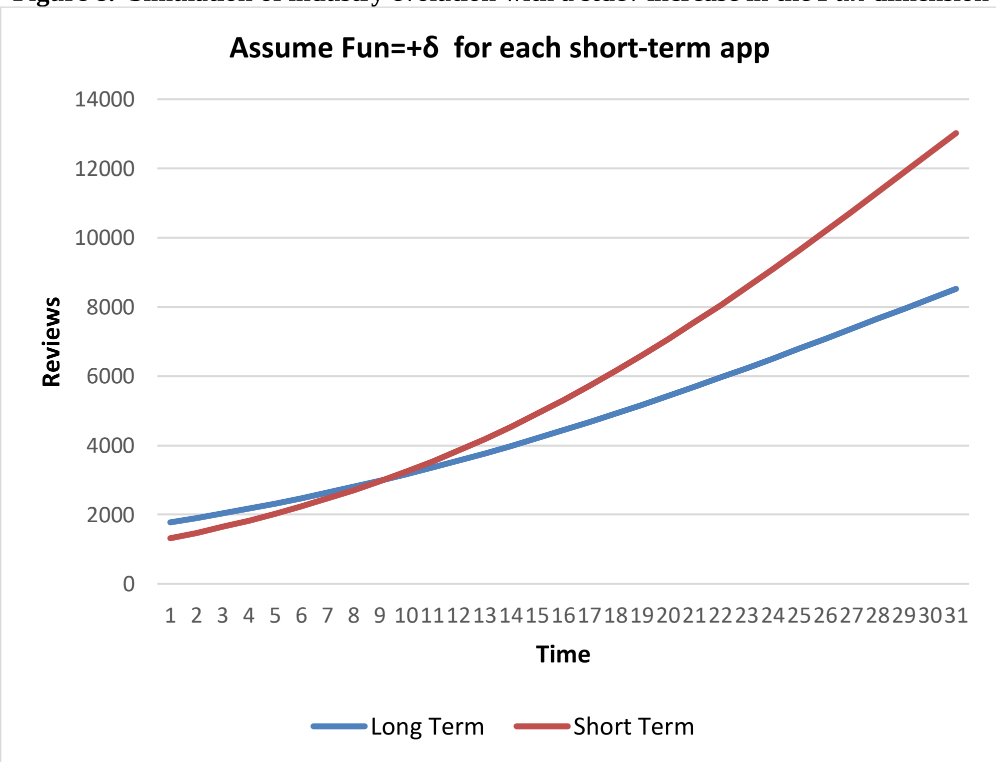


Figure 7. Simulation of industry evolution without the *Fun* dimension



*We assume all the apps have *Fun*=0

Figure 8. Simulation of industry evolution with a stdev increase in the *Fun* dimension



*We assume all the short-term apps increase *Fun* by one standard deviation

Table 1. Summary Statistics (N=131) Cross Section

Variable	Mean	Std. Dev.	Min	Max
Downloads	9.298457	1.202951	8.517193	14.50866
Revenue	9.600632	1.699180	8.517193	16.52356
Short_Term	0.503759	0.501876	0	1
Year First Version	2012	1.913069	2009	2016
Specialized	0.233083	0.424393	0	1
Paid	0.030075	0.17144	0	1

Table 2. Summary Statistics (N=87, T=27) Longitudinal

Variable	Mean	Std. Dev.	Min	Max
Reviews	109	236	1	2,505
Cumulated Reviews	2,281	3,855	1	22,007
Fun	0.000694	0.002251	0	0.047619
User Quantity	0.002739	0.003416	0	0.045455
Matching Quality	0.00134	0.002845	0	0.076923
Social Network	0.001024	0.001588	0	0.02381
Advanced Features	0.00101	0.003689	0	0.125
Poor Technology	0.001067	0.00246	0	0.03876

Table 3. The effects of app's orientation on the number of downloads

VARIABLES	(OLS) Downloads	(OLS) Downloads	(OLS) Downloads	(Tobit) Downloads
Fun	-1.010	-139.1**	-109.2	-161.3
	(48.82)	(57.75)	(68.22)	(175.1)
Short_Term		-1.126***	-1.066**	-1.727
		(0.366)	(0.524)	(1.113)
Fun*Short_Term		234.0**	212.1**	356.8*
		(90.51)	(91.30)	(213.4)
Matching Quality* Short_Term			-18.95	-303.1
			(266.3)	(585.2)
User Quantity			-86.33	-258.1*
			(58.48)	(153.4)
Matching Quality			-14.27	64.61
			(224.0)	(403.7)
Social Network			-46.66	-299.8
			(137.3)	(345.5)
Advanced Features			-61.92	-401.6
			(284.0)	(645.5)
Poor Technology			138.7	322.0
			(164.3)	(373.3)
Specialized			-0.372*	-0.817*
			(0.191)	(0.490)
Paid			-0.0463	-0.459
			(0.881)	(1.958)
Constant	9.302***	10.13***	10.44***	11.08***
	(0.197)	(0.484)	(0.616)	(1.257)
Year First Version Dummies	No	Yes	Yes	Yes
Number of apps	131	131	131	131
R-squared	0.000	0.157	0.198	

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

Table 4. The effects of app's orientation on revenue

VARIABLES	(OLS) Revenue	(OLS) Revenue	(OLS) Revenue	(Tobit) Revenue
Fun	-42.90	-176.7**	-62.61	-36.32
	(62.69)	(78.66)	(93.40)	(255.3)
Short_Term		-1.364**	-0.837	-1.221
		(0.533)	(0.768)	(1.602)
Fun*Short_Term		245.1**	180.0	300.9
		(121.1)	(118.0)	(295.1)
Matching Quality* Short_Term			-18.95	-303.1
			(266.3)	(585.2)
User Quantity			-169.1**	-481.1**
			(69.58)	(192.7)
Matching Quality			305.1	787.4
			(365.9)	(616.6)
Social Network			-95.46	-574.9
			(214.7)	(505.0)
Advanced Features			-517.1	-1,366
			(366.7)	(887.3)
Poor Technology			-93.99	-467.8
			(229.9)	(579.9)
Specialized			0.0986	0.309
			(0.324)	(0.672)
Paid			0.151	0.827
			(1.261)	(2.197)
Constant	9.768***	10.70***	11.01***	12.22***
	(0.278)	(0.689)	(0.895)	(1.743)
Year First Version Dummies	No	Yes	Yes	Yes
Number of apps	131	131	131	131
R-squared	0.004	0.108	0.172	

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

Table 5. The effects of app's orientation on downloads and revenue (dichotomous scores)

VARIABLES	(OLS) Downloads	(Tobit) Downloads	(OLS) Revenue	(Tobit) Revenue
Fun_Dummy	-0.204	-0.402	-0.204	0.0368
	(0.428)	(0.900)	(0.512)	(1.114)
Short_Term	-0.611***	-1.526***	-0.831***	-1.987**
	(0.212)	(0.547)	(0.314)	(0.777)
Fun_Dummy*Short_Term	1.140**	2.528**	1.312*	2.684*
	(0.550)	(1.101)	(0.686)	(1.407)
User Quantity_Dummy	0.301	0.382	0.646	1.354
	(0.345)	(0.853)	(0.424)	(1.196)
Matching Quality_Dummy	-0.0860	-0.112	-0.0536	-0.0764
	(0.203)	(0.472)	(0.287)	(0.644)
Social Network_Dummy	0.580	1.044	0.868	1.646*
	(0.378)	(0.699)	(0.550)	(0.989)
Advanced Features_Dummy	0.0709	0.202	-0.319	-0.463
	(0.258)	(0.597)	(0.297)	(0.754)
Poor Technology_Dummy	-0.0136	-0.306	-0.285	-1.349
	(0.367)	(0.776)	(0.525)	(1.152)
Year First Version	-0.0422	-0.0152	-0.0976	-0.0902
	(0.0617)	(0.126)	(0.0883)	(0.167)
Specialized	-0.253	-0.476	0.274	0.891
	(0.217)	(0.547)	(0.335)	(0.686)
Paid	-0.0378	-0.537	0.0520	-0.116
	(0.796)	(1.750)	(1.037)	(1.767)
Constant	94.18	38.71	205.7	188.7
	(124.1)	(253.6)	(177.6)	(336.2)
Number of apps	131	131	131	131
R-squared	0.132		0.141	

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

Table 6. Network effect in the long and short term segment of the market.

VARIABLES	(OLS) Reviews (All sample)	(OLS) Reviews (Short_Term=0)	(OLS) Reviews (Short_Term=1)
Cumulated Reviews (t-1)	0.00343	0.0268***	-0.00740
	(0.00585)	(0.00435)	(0.00940)
Constant	96.53***	41.66***	165.8***
	(20.81)	(10.56)	(53.67)
Month dummies	No	No	No
Fixed effects	No	No	No
Observations	1,274	786	488
Number of apps	87	54	33

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

Table 7. The effects of app's orientation on network effect.

VARIABLES	(1) Reviews (Short_Term=0)	(2) Reviews (Short_Term=1)	(3) Reviews (Short_Term=0)	(4) Reviews (Short_Term=1)
Cumulated Reviews(t-1)	0.0314***	-0.0225***	-0.0125	-0.0460***
	(0.00748)	(0.00632)	(0.0166)	(0.0134)
Fun* Cumulated Reviews(t-1)	-1.090	17.22**	6.750	18.09**
	(4.490)	(7.258)	(4.451)	(8.166)
Fun	4,040	1,678	1,005	1,780
	(4,613)	(2,036)	(3,816)	(1,630)
User Quantity	-1,183	-982.5	-151.3	-782.7
	(1,118)	(2,132)	(769.8)	(1,891)
Matching Quality	2,274	1,181*	2,372*	1,137**
	(1,845)	(604.5)	(1,211)	(445.9)
Poor Technology	-99.98	-1,774	-1,642	-2,032
	(3,770)	(1,309)	(4,377)	(1,427)
Social Network	2,167	1,185	-3,239*	353.6
	(2,767)	(7,161)	(1,720)	(6,093)
Advanced Features	-347.5	110.4	-235.5	1,382
	(300.4)	(3,670)	(205.2)	(3,403)
Constant	37.38	224.7**	74.70***	246.9***
	(30.52)	(90.68)	(23.13)	(53.40)
Month dummies	Yes	Yes	Yes	Yes
Fixed effects	No	No	Yes	Yes
Observations	786	488	786	488
Number of apps	54	33	54	33

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

Table 8. The effects of app's orientation on network effect (curvilinear relationship)

VARIABLES	(1) Reviews (All sample)	(2) Reviews (Short_Term=0)	(3) Reviews (Short_Term=1)
Cumulated Reviews(t-1)	0.0452***	0.0690***	0.0361
	(0.0161)	(0.0120)	(0.0291)
Fun* Cumulated Reviews(t-1)	14.86**	4.097	21.02**
	(7.118)	(5.507)	(8.810)
Cumulated Reviews(t-1)^2	-3.54e-06***	-4.30e-06***	-3.52e-06***
	(7.88e-07)	(1.02e-06)	(1.35e-06)
Fun	-2,207	97.47	-1,777
	(1,920)	(3,600)	(1,428)
User Quantity	564.9	1,189	43.05
	(671.9)	(982.8)	(1,473)
Matching Quality	905.5	1,340	499.9
	(686.2)	(1,716)	(577.5)
Poor Technology	-1,702	1,146	-1,991
	(1,828)	(2,774)	(1,402)
Social Network	152.5	288.4	3,936
	(2,346)	(2,041)	(5,313)
Advanced Features	195.6	2.475	1,475
	(249.4)	(194.3)	(1,559)
Specialized	87.61	-50.46**	156.0
	(86.37)	(23.55)	(142.5)
Paid	175.1	-35.74***	416.4
	(170.2)	(12.01)	(307.2)
Constant	35.53**	13.57	44.73*
	(16.86)	(8.398)	(25.79)
Month Dummies	No	No	No
Fixed Effects	No	No	No
Observations	1,274	786	488
Number of id	87	54	33

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

Table 9. Word of mouth coefficient *q* estimates using parameters in Table 8.

Parameter	Estimate
All sample *q*	0.047
Short_Term=0 sample *q*	0.069
Short_Term=1 sample *q*	0.039
Short_Term=1 sample *q* + 1 standard deviation in *Fun*	0.087