The London School of Economics and Political Science

Essays in Corporate Finance

Luana Zaccaria

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Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

I declare that my thesis consists of 22,455 words

Statement of conjoint work

I confirm that Chapter 2 was jointly co-authored with Dr Juanita Gonzalez-Uribe and I contributed 50% of this work.

Abstract

In most countries financial authorities regulate capital markets by monitoring banks' lending activity and imposing disclosure requirements on issuers of publicly traded securities. However, most companies' financial claims are not listed and many different investors, outside of the banking industry, affect credit expansion and capital provision to the real economy. Examples of non-banks capital providers include venture capital firms and money market funds. This PhD thesis focuses on the growing and largely unsupervised finance arena that lies outside of traditional banking intermediation or public capital markets. In the first chapter, "Are Family and Friends the Wrong Investors? Evidence from U.S. Start-ups", I investigate the effects of funding from family and friends on firms' subsequent access to venture capital. To address potential endogeneity of informal finance, I use an instrument that hinges on founders' family size as an exogenous constraint on the supply of informal funds. My results show that informal finance reduces the probability of future financing events. In the second chapter, "Private Capital Markets and Entrepreneurial Debt: Evidence from U.S. Unregistered Securities Offerings" co-authered with Dr. Juanita Gonzalez-Uribe, we investigate the use of non-bank private debt by very early stage firms. Contrary to many accounts of start-up activity, we document that entrepreneurial firms have an important reliance on private debt. We show that late stage rounds are 3% more likely to be conducted with debt contracts but we find little evidence that collateral availability affects the issuance of private debt. Finally, in "Discipline in the Securitization Market", I examine how investors' sophistication in securitization markets affects efficiency of credit generation and loan performance. I find that it is never optimal to have a perfectly informed Buy Side, as it would constrain high quality credit generation. Furthermore, market discipline is facilitated by high risk free rates and diminished volatility in loan payoffs.

Contents

List of Figures

List of Tables

"If I wanted to shake this tree with my hands I should not be able to do it. But the wind, which we do not see, tortures and bends it in whatever direction it pleases. It is by invisible hands that we are bent and tortured worst."

F. Nietzsche, "Thus Spoke Zarathustra"

Chapter 1

Are Family and Friends the Wrong Investors? Evidence from U.S. Start-Ups

1.1 Introduction

In the staged investment process that characterizes entrepreneurial finance, reaching the next round of funding is often decisive for early-stage firms. Initial rounds, typically conducted with angel investors and *informal* funders (e.g., family and friends), are the stepping stone to obtaining follow-on capital provided by Venture Capital (VC) firms and subsequently exiting the venture via an acquisition or an IPO.[1] Progression towards later financing rounds is mostly driven by the profitability of the entrepreneurial project, but other factors, unrelated to firms' growth opportunities, can disrupt the funding process. For example, the background and investment objectives of funders in one round can prevent entrepreneurs from securing the next one. This may be due to conflicting views between early and late capital providers on management style, allocation of claims or distribution of control rights. Michael Arrington, founder of the influential blog TechCrunch, refers to this issue as follows: "Pick the wrong investor and you' ve closed the door on

[1]It is common among practitioners and researchers to view the relationship between angel and VC investments as one of complementarity. Hellmann et al. [2013] explore the alternative substitution hypothesis, i.e. angel and VC are two distinct and incompatible sources of funding.

others".[2] This paper elaborates on the idea behind this quote, focusing on informal finance. Are family and friends the *wrong* investors, in the sense that they deter subsequent funding? If so, what is the nature of their conflict with other investors? The relevance of these questions extends beyond entrepreneurial finance and venture capital literature, since, due to a lack of accounting or market data, there is little empirical evidence on whether and how informal finance affects firms' outcomes. This is despite entrepreneurs' social circle provides the most accessible form of funding for young firms around the world (Bygrave and Quill [2006]).

I investigate the effects of informal finance on startups' ability to access additional capital during later funding stages. To do so, I select a sample of early-stage firms at the time of their seed funding round and track their future financing events. Differently from previous studies on early-stage and seed financing that largely rely on survey data and self reporting investors' documentation, I use a novel hand-collected dataset based on SEC filings for private placements (Form Ds) of small and young U.S. firms.[3] The advantages provided by this data are twofold. First, it relaxes sampling bias concerns, as filing is mandatory for firms that sell unregistered securities to outside investors such as family and friends, angels or investment funds.[4] Therefore, this dataset provides a more complete picture of private capital markets, including seed funding which precedes access to VC investments. This early investment phase has not been fully documented by the existing literature. Second, it provides new information on characteristics and financing choices for a large sample of startups. For example, along with industry, location and amount of capital raised, Form Ds contain data on the age of the company, its management team, the size of its revenues and the type of security offered in the private placement.

Crucially for the purpose of this paper, Form Ds also contain information on informal finance, as issuers must disclose whether informal investors are allowed to participate in the offering. Thus, this is one of the first studies that attempt to quantify and characterize recourse to informal finance in entrepreneurial literature. In this sample, only 17% of firms use family and friends funding and when informal funders participate in initial rounds they typically co-invest with formal

[2] *"VCs And Super Angels: The War For The Entrepreneur"* posted on TechCrunch on 15 August 2010.

[3] See for example Lerner et al. [2015], Kerr et al. [2014], Robb and Robinson [2012], Hellmann et al. [2013].

[4] Although failing to file a form D does not result in the loss of the federal registration exemption, the SEC can seek to have the issuer enjoined from future use of Regulation D under rule 507. The violation can also constitute felony. It can be argued that enforcement of this requirement may be currently weak, but firms that have access to legal advice and that intend to proceed towards further VC funding are reasonably likely to comply. There are no filing fees and the "estimated average burden hours per response" is 4, as stated on the form.

funders.[5] More importantly, I find that firms that raised capital with the support of informal funders have a lower probability of accessing future funding. The difference - at least -9% - persists after controlling for firm, seed round and management team related characteristics. This observation constitutes the basis for my empirical investigation.

The ideal setting for such investigation is one where the researcher randomly assigns either A) formal or B) a mix of formal and informal seed funding to firms with identical investment opportunities and observes subsequent financing events. In this framework, the lower probability of accessing follow-on capital associated with B) can be interpreted as a direct effect of informal finance on the supply of funds in later stages. The analysis of the interaction between informal finance and access to capital, however, is complicated by the possibility that recourse to informal finance is correlated with unobservable project qualities, which may ultimately cause the observed negative relationship. For example, suppose that financial arrangements among members of a family or social network negatively affect entrepreneurs' social relationships.[6] If these social costs play a relevant role and entrepreneurs are more keen on formal rather than informal financing, then firms that resort to informal finance in seed rounds are the ones that were turned down by formal funders, who rank higher in the pecking order of financing sources.[7] It is also possible that entrepreneurs that choose family and friends funders over professional investors have a distinctive managerial style, perhaps not strictly profit oriented, that affects firm outcomes. These mechanisms establish an indirect link between informal finance and firms' performance through selection. Therefore, any attempt to empirically assess the effects of informal finance is exposed to the issue of the endogeneity of this explanatory variable.

My identification strategy relies on the idea that availability of informal funding is exogenously affected by the number of entrepreneurs' extended family members.

[5]Formal investors in seed rounds can be angels, seed firms, incubators or small VC firms.

[6]Economic sociology provides support for this argument and suggests that the perception of financial obligations changes with the social distance between the receiver and the provider of capital, to the extent that formal, more impersonal sources of funding may be preferred because of the lower emotional burden attached to them. Dalits, the untouchables in the Indian caste system, often accept to be charged with extremely high rates by lenders outside of their village to avoid financial bonds within the community, as they create additional social obligations and dependency (Guérin et al. [2013]). In France, low income individuals seeking consumer credit seem to prefer the discretion of financial companies that conduct their transactions over the phone or Internet, rather than negotiating in person with a banker, thus exposing themselves to (real or perceived) moral judgement (Ducourant [2009]). Although arguably distant from the American entrepreneurial environment, these examples illustrate how financial transactions within social networks and outside of them may be subject to different evaluation criteria, even when controlling for financial terms.

[7]In private capital markets, a preference for formal financing may arise if entrepreneurs derive personal validation and prestige by being funded by renowned angels or VC firms.

I construct an instrument that proxies for the size of founders' family using the Census Frequently Occurring Surnames (FOS) dataset on U.S. surnames. The instrument is a dummy variable (*SmallFamily*) that takes a value of 1 when a firm's founder team has a small combined family network, that is when the team has a higher than average component of individuals with *rare* last names. I classify last names as rare if they occur less than 100 times in the FOS. While details on each rare name's frequency are not provided, the summary statistics reported in the FOS show that the expected number of individuals that bear any one of these rare names is 4.5. Therefore, founders with rare surnames are statistically likely to have a small extended family. To illustrate the logic behind this approach, consider the example of a married male. Exactly five occurrences of his last name in the national survey may include records of himself, his spouse, one child and two parents. The count would easily exceed 5 if other relatives (siblings, cousins, uncles, etc.) were included.[8]

The relevance of this instrument is supported by its negative and significant first stage coefficient: firms with $SmallFamily = 1$ are 5% less likely to resort to informal finance. Importantly, the *SmallFamily* instrument has a significant positive effect (+4%) on the probability of future financing events. Its validity, however, relies on the hypothesis that founders with rare last names have no advantage in managing a business or accessing capital markets. Clark and Cummins [2015] suggest that rare last names typically belong to recent immigrants or small local families. It can be argued that foreign-born individuals are particularly prolific innovators (Kerr [2008]) or that small families' offspring is wealthier and better educated because of lower dispersion of family resources (Goodman et al. [2012], Downey [2001]). By means of a matching algorithm (Ambekar et al. [2009]), I associate founders' surnames with their ethnicities. I show that the positive relationship between the instrument and the outcome variable mostly originates from the subgroup of individuals with European origins and therefore it is unlikely to be due to recent immigration to the U.S. Furthermore, I collect on-line curricula for a subsample of founders. Startup founders are likely to have a college or higher degree and approximately ten years of working experience, but differences between the rare last names group and the rest of the sample are not significant. Thus, in my sample, I find no evidence that individuals belonging to small families possess higher education or business skills.

[8]There are few data available on size and structure of families for the general population in the U.S. In a study conducted by Garceau et al. [2008] on a sample of 1,019 individuals residing in Connecticut the average number of blood related immediate family members is 5.07 and the average number of blood related extended family members (aunt/uncle, niece/nephew, grandmother/grandfather) is 7.41. In Hampton et al. [2011], a survey of American Facebook users shows that immediate and extended family members account for 21 of the active contacts on average.

At the firm level, the *SmallFamily* variable is not correlated with measures of profitability and growth opportunities. Revenues as reported at the time of the seed round are marginally lower than for the rest of the firms in the sample and, conditional on receiving additional funding, the instrument does not predict changes in revenue size between the seed and the follow-on round.

The endogeneity problem is formally addressed by means of a bivariate probit model (as in Greene [1998] and Evans and Schwab [1995]), where I simultaneously estimate the probabilities of accessing follow-on funding and of resorting to informal finance in the seed round. The instrument is included in the regression for the binary endogenous variable. My results show that recourse to informal finance has a negative and significant effect on the probability of future financing events ranging from -15% to -19%, with the strongest effect associated with later funding provided exclusively by formal investors. The magnitude of these estimates implies that marginal effects or coefficients computed from a single equation probit or a linear probability model, which range from -5% to -13%, underestimate the negative impact of informal finance.

The main results in this paper suggest that funding from family and friends affects future financial constraints. Therefore, while informal finance may constitute a cheaper source of capital as it mitigates some frictions in the formal capital market (Stiglitz [1990] and Besley and Coate [1995]), it may also impose costs further down the line.[9]

There are at least two explanations for these findings. First, informal funders may introduce corporate governance issues that deter professional investors from participating in later rounds. Goldfarb et al. [2012] and Wong [2002] argue that, unlike angels, VC firms use staging and various contractual provisions to monitor managers, protect their claims and pursue their investment objectives.[10] The most direct way to exert control is to gain board seats and replace founders in the management team (Wasserman [2012]). Founders with a pronounced desire for control are likely to resist this process, and resistance can be difficult to overcome if family and friends stakeholders side with founders. Such unofficial shareholder agreements can originate from altruistic preferences of informal funders or from

[9] Informal finance can relax capital constraints by mitigating asymmetric information and moral hazard problems. Social and physical proximity to the entrepreneurs provide informal funders with superior information and lower monitoring costs as compared to other financial intermediaries (Stiglitz [1990]). Also, reputational concerns enhance and correct incentives when capital transactions are conducted within a narrow community (Besley and Coate [1995]).

[10] Control is not usually claimed by angel investors because geographic proximity and higher equity stake left to founders allow for low monitoring. Also, firms in their early stages are presumably testing products and business models, which requires founders' specific skills, making external supervision unnecessary or even counterproductive.

non-pecuniary private benefits of retaining control within the close social circle.[11] The expectation of a costly or time consuming negotiation over control with this informal coalition can discourage investments from outsiders.[12] The novel dataset employed in this paper allows to explore this hypothesis. I provide evidence that late stage investors are less likely to gain control over firms that have informal funders. Specifically, founders are more likely to retain executive positions after receiving follow-on capital if they sourced seed funding from family and friends.

A second explanation for the negative effect of informal finance on subsequent access to capital resides in its potential direct impact on businesses profitability and growth, which ultimately determines the likelihood of receiving additional funding. Using survey data for Chinese firms, Ayyagari et al. [2010] show that informal financing is associated with lower sales growth and reinvestment rates. Informal finance is unlikely to provide entrepreneurs with the same level of guidance and monitoring offered by professional investors. Moreover, having relatives or friends as initial shareholders may affect the management style, for example by inducing too much risk aversion and causing firms to forgo profitable growth opportunities (Lee and Persson [2013]), or by introducing poor governance practices. If this conjecture is true, lower probabilities of raising additional funds simply reflect inferior business performance. Evidence based on survival data for a subsample of firms located in California does not support this argumentation. Like in the full sample, informal finance is negatively correlated with subsequent formal capital raising, but it does not predict lower survival probabilities.

To summarize, family and friends seem to be the wrong investors, as they deter formal venture capital, which improves firms' chances of survival. Then why do entrepreneurs resort to them? Informal finance may be cheaper than formal. However, my data show that it is usually not sufficient to cover initial investment needs in full. Formal capital providers (e.g angels) who co-invest with family and friends may anticipate the lower probability of follow-on rounds and raise the bar for access to seed rounds, thus undoing the cheapness of informal finance. If informal capital does not materially reduce the cost of funding, the benefits of involving family and friends must have a non pecuniary nature. The data on founder-manager turnover indicate that recourse to informal finance may depend on entrepreneurs'

[11] In the related family firms literature, Demsetz and Lehn [1985] refer to these benefits as the "amenity potential" of control. Informally funded firms are similar to family firms insofar as informal stakeholders are motivated by goals that are not purely related to financial performances. However, these firms do not necessarily share other distinctive features of family firms such as direct involvement of the family in the management or preference for within firm inter-generational transfers (Bennedsen et al. [2010])

[12] To continue the parallel with family firms literature, this mechanism can also explain why VC rarely invest in family firms. See for example Martí et al. [2013].

taste for control and on VC investment practices. Having trustworthy stakeholders increases the probability of retaining control in founders' hands, counterbalancing the negative effects on access to formal capital.

Thanks to the novelty and the scope of the SEC Form D dataset, this paper contributes to the entrepreneurial finance literature by significantly expanding empirical evidence on firm and founders' characteristics and financing choices of private ventures in their early-stage investment phase. Importantly, my focus on informal finance adds to the current understanding of the role of this source of finance in startups' capital structure (Robb and Robinson [2012]) and firms' outcomes. The results on the negative effects of family and friends funding on access to formal capital are also new to the existing body of theoretical literature on informal finance (Stiglitz [1990], Besley and Coate [1995], Lee and Persson [2013]). Finally, by providing suggestive evidence on corporate governance and performance related mechanisms, I connect informal finance literature with previous empirical and theoretical work on entrepreneurship (Hurst and Pugsley [2010], Hamilton [2000]), family firms (Demsetz and Lehn [1985], Burkart et al. [2003], Bennedsen et al. [2007], Miller et al. [2007]) and stage financing (Hellmann and Thiele [2015]).

The remainder of the paper is organized as follows. Sections I describes the data. Section II illustrates the empirical methodology and Section III presents the results. Possible mechanisms are explored in Section IV. Section V concludes.

1.2 Data Description and Summary Statistics

The main dataset employed in this study is constructed using filings for unregistered securities offerings (Form Ds) submitted by firms to the SEC. These filings contain information on firms, investors, terms of the offering and managers. I expand the dataset with information on the ethnicity of founders-managers by means of a name-ethnicity matching algorithm. The proxy for the size of founders' extended family is derived using the Frequently Occurring Surnames Dataset provided by the Census Bureau.

1.2.1 Small and Medium Sized Firm Financing: Capital Raising with Unregistered Securities Offerings

Currently available data on financing choices of early-stage firms rely primarily on surveys that cover a small portion of total capital raising. In order to attenuate this problem, I construct a dataset based on online filings for private offerings conducted in exemption to US securities laws.[13] Securities laws ("Securities Act" 1933, "Exchange Act" 1934) apply to all companies that issue securities. The main purpose of these laws is to protect investors as they enforce transparency and disclosure of companies' business and risk profile. The most common exemption for small businesses is the private placement exemption under SEC Regulation D,[14] which requires non-reporting firms to notify the SEC of the sale of securities via Form D. Angel investors and VC firms, for example, make their investments by purchasing in these private offerings of unregistered securities.[15] Regulation D requires that Form D must be filed within 15 days of securities first sale date, regardless of whether the total amount offered has been sold in full or not. No submission fees are charged and, beginning in March 2009, the SEC has made it obligatory to file Form D online. Despite the light work load that filing involves, it is reasonable to expect that this requirement may not be fulfilled by the totality of the firms subject to it but only by a selection of them. This can happen if entrepreneurs are unaware of the regulation or have no access to legal counseling. In this case, my sample may be tilted towards more sophisticated and experienced entrepreneurs. This circumstance, however, is unlikely to spuriously drive results on the negative effects of informal finance on access to venture capital. To the contrary, it may relax concerns over adverse selection of informally funded firms, as the sample excludes subsistence enterprises.

Any Form D filed is publicly available on the SEC website and contains the following information: issuer characteristics (year and state of incorporation, address, industry group, revenue range), type of securities issued (equity, debt, hybrid securities), offering and sales amount and the total number of investors who participated to the offering.

I collect all Form Ds that were filed with the SEC between March 2009 and October 2014. For the purpose of investigating the effects of informal finance, I identify a

[13]See http://www.sec.gov/info/smallbus/qasbsec.htm

[14]Private offering can also be conducted under Section(a)(2) of the Securities Act. Ivanov and Bauguess [2013] show that the amount of capital raised through Section(a)(2) during the years 2009 to 2012 is less than 20% of the amount raised through Regulation D.

[15]Tracking investments in private firms via Form D filings is becoming increasingly popular in the business community. See for example the website www.FormDs.com .

sample of issuers that display early stage business features and follow their capital raising activity over time. Each firm is uniquely identified by the Central Key Code, a numeric code assigned by the SEC.

Specifically, this restricted sample includes 6,717 non-financial firms, selected according to the following criteria:

1. All firms filed a Form D for the first time in years 2011-2012[16]
2. Firms are less than 2 years old at the time of the first offering
3. First offerings are smaller than $6M[17]
4. Disclosed revenues at the time of the first offering are smaller than $5 million
5. Firms operate in the U.S. and are incorporated (if already so) in Canada or the U.S.

Filters 1. and 2. are used in order to identify young firms that access entrepreneurial finance for the first time. Filters 3. and 4. are added in order to exclude firms that, despite being young and new to private capital markets, are large in size and in a mature stage, as it would be the case for spin-offs of established companies. Filter 5. rids the analysis of potential additional complexity due to frictions in international capital markets.

Table 1.1 shows the industry breakdown: Technology (other than Biotechnology and Telecommunications) dominates the sample with 24.2% of the observations. Other relevant sectors are Commercial (7.4%), Health Care (other than Hospitals and Health Insurance, 6.1%) and Oil and Gas (6.1%). Most firms are located in California (19.2%), Texas (10.8%), New York (9.8%), Florida (4.7%) and Massachusetts (4.7%) (Table 1.2). The total amount offered by firms in the sample at the time of their first access to private capital markets ranges between $1.2 billion and $1.4 billion per quarter, while the average size of the offering is $1.5 million (see Figures

[16]Choosing observations from the middle years of the larger sample makes sure that it is possible to track all previous offerings and restrict the sample only to first rounds for firms less than 2 years old and allows a little over 6 quarters after the first issuance to track future financing events.

[17]The rational for this threshold is that VC firms usually participate in larger, late stage deals. Average Series A VC deal size was $6.2 million, $6.5 milion and $8.6milion in years 2012, 2013 and in the first three quarters of 2014 respectively, according to Prequin Venture Capital Deals report October 2014.

1.2a and 1.2b).[18] These descriptive statistics are consistent with survey-based data on seed financing as they match evidence and trends on angel investing highlighted by Halo Reports (provided by ARI, SVB and CB Insights) for the corresponding years.[19]

The granularity of the information contained in these filings allows for the analysis of private capital markets along novel dimensions. In terms of firm characteristics, common legal entity types are Corporations (45.8%) and LLCs (44.4%), most firms are incorporated in Delaware (49.4%), while only 0.67% of the firms were not yet incorporated at the time of the deal. Half of the firms in the sample decline to disclose revenues, 27% of them had no revenues and the rest disclose revenues smaller than $5 million. Table 3 reports characteristics of the seed round. The security type used is equity (alone or in combination with other securities) for 79.7% of the observations and debt (alone or in combination with other securities) for 14.8% of the observations. The issues are rarely conducted with the support of a registered financial intermediary (less than 5%). The average number of investors per deal is 11.42 and the median is 6 (Figure 1.2a).

In order to assess firms' ability to access private capital markets, I analyze follow-on rounds filed within six quarters of the initial round.[20] Only 19% of firms in the sample raise capital in a second offering.[21] The average amount offered is substantially higher than in first rounds ($3.2 million on average) and debt (alone or in combination with other securities) is more widely used (26%). Firm characteristics are essentially unchanged: 99% of the issuers are still incorporated in the same state, only 7% report to operate in a different sector and 14% report a change in revenue size (see the revenue size transition matrix in Table 1.4).

1.2.2 A Proxy for Informal Finance: Non-Accredited Investors

SEC disclosure requirements for private placements allow researchers to construct an empirical proxy for informal finance. Firms filing Form D must disclose whether

[18]Since filing of Form D is required within 15 days since the day of the first sale, amounts offered and amounts sold by the filing date can differ. On average, firms report to have sold 58% of the amount offered.

[19]http://www.angelresourceinstitute.org/research/halo-report/halo-report.aspx

[20]Conditional on observing a second offering after the first one, the average time between the first and the second issuance in the sample is 3.86 quarters, but decreases over time due to observability. 6 quarters represents the 75th percentile in the distribution of time elapsed between the first and the second offering for all of the 8 subsamples of firms by quarter of first issuance.

[21]For a comparison, the Angel Capital Association reports that in 2012 the number of VC deals was approximately 15% of the number of seed round deals provided by angels (https://www.sec.gov/info/smallbus/acsec/acsec-091713-verrill-hudson-slides.pdf)

non-accredited investors can purchase the security offered: I use this information as the indicator for recourse to informal finance.

Regulation D (in its most commonly used rule, 506(b)) imposes restrictions to securities sales based on financial sophistication and need for protection of investors.[22] Specifically, buyers in a private offering are assumed to be sophisticated if they comply with the definition of accredited investor. In the context of this study, the relevant accredited investor definition includes: registered financial intermediaries, charity organizations, directors or executives of the firm, individuals with net worth greater than $1 million or income exceeding $200 thousands per year.[23] Under Rule 506(b) there are no restrictions on participation and disclosures if securities are sold to accredited investors, while non-accredited investors cannot be more than 35 in each single offering and must be provided with specific disclosure documents, such as certified financial statements.[24] Since general solicitation, i.e. any form of advertisement of a private securities sale, is forbidden, investors must be approached directly by the issuer.[25] While financial intermediation companies are well known to the general public through websites or advertisement, angel investors usually organize themselves in groups operating via a website, in order to increase their visibility to entrepreneurs. The Angel Capital Association, the largest angel organization in the world, and the vast majority of angel groups in U.S.A., only accept accredited investors as members. Thus, non-accredited in-

[22]Private offerings in exemption of securities laws can be conducted also under Rule 504, Rule 505 and, since September 2013, Rule 506(c). Rules 504 and 505 are applicable to smaller issuances ($1 million or $5 million) and, under certain circumstances, they relax constraints on non-accredited investors participation . However, only Rule 506(b) exempts from Blue Sky law registration. This seems to be the reason why Rule 506(b) has been used in 94% of the offerings between 2009 and 2012. See Ivanov and Bauguess [2013].

[23]The standards for accredited investor qualification were first set 1982 when Regulation D was issued. The first revision of these criteria was introduced in 2011 with the Dodd-Frank Act and enacted in December 2012. It excluded the house of first residence from the calculation of natural persons net worth. According to the Dodd-Frank Act, the SEC is now required to revise the accredited investor definition every four years.

[24]The constraint on the number of non-accredited investors does not appear to be binding for firms in this sample, as 96% of first round filings for completed offerings report less than 35 investors in total.

For offerings up to $2,000,000 financial statements requirements are the following : balance sheets as of the end of each of the two most recent fiscal years (only the balance sheet, dated within 120 days of the start date of the offering, must be audited);statements of income, cash flow and changes in stockholders' equity for each of the two years preceding the date of the most recent audited balance sheet (or such shorter period as the issuer has been in business); and interim financial statements as of the end of the issuer's most recent fiscal quarter. For offerings up to $7,500,000 the same requirements apply. However, the financial statements must be audited unless the issuer cannot obtain audited financial statements without unreasonable effort or expense. For offerings over $7,5000,000 the issuer must provide the financial statements required to be filed in a registration statement that the issuer would be entitled to use.

[25]The solicitation of an offering became less restricted with the JOBS act in 2012. The new Rule 506(c) allows general solicitation provided that the offering is addressed only to accredited investors.

vestors participating in these offerings are likely to be individuals within the entrepreneur's social network (such as family, friends or employees). This identification criterion is strict: depending on their wealth, family and friends of the entrepreneur may qualify as accredited investors and participate in the offering as such. As a consequence, the informal finance proxy may underestimate the extent to which firms rely on this type of investors for funding.

Table 1.5 provides descriptive statistics for the 1,117 firms (16.63% of the whole sample) that have informal funders among their initial investors (I will refer to this group as *IF-firms*) and compare them with the rest of the sample (*NonIF-firms*). Consistent with economic intuition, IF-firms are smaller (in terms of number of founders and amount offered in the first round) and at an earlier stage of business operations (as per revenue size, years since incorporation and entity type). Moreover, location and sector distributions are more dispersed than for NonIF-firms, with smaller weights on California and Tech companies.

97% of the completed IF-firms' first offerings have accredited investors participating alongside non accredited investors. Informal finance is rarely the only source of funding and it is usually combined with professional investments.

Crucially in the context of this paper, the likelihood of raising capital in a second offering drops dramatically for the IF-firms subsample: approximately 10% of the firms access capital markets for a second time, and less than 5% do so via offerings conducted exclusively with formal investors (see Table 1.5).

1.2.3 The Founders Team

"Have you ever noticed how few successful startups were founded by just one person?" asks Paul Graham in his blog.[26] Undoubtedly, the size of the management team matters for professional investors when deciding whether to finance a project. Ability to work in teams and complementarities in product development and management skills are often quoted as the motive for easier access to VC capital of firms with two or more founders.

Form D contains the full name and address of "related persons", namely issuer's executive officers, directors or promoters.[27] I refer to the group of related persons

[26] Paul Graham is a known tech entrepreneur, venture capitalist and co-founder of Y Combinator, a seed capital firm.

[27] The definition of promoter includes: (i) Any person who, acting alone or in conjunction with one or more other persons, directly or indirectly takes initiative in founding and organizing the business

in each deal as the management team. In the absence of any legal or conventional definition, I assign the *founder* status to individuals with managerial positions in the firm at the time of its first round of capital raising, provided that it takes place within two years since incorporation. Therefore, I refer to the group of managers in the seed round as the founders.

This sample contains the names of 19,498 founders: 44.13% of the individuals in this group are directors, 46.31% are executive officers and 9.56% are promoters, with 4% of them being other business entities. The size distribution of the founders management team is illustrated in Figure 1.2b. Mean and median size of founders teams is 3 and 99% of the firms have less than 9 founders. Consistently with Graham's quote, single-founder firms (20% of the sample) are less likely to raise capital after the first deal: 13% of these issuers access the market a second time, versus 20% of firms with 2 or more founders.

In order to gain further insight on founders' demographics and lacking any information on their biographies, I match founders' last names with linguistic group/ethnicity according to the algorithm in Ambekar et al. [2009]. This automated ethnicity classifier uses hidden Markov models and decision trees to assign names to one of 13 ethnic/linguistic categories (Table 1.6, Panel A shows the hierarchical structure of the categories). Panel B in Table 1.6 illustrates the ethnic mix of the founders teams. The average founders team is mostly composed of individuals with a European descent (84%). Interestingly, the average composition of teams that access capital markets for a second time is broadly similar to the full sample's. Similarly, teams with a majority of European descendants do not seem to be more likely to raise more funding after the first round when compared to the full sample or the subsample of firms with a balanced ethnic mix (i.e. firms where no ethnicity represents more than 50% of the team).

1.2.4 Rare Surnames and Informal Finance

Since financing decisions are made by firms' managers, investigating personal characteristics of founders can help identify sources of variation in the use of informal finance. For example, the size of founders' extended family network might affect the supply of informal funds. I construct a proxy for small combined family

or enterprise of an issuer; or (ii) Any person who, in connection with the founding and organizing of the business or enterprise of an issuer, directly or indirectly receives in consideration of services or property, or both services and property, 10 percent or more of any class of securities of the issuer or 10 percent or more of the proceeds from the sale of any class of such securities. However, a person who receives such securities or proceeds either solely as underwriting commissions or solely in consideration of property shall not be deemed a promoter within the meaning of this paragraph if such person does not otherwise take part in founding and organizing the enterprise. Securities Act of 1933, Rule 405, 17 C.F.R. § 230.405.

network of the founder team, based on information on founders' surnames contained in the Frequently Occurring Surnames dataset (FOS) provided by the Census Bureau.

The FOS ranks all American last names (6.2 million) in order of occurrences, i.e. in terms of number of U.S. residents with each surname. This dataset shows, along with names and occurrences, statistics on ethnicity and race of individuals associated with each name. For example, the last name Smith ranks first with over 2.3 million occurrences and is mostly borne by non-Hispanic white (73%) and non-Hispanic black (22%) individuals. For privacy reasons related to the disclosure of such sensitive demographic data, the list is truncated to exclude names that occur less than 100 times. However, summary statistics for these *rare* names are provided by Word et al. [2008]. There are 6,096,744 rare names that correspond to over 27 million people (10% of the surveyed population). Thus, each rare name corresponds on average to 4.5 individuals. Furthermore, over 90% of these rare names occur less than 10 times.[28]

As a consequence of this truncation, some founders' names in my sample (13.87%) cannot be matched with the FOS list and are classified as rare. On the basis of the judgment that 4.5 expected occurrences of a last name reveal an exiguous number of familiar links, I identify founders with small family networks as the ones bearing a rare surname.

I define the $SmallFamily$ dummy variable $S_i = 1$ if the proportion of founders in firm i with rare last names is greater than the sample average. Consistently with the intuition above, firms with $S_i = 1$ (1,954 observations) are less likely to resort to informal finance as compared to the full sample (12.69% versus 16.67%).[29] Importantly, these firms also seem to be associated with a higher probability of raising capital more than once (21.85% versus 19.04%).[30] The issue of robustness of the correlation between S_i and informal finance and the question of whether channels other than family size can affect the relationship between S_i and subsequent financing events are addressed in the next section.

[28]Similar distributional properties of Spanish and English last names have been exploited by Güell et al. and Clark and Cummins [2015] to establish family links among individuals and track inter-generational mobility.

[29]This difference is significant at 1% confidence level

[30]This difference is significant at 1% confidence level

1.3 Empirical Strategy

1.3.1 Empirical Specifications

A simple way to estimate the impact of informal finance on future financing events is via a single equation probit model. Let the indicator variable $Y_i = 1$ if firm i raises capital in private markets within 6 quarters since its first offering. The probability of $Y_i = 1$ can be described by

$$\Pr\left[Y_i = 1\right] = \Pr\left[X_i\beta + IF_i\delta + \epsilon_i > 0\right] = \Phi\left[X_i\beta + IF_i\delta\right] \tag{1.1}$$

where $\Phi\left[\cdot\right]$is the standard normal cdf, X_i is a vector of firm, seed round, founders and time variables and IF_i is a dummy variable that takes value 1 when non-accredited investors are allowed to participate in the first offering and ϵ_i is a standard normally distributed random error.

In this single-equation probit model the informal finance coefficient is treated as exogenous. There are, however, reasons why this may not be the case. Entrepreneurs who involve individuals from their social network as investors in their venture may be the ones that enjoy non-pecuniary benefits from running a business that is strongly connected with their communities and, as a consequence, they are not purely profit-oriented. This attitude may discourage outside investors. Alternatively, if entrepreneurs prefer formal to informal finance and the supply of capital is limited, the best projects will receive full financing by professional investors while other projects will either not receive funding or will be funded by informal investors.[31] The best projects are also more likely to successfully raise capital in a second round. Thus, the informal finance effect is due to an unobservable omitted "project quality" variable rather than a causal link with future access to capital. Notice however that the richness of the SEC data allows for extensive controls on size, revenues and age and, more importantly, almost all of the seed round offerings with informal funders are also subscribed by other investors. Informal finance thus does not seem to be correlated with rejection by early stage professional investors like angels.

In order to allow for the possibility of endogeneity, I estimate model (1.1) jointly with a probit model for the informal finance variable (see Greene [1998] and Evans and Schwab [1995] for applications in education economics).

[31]Entrepreneurs' preference for one source of funding over the other is not an uncontroversial issue. While informal finance imposes regulatory and "emotional" burdens on founders, it might be significantly cheaper than formal finance, especially when capital supply is exiguous and there is strong inequality of bargaining power between entrepreneurs and professional investors.

Suppose that the probability of $IF_i = 1$ is described by

$$\Pr[IF_i = 1] = \Pr[Z_i\theta + \mu_i > 0] = \Phi[Z_i\theta] \tag{1.2}$$

where Z_i is a vector of observable and μ_i is a random error.

In this setting, both the outcome variable and the potentially endogenous regressor are dichotomous and as a consequence both the first stage and the structural model are non linear. Following Heckman [1978], I employ a bivariate probit model approach.[32]

This model is identified if at least one variable (the instrument) in Z_i is not contained in X_i.[33] Equation (1.2) can be rewritten as

$$\Pr[IF_i = 1] = \Pr[X_i\lambda + S_i\pi + \mu_i > 0] = \Phi[X_i\lambda + S_i\pi] \tag{1.3}$$

where the instrument S_i is the proxy for small combined family as defined in the previous section.[34]

Finally, since large social networks may support founders through multiple stages of financing, the indicator dependent variable can be redefined as $Y_i = 1$ if firm i raises capital in private markets with *accredited investors only* within 6 quarters since its first offering. With this specification I evaluate the impact of informal finance on funding from formal investors.

In all of the above specifications, the full vector of covariates X_i includes:

[32] To account for the possibility that IF_i and Y_i are determined by correlated unobservable variables (say "project quality") I assume that ϵ_i in (1.1) and μ_i in (1.2) are distributed bivariate normal with $E[\epsilon_i] = E[\mu_i] = 0$, $var[\epsilon_i] = var[\mu_i] = 1$ and $corr[\epsilon_i, \mu_i] = \rho$. In this model there are 4 possible states of the world ($IF_i = 0$ or $IF_i = 1$ and $Y_i = 0$ or $Y_i = 1$) and corresponding likelihood function is a bivariate probit.

[33] Han and Vytlacil [2013] extend this identification result to a wider class of models that includes bivariate probit models as a special case

[34] An alternative strategy consists in a 2SLS estimation where non linear fitted values for IF_i from (1.3) are used as instrument (Angrist and Pischke [2008]). While the linear IV method provides consistent estimates of the average effect, it can be biased in small samples and its performance can be inferior to a correctly specified maximum likelihood estimation approach. Despite these drawbacks, in the next section I present 2SLS estimates along with bivariate probit model results for comparison.

- Firm characteristics: industry, revenue size, legal entity type, state of location, state of incorporation, year of incorporation
- Founders Team characteristics: size, ethnicity mix (based on Level 2 as per Table 1.6), a *Corp* dummy that takes value 1 if one or more of the related persons are other business entities, a *family* dummy that takes value 1 is two or more founders have the same last name
- Seed Round characteristics: amount offered, number of investors, quarter of issuance, type of security issued, an *Intermediation* dummy that takes value 1 if the offering was conducted with the support of a registered financial intermediary, a *Hot Deal* dummy that takes value 1 if more than 80% of the amount offered was sold at the time of the filing (approximately half of the sample).
- An interaction term between year of incorporation and quarter of first issuance, to capture the effect of firms' age in different capital markets conditions

The coefficient of interest is δ in equation (1.1), which captures the effect of informal finance on future financing.[35] Any claim of causality relies on the relevance and validity of the instrument, which are discussed next.

[35] In order to measure the qualitative importance of the covariates I report Average Marginal Effects. For the j-th covariate, these are given by

$$AME_j = \gamma_i \frac{1}{n} \sum_{i=1}^{n} \varphi(A_i \gamma)$$

for continuous covariates and

$$AME_j = \frac{1}{n} \sum_{i=1}^{n} \left\{ \Phi\left(A_i \gamma \mid \gamma_i^j = 1\right) - \Phi\left(A_i \gamma \mid \gamma_i^j = 0\right) \right\}$$

for dummy variables , where n is the sample size, A_i is the full vector of covariates and $\varphi(\cdot)$ is the first derivative of $\Phi(\cdot)$

1.3.2 Rare Last Names, Informal Finance and Access to Private Capital Markets

For the bivariate probit model to be identified we need a) the instrument to belong to the set of explanatory variables in (1.2) and b) the instrument to be excluded from the structural model in (1.1). In order to verify the relevance of instrument S_i I estimate the first stage single equation probit in (1.3).

Estimated coefficients and average marginal probabilities are reported in Table 1.7 together with coefficient estimates for a linear probability model . Results show that S_i has a significant negative effect (-5%) on the probability of firms resorting to informal finance. The interpretation of this coefficient is relatively straightforward: if the founders team has a small combined family network it is less likely for the firm to have informal investors. The magnitude is considerable when compared with the unconditional probability of resorting to informal finance for firms in my sample (17%). Incidentally, coefficients estimates of equation (1.3) offer an interesting insight on startups financing choices. Informal finance is less likely for larger offerings, but the size of the management team does not seem to play a significant role. The estimated coefficient for the *Hot Deal* dummy is negative and significant: first rounds that are open to professional investors only are subscribed faster.

As the relevance of the instrument is confirmed, the credibility of the identification strategy relies on the hypothesis that the proxy for founders family network size does not affect the ability of the firm to raise capital in private markets a second time (other than via less frequent recourse to informal finance). At the firm level, small combined family networks do not seem to be associated with higher growth potential. Table 1.8 shows that the instrument is not correlated with higher revenue size or capital raised in the seed round, nor it is predicts changes in revenue size for firms that access follow-on financing. Hence, in this sample, availability of family and friends' financial support does not make it easier for entrepreneurs to kick-start their business. Furthermore, the instrument does not explain faster expansion processes where financing needs (measured by proportional change in capital raised between seed and follow-on round) grow more rapidly. This evidence is consistent with the idea that founders' preferences for non-pecuniary benefits of entrepreneurship are orthogonal to family size, while correlated with family and friends' investments.

It remains to be assessed whether founders with rare last names somehow "special" in their ability to run a business or securing funding. In order to address this question, I examine further the demographics of the rare last names group and compare it with the rest of the sample. As suggested by Clark and Cummins [2015], individuals' surnames classify as rare in three instances

1. Small local families
2. Early generations immigrants
3. Spelling mistakes/name mutations.

Each of the above classification groups poses specific challenges to the identification strategy.

Firstly, an instrument that oversamples individuals belonging to small American families can fail the validity test if these families have larger wealth or more powerful social networks, as this might imply better access to funding. Such conjecture is consistent with the idea that lower fertility can improve the socioeconomic conditions of descendants because of lower dispersion of family resources (Goodman et al. [2012], Downey [2001]). Concerns over the validity of the instrument motivated by the argument above are mitigated by the fact that the population of start-up founders in this sample is likely to be more homogeneous in terms of social background and education than the broad U.S. population.[36]

Second, Immigrants may have better or more innovative ideas, perhaps because of better education systems outside of U.S. or because they are more motivated. Previous literature explored the role of immigration in innovation and entrepreneurship. Kerr [2008] shows how Chinese and Indian inventors were important contributors to innovation in the U.S in the 1990s by matching a name-ethnicity database with individual patent records. On the other hand, Michelacci and Silva [2007] provide evidence that entrepreneurs who work in the same region where they were born are more successful than outsiders as they are better at taking advantage of financial opportunities arising in that region. Although geographical distance from family can certainly discourage informal finance, if the first effect dominated, the instrument proposed would be also picking up better unobservable project quality. Notice that, in this study, the "recent immigrant" status does not necessarily associate with the rare last name category: an entrepreneur named Elena Garcia

[36]According to a report published in 2010 by CB Insights, 52% of the founders of firms involved in Internet Seed and Series A rounds have graduate level education, with 7% of the sample holding a PhD degree.

would not be part of the rare surname subsample (Garcia is the 8st most common surname in U.S.), even if she just moved from Mexico to California.

Finally, while unable to verify the incidence of name mutations (i.e. surname spelling mistakes at the time of registration in public records), spelling mistakes are unlikely to be frequent in the dataset as the filings are filled in by the founders themselves (or their representative) and machine readable. Of course, if name mutations and spelling mistakes were the major reason why surnames are classified as rare the conjectured link with the family size would no longer be grounded. In that case, however, it would be difficult to make sense of the first stage results presented in Table 1.7.

To investigate whether individuals with small families in my sample are more likely to have higher social stata or business skills, I extract information on founders education and past working experience from LinkedIn, an internet-based professional network. Each individual j, founder of firm i is uniquely identified if first and last name correspond to a member of the network and if this member's curriculum includes a working experience in firm i. Although the working experience criterion reasonably ensures that individuals in the sample are correctly paired with network members, it reduces the probability of matching, as legal entity names often do not coincide with company names used on CVs or for commercial purposes. As a result, only 24% (4,422 individuals) of the founders were uniquely matched with a member's profile. The matched subsample however appears to be representative of the population, as the differences in the distributions of matched and unmatched individuals by location, sector, revenues size, team size, role and ethnicity are not statistically different from zero.[37] Insofar as education is strongly correlated with socioeconomic background and business skills, the results support the validity of the instrument. Education attainments and the length of past working experience are remarkably similar between the two groups (see Table 1.9 and Figure 1.3). The representative founder has college or higher level education and approximately 10 years of previous working experience, with no significant difference between individuals with rare and non rare last names.[38]

[37]The test statistics and p-values for Chi-squared tests of homogeneity in the distributions of matched and unmatched individuals by State, Sector, Revenue Size, Team Size, Role and Ethnicity are as follows: $\chi^2_{(df)} = 46.33_{(51)}$, Prob=0.659; $\chi^2_{(df)} = 9.25_{(6)}$, Prob=0.16; $\chi^2_{(df)} = 1.76_{(3)}$, Prob=0.624; $\chi^2_{(df)} = 20.44_{(18)}$, Prob=0.093; $\chi^2_{(df)} = 1.06_{(2)}$, Prob=0.588; $\chi^2_{(df)} = 16.62_{(12)}$, Prob=0.165;

[38] This result does not necessarily contradict the idea that individuals who belong to small families achieve higher than average sociology-economic conditions, but rather it highlights how such achievements are common among the population of entrepreneurs in this sample, regardless of the size of their families.

Finally, Panel A in Table 1.10 shows the ethnic classification of the rare last names group versus the full population sample. The comparison of the two distributions is largely in line with the idea of foreign born individuals being over-represented, but presents some peculiar features, especially when examined in juxtaposition with U.S. immigration dynamics over the last century (Figure 1.4). East Asian and Hispanic ethnicities are under-represented in the rare last names group, despite China and Mexico being the largest contributors to recent immigration in terms of country of origin. Indian origin is over-represented, consistently with strong Indian immigration flows in the 2000s, but so is the Italian, even though strong immigration flows from this country substantially stopped in the 1980s. This mixed picture reveals that rare last names do not predominantly belong to early generation immigrants. Different surnames distributions of different linguistic groups are due to historical, cultural, geographical and biological evolution (Manrubia and Zanette [2002]) and affect the probability of surnames from these groups to fall into the rare category. Italian last names distribution, for example, is one of the most dispersed while the Chinese and Korean ones are very concentrated.[39] As immigrants over time bring the name distribution feature of their linguistic group into the host country, names belonging to groups with more (less) dispersed distributions can qualify as rare (non-rare) even for second-or-later (first) generations. Therefore, the ethnicity classification is insightful but not fully informative of whether rare last names mostly belong to foreign born individuals.

An additional characterization of the rare last names group in terms of early immigrants versus small American families can be provided by looking at first names. I split the sample in *American* versus *Early Generation* individuals by matching first names with the list of the 2,438 most common given names as reported in the 1990 Census. The logic behind this classification is that names that were popular at the beginning of the 1990s must belong to the dominant cultural/ethnic heritage of current second-or-later generation Americans. Therefore, names within the list are labeled as American and unmatched names are labeled as Early Generation. In the rare subsample, American individuals have mostly European origins (88%) while Early Generation ones have more diverse ethnic background (Table 1.10, Panel B). Importantly, the American component in the non-rare subsample is significantly higher than in the rare group (89% versus 75%).

The ethnicity mix of founders is included in the set of explanatory variables X_i, but an exact control for recent immigration is not viable due to lack of data. Thus, I use the notion that European origins are mostly associated with second or later

[39]Rossi, the most common Italian last name approximately belongs to 0.2% of the population while more than 20% Koreans bear the family name Kim

generations Americans to conduct robustness checks.

1.4 Results

Firms with small combined founders' family are 4% more likely to access follow-on capital. Coefficient estimates and average marginal effects for a probit model of the follow-on funding outcome on the exogenous variables and the *SmallFamily* instrument S_i are presented in Table 1.11, together with estimates for a linear probability model. The full set of covariates is employed as control. In Panel B the outcome variable is redefined as $Y_i = 1$ if firm i raises capital in private markets with *formal investors only* within 6 quarters since its first offering. The coefficient on the instrument S_i is significant at conventional levels in both specifications. Other results in Table 1.11 are consistent with the intuition and anecdotal evidence on entrepreneurial finance. Firms with larger founders teams are more likely to secure subsequent financing while larger initial offerings are less likely to be followed by second offerings in the immediate future.

The main results on the effect of informal finance on subsequent access to venture capital stem from the joint estimate of (1.1) and (1.3) with a bivariate probit model and are illustrated in Table 1.12. Columns 1, 2 , 5 and 6 show coefficient estimates and average marginal effects using the two proposed definitions for the outcome variable Y_i. Results of 2SLS estimations are presented for comparison in columns 3 and 7. Despite the potential endogeneity issue related to the informal finance choice, I include estimates of average marginal effects for the single equation probit model in (1.1) in columns 4 and 8. Informal finance has a negative and significant effect on the probability of future financing events ranging from -15% to -19%, with the strongest effect associated with follow-on funding from formal investors only.[40] Notice that the Hot Deal variable does not affect probability of future financing events, while it is negatively correlated with the use of informal finance. This suggests that seed rounds conducted with no informal investors are subscribed faster for reasons that are unrelated to higher unobservable quality of

[40]The significance of the informal finance variable is not overstated by its dichotomous specification. In unreported estimations, I replicate the analysis using the proportion of non-accredited investors over total number of investors as proxy for informal finance. The coefficient estimates are negative and significant at 1% level in both the probit and the linear probability model and with both specifications for the dependent variable. However, the categorical definition is preferred because it is more accurate as the proportion of non-accredited to accredited investors may change after the filing date, once the offering is completed.

the entrepreneurial idea. It is possible that some early stage formal investors anticipate a lower probability of securing further finance in the future for informally funded firms and this drives the negative relationship between the Hot Deal variable and informal finance in the seed round. This interpretation is supported by the fact that informal finance coefficients and marginal effects as computed with the single equation probit model are smaller in absolute value as compared to the ones computed using the instrument. In other words, it appears that the bar for accessing formal seed financing is set higher for firms open to informal funding, effectively producing a positive, rather than adverse, selection bias.

Revenue size is arguably a relevant variable for this analysis and unfortunately approximately 50% of the firms in the sample decline to disclose this information. In order to check whether the results above are driven by bad controls for revenues size I estimate the same models for the restricted sample of firms that disclose revenues: the average effect of informal finance is still negative (-14%) and significant when follow-on rounds are conducted exclusively with formal investors (Table 1.13).

The main results presented above are computed using models that include all variables in the control set X_i defined in Section 3.1. Table 1.14 shows that average marginal effects in a bivariate probit model that only includes firm size controls (column 2) or firm size, industry and location controls (column 3) are not significantly different from estimates for the full model.[41] Thus, a more parsimonious specification with only size, industry and location controls is viable with no significant loss in the explanatory power of informal finance. Further robustness checks are presented in Table 1.14. In columns 4 and 5 I make use of the ethnicity classification for founders in different ways. Instead of using the proportion of people belonging to each ethnic/linguistic group for each firm, I include either a dummy variable that takes value 1 if the majority of the founders have European descent or a dummy variable that takes value 1 if no ethnic group represents more than 50% of the founders team. The purpose of these different specifications is to account for homogeneity versus multiethnicity of the founders team composition rather than focusing on the specific ethnicity breakdown. This different approach does not yield different estimates for the effects of informal finance. In column 6 I restrict the sample to firms where the majority of the founders have European origins. In doing so, I verify that the effects of informal finance are not related to recent immigration of founders. Finally I restrict the sample to Hot Deals, namely firms that sold at least 80% of the offering amount at the time of the filing for their seed round. Column 7 shows that the magnitude and significance of marginal ef-

[41]Size controls include revenue size, legal entity type and amount offered in the seed round.

fects on funding from all investors types drop for this subsample but stay constant when follow-on funding from formal investors only is used as dependent variable.[42]

1.5 Direct Effects on Performance or Frictions in Private Capital Markets?

Having documented the effect of informal finance on the ability of firms to secure financing, I now turn to explore some possible explanations.

Family and friends stakeholders can directly affect firms performance by influencing the management style. For example, they can induce higher risk aversion, which can curb growth and expansion or even generate losses. Informal finance could also lead to bad management practices, such as hiring under-qualified family members or friends in return for financial support. IF-firms will then be less suitable for follow-on rounds within a short period of time. If that is the case, a lower ability of raising new capital further down the line stems from lack of success of the entrepreneurial project. In order to verify this conjecture, alternative measures of firm performance are needed. Given the modest size of the firms in my sample, usual accounting or market performance indicators are not available. As a second best approach, I examine survival probabilities for the subsample of California firms.

1.5.1 Direct Effects: The California Subsample

I collect data on corporate status as reported on the Business Entities section of the Secretary of State (SoS) webpage (as of June 2015) for California-based firms. California SoS provides information on the status of companies registered in California and companies that perform repeated and successive transactions in the state, regardless of the jurisdiction of incorporation. The search criterion is the legal entity name. Records of corporate status were found for 1046 out of 1288 California firms in the sample.

Corporate status can be recorded as: active, canceled (if the formation or qualification filing was canceled because the payment for the qualification status was not honored), suspended or forfeited (if the business entity failed to file the required forms with the SoS or failed to meet tax requirements), dissolved, surrender (if the business entity surrendered its right to transact business in the State of California), merged out (the business entity merged out of existence in California into

[42]For this specification, given the sensible reduction in the number of observations, I used a more parsimonious model where I included only size, industry and location as control variables

another business entity), converted out (the business entity converted to another type of business entity or to the same type under a different jurisdiction as provided by statute), term expired (if the business entity's term of existence has expired, as provided by the entity's Articles of Incorporation), inactive.[43]

Descriptive statistics are provided in Table 1.15. Not surprisingly, the technological sector dominates this subsample. IF-firms are more likely to operate in the service industry and are smaller in terms of revenues size. The interesting fact emerging from Table 1.15 is that the distributions of corporate status are identical (differences are not statistically significant) for IF and NonIF firms. In other words, informal finance does not seem to affect survival probabilities. Moreover, among firms that did not raise further capital after the first offering, IF-firms are marginally more likely to survive. This evidence is investigated more formally in what follows.

Define $Y_i^S = 1$ if firm i's status is reported as active or merged out. I estimate

$$\Pr\left[Y_i^S = 1\right] = \Pr\left[Z_i\gamma + IF_i\delta + u_i > 0\right] = \Phi\left[Z_i\gamma + IF_i\delta\right] \tag{1.4}$$

where $Z_i \equiv [X_i, Y_i]$ and u_i is a random error. Thus, Z_i includes all controls in (1.2) plus the financing event dummy Y_i . Marginal effects of IF and Y are reported in Table 1.16, together with marginal effects obtained by estimating (1.2) on the California sample.[44]

The effect of informal finance on the probability of future financing events confirms the general findings based on the analysis of the full sample and discussed in the previous section. In model (1.4), follow-on financing events are associated with higher probabilities of survival. There are several possible explanations behind this result. Formal investors in follow-on rounds may be able to select successful firms or they may directly contribute to performance improvement with mentoring and guidance. Crucially, marginal effects of informal finance are positive but not significant. Hence, informal finance does not negatively affect performance (proxied by survival probabilities).

[43] See http://www.sos.ca.gov/business-programs/business-entities/cbs-field-status-definitions/

[44] In unreported estimations, I use the same instrumental variable approach employed for deriving the main results in Section 4. Because of the sensible drop in the sample size I use a more parsimonious model, where only size controls are included in the set of the exogenous covariates. Marginal effects of financing events on survival probabilities range between 12.7% (follow-on events conducted with formal investors only) and 13.3% (all follow-on events) and are statistically significant at 1% confidence level. Marginal effects of informal finance on survival probabilities are not statistically different from zero.

A consistent interpretation of these results suggests that late stage professional investors are more inclined to provide capital to firms where family and friends of founders are not involved as stakeholders but the motivations behind such preference are not directly related to the quality of the entrepreneurial project.

1.5.2 Frictions in Private Capital Markets: the Fight for Control

An alternative explanation is related to the business model of the venture capital industry. Late stage, VC-type investors typically demand some degree of managerial control over the firms they finance. This praxis is generally grounded on the premise that, once the start-up has successfully overcome its embryonic phase and the business idea has been proven commercially viable, professional management is needed in order to grow revenues and scale up operations. This often implies displacing founders' leadership, for example by replacing existing managers and directors with individuals chosen by the investors. In a 2008 article on the Harvard Business Review, this is how Noam Wasserman describes his findings on the issue of founders control: "When I analyzed 212 American start-ups that sprang up in the late 1990s and early 2000s, I discovered that most founders surrendered management control long before their companies went public. By the time the ventures were three years old, 50% of founders were no longer the CEO; in year four, only 40% were still in the corner office; and fewer than 25% led their companies' initial public offerings".[45]

Founders-entrepreneurs, who are often motivated by non pecuniary goals such as decisional autonomy in the workplace (Hurst and Pugsley [2010], Hamilton [2000]), are likely to resist this transition process. In the article cited above, Wasserman continues: "Founders don't let go easily, though. Four out of five entrepreneurs, my research shows, are forced to step down from the CEO's post. Most are shocked when investors insist that they relinquish control, and they're pushed out of office in ways they don't like and well before they want to abdicate".

The clash over managerial leadership can be costlier and more time consuming for outside investors if existing shareholders/friends side with the founders. Such support may be granted on the basis of altruistic preferences of informal funders. A plausible conjecture follows: informal finance may discourage funding from formal investors because it makes it harder to impose control on funded firms.

To test this hypothesis, I examine changes in the management team for the subsample of firms that tap private capital markets at least 3 times (674 observations).

[45]https://hbr.org/2008/02/the-founders-dilemma

For all of these firms, I can observe the names of managers in office *after* the follow-on round. The majority of these companies (55%) operate in the technological industry and are mostly located in California (24%), New York (11%), Massachusetts (8%) , Washington (6%) and Texas (5%). The proportion of founders in the management team at the time of the third round of funding is higher for IF-firms. The median (mean) value for this proportion is 82% (71%) for IF-firms and 67% (63%) for NonIF-firms. Moreover, IF-firms are more likely to have founders controlled teams (proportion of founders>51%): 67% versus 59% for NonIF-firms, on average. At the time of the seed round, 846 founders had an executive officer role and, in line with Wasserman's findings, only 46.2% of them retained this position after the follow-on round. I use this sample of founders-CEOs to estimate the effects of informal finance on the probability of founders retaining executive positions.

Define $E_{j,i} = 1$ if founder j of firm i still holds an executive position at the time of the third financing event. I estimate

$$prob\left[E_{j,i} = 1\right] = \Phi\left[A_{j,i}\theta + IF_i\vartheta\right]$$

where $A_{j,i}$ is a set of controls that includes industry, revenue size, location, number of quarters between round 1 and round 3, founder's ethnicity.[46] Both the marginal effect of the single equation probit and the coefficient of a linear probability model are positive and significant, indicating that informal finance increases the probability of executive-founders maintaining their roles by approximately 19% (Table 1.17).

1.5.3 Alternative mechanisms

The evidence provided so far suggests that family and friends are the *wrong* investors for start-ups because, by helping founders retain control, they discourage late stage outside investors.

A different but related motivation for my findings is that informal finance may directly affect *demand* for funds, by shifting founders' preferences from venture capital to alternative forms of funding. In other words, the "amenity potential" of

[46] In this subsample, given the substantial drop in the number of observations, the negative correlation between the instrument and recourse to informal finance is too weak to support an IV approach. However, concerns on endogeneity are alleviated by the fact that all these firms are equally successful, as they access private capital markets at least three times in 3 years. Nevertheless, the evidence provided here is also consistent with entrepreneurs with strong taste for control choosing informal finance at the time of the seed round.

control increases for entrepreneurs when family and friends are involved in the venture. In this case, some of the informally funded firms that did not receive follow-on capital may have successfully financed expansion differently, for example with bank loans. This mechanism places the origin of the causal effect of informal finance on a reshuffle of firms' financing sources pecking order, but hinges on the same argument based on control as the supply driven explanation proposed above.

Alternatively, professional investors may forgo investment opportunities in firms with informal stakeholders because of potential constraints on exit options, such as IPOs or acquisitions. An IPO process can be suspended by the SEC if the issuer has not previously complied with the regulations concerning exemptions to securities laws (such as Regulation D). The length of the necessary checks and the probability of a breach can increase with the higher regulatory fulfillment requirements associated with offerings conducted with non accredited investors, increasing legal risks for existing shareholders. If, instead of going pubic, the firm is acquired by another company, the merged entity will have to disclose its financial statements to non accredited shareholders. This can discourage acquisitions by non publicly traded companies.

Whether regulations imposed to financial markets in order to protect unsophisticated investors can impose additional constraints to entrepreneurship, as the argument above suggests, is an interesting and relevant question. However, because of lack of exit data, it cannot be addressed within this study.

1.6 Conclusions

Despite the strong interest that entrepreneurship and its role in economic growth attracts among the general public and policy makers, there is limited empirical knowledge on small and young firms choices in terms of financing sources and what repercussions these may have on firms' survival and success. This is mostly due to lack of relevant and readily available databases. In this paper I contribute closing this gap by examining whether recourse to family and friends financing during the early stages of business investment affects firms ability to raise capital in later rounds.

To answer this question empirically, I employ a novel dataset based on SEC filings for securities offerings conducted by small and young firms raising capital in private markets. The information contained in these filings includes recourse to funding from non-accredited investors, which I use as an indicator for informal finance. Incidentally, the extensiveness of the collected dataset sheds new light on a blind spot of entrepreneurial finance literature, namely the pre-VC phase of startups.

In order to address the issue of endogeneity of informal finance, I construct an instrument based on founders' surnames which is employed as a proxy for small family size. A bivariate model is estimated, where the instrument is included in the regression for the potentially endogenous variable. I find that informal finance reduces the probability of future financing events in private capital markets by 15% to 19% . These results suggest that, while informal finance can relax financial constraints in early stages, it can impose additional restrictions on future access to capital.

I provide arguments and formal tests for two possible mechanisms underlying the documented effects. Informal finance may cause a deterioration of the entrepreneurial project, due to, for example, lower risk tolerance, and this ultimately decreases the probability of receiving funds from professional investors. Alternatively, the second mechanism proposed relies on a corporate governance argument and on the VC industry business model. In particular, concerns over the ability of gaining control, due to conflicting objectives between existing and prospective shareholders, can discourage professional investors. Evidence from subsamples of this dataset supports this last hypothesis while it is less consistent with the first argument.

Table 1.1: Seed Round Summary Statistics: Industry

Frequency of first financing events (i.e. seed rounds) by Industry. The list of industry categories is provided on Form D. The filing issuer chooses the one that best qualifies its business.

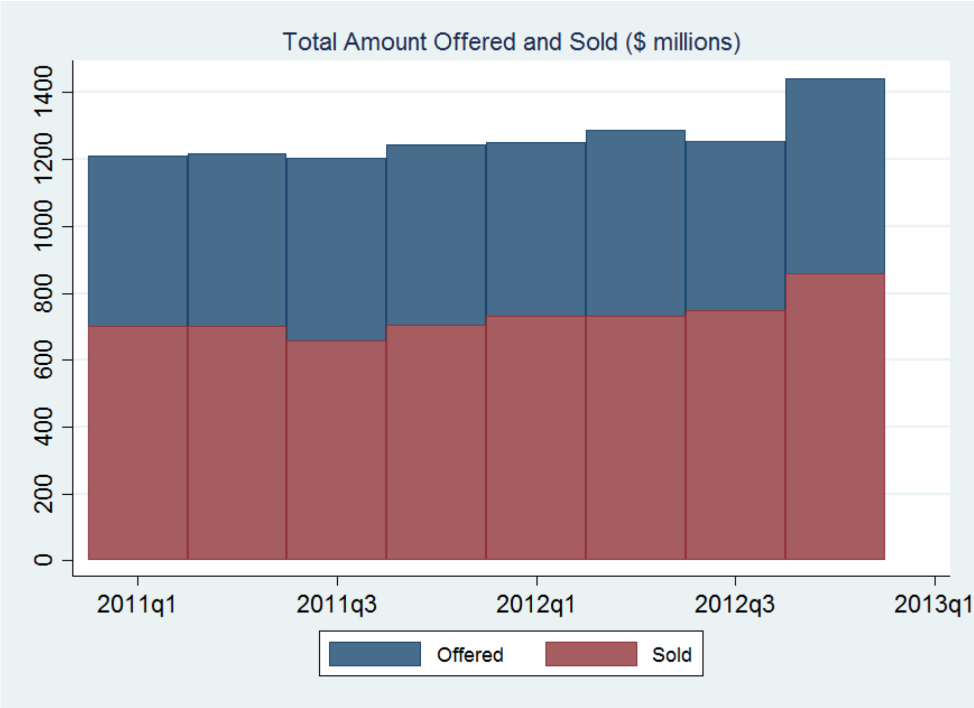
Industry	**Freq.**	%
Agriculture	41	0.6%
Airlines and Airports	4	0.1%
Biotechnology	157	2.3%
Business Services	178	2.6%
Coal Mining	1	0.0%
Commercial	497	7.4%
Computers	160	2.4%
Construction	32	0.5%
Electric Utilities	23	0.3%
Energy Conservation	31	0.5%
Environmental Services	14	0.2%
Health Insurance	3	0.0%
Hospitals and Physicians	28	0.4%
Lodging and Conventions	24	0.4%
Manufacturing	238	3.5%
Oil and Gas	411	6.1%
Other	1,568	23.3%
Other Energy	128	1.9%
Other Health Care	413	6.1%
Other Real Estate	344	5.1%
Other Technology	1,627	24.2%
Other Travel	14	0.2%
Pharmaceuticals	56	0.8%
Residential	321	4.8%
Restaurants	183	2.7%
Retailing	155	2.3%
Telecommunications	53	0.8%
Tourism and Travel Services	14	0.2%
Total	6,718	100.0%

Table 1.2: Seed Round Summary Statistics: State of Location

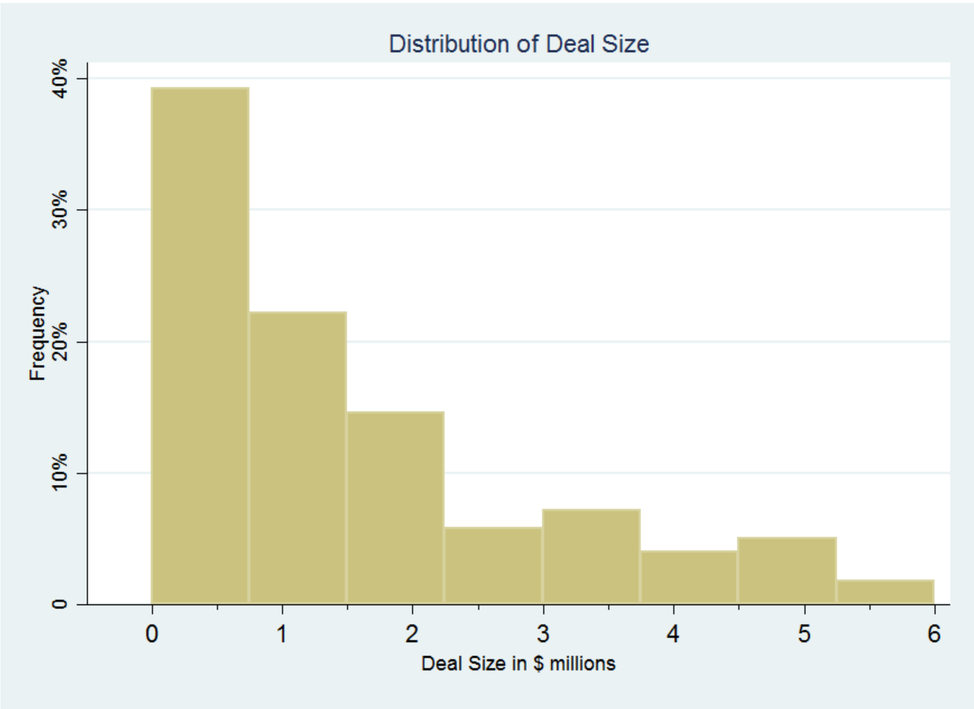
Frequency of first financing events (i.e. seed rounds) by State of location of the firm.

State	Freq.	%	State	Freq.	%
ALABAMA	34	0.5%	MONTANA	11	0.2%
ALASKA	4	0.1%	NEBRASKA	27	0.4%
ARIZONA	138	2.1%	NEVADA	77	1.1%
ARKANSAS	28	0.4%	NEW HAMPSHIRE	30	0.4%
CALIFORNIA	1,288	19.2%	NEW JERSEY	108	1.6%
COLORADO	257	3.8%	NEW MEXICO	20	0.3%
CONNECTICUT	108	1.6%	NEW YORK	661	9.8%
DELAWARE	22	0.3%	NORTH CAROLINA	144	2.1%
DISTRICT OF COLUMBIA	34	0.5%	NORTH DAKOTA	10	0.1%
FLORIDA	319	4.7%	OHIO	123	1.8%
GEORGIA	157	2.3%	OKLAHOMA	36	0.5%
HAWAII	12	0.2%	OREGON	116	1.7%
IDAHO	20	0.3%	PENNSYLVANIA	177	2.6%
ILLINOIS	243	3.6%	RHODE ISLAND	12	0.2%
INDIANA	76	1.1%	SOUTH CAROLINA	32	0.5%
IOWA	16	0.2%	SOUTH DAKOTA	24	0.4%
KANSAS	36	0.5%	TENNESSEE	112	1.7%
KENTUCKY	120	1.8%	TEXAS	726	10.8%
LOUISIANA	22	0.3%	UTAH	94	1.4%
MAINE	21	0.3%	VERMONT	18	0.3%
MARYLAND	117	1.7%	WEST VIRGINIA	10	0.1%
MASSACHUSETTS	316	4.7%	WISCONSIN	82	1.2%
MICHIGAN	90	1.3%	WYOMING	11	0.2%
MINNESOTA	87	1.3%	VIRGIN ISLANDS, U.S.	1	0.0%
MISSISSIPPI	15	0.2%	VIRGINIA	121	1.8%
MISSOURI	43	0.6%	WASHINGTON	312	4.6%

Figure 1.1: Summary Statistics: The Seed Round



(a) Amounts Offered and Sold: Aggregate Value. Total capital solicited (*i.e. Offered*) and raised (*i.e. Sold*) in seed rounds by firms in the sample, as per Form D filings. The data covers the time period between 2011 Q1 and 2012 Q4.



(b) Deal Size. Cross sectional distribution of capital solicited per deal in dollar amounts

Table 1.3: Seed Round Summary Statistics: Deal and Firm Characteristics

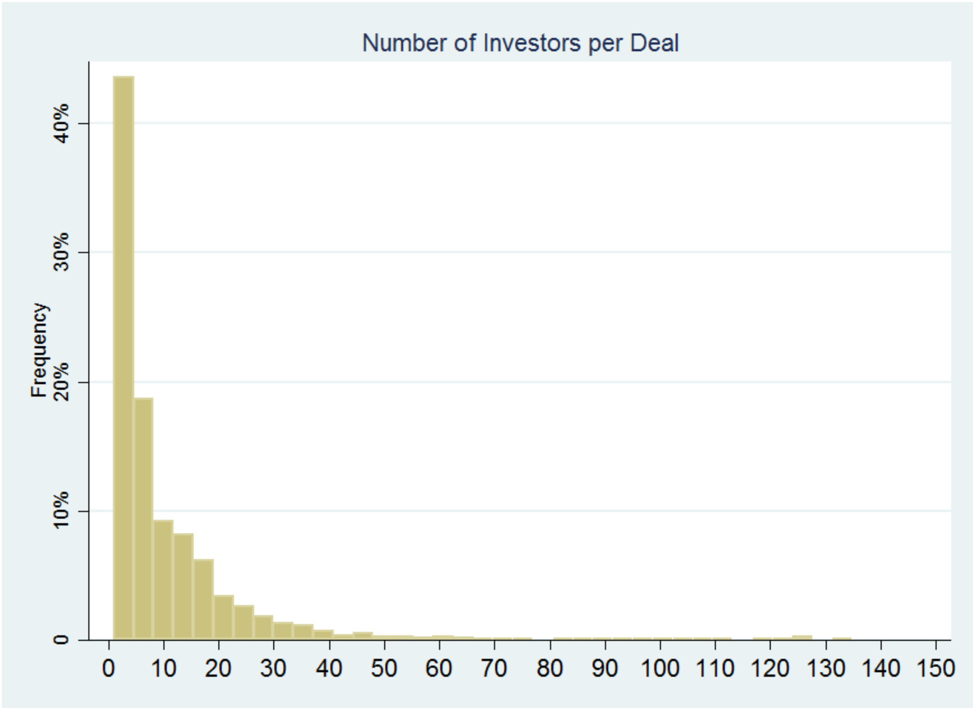
The table presents selected characteristics of the seed round and selected characteristics of the firm at the time of the financing event. *Security* refers to the security (*Debt*, *Equity* or *Other*) or combination of securities used. The category *Other* includes: option, warrant or other right to acquire another security, security to be acquired upon exercise of option, warrant or other right to acquire security, tenant-in-common securities, mineral property securities, other securities (unspecified). *Intermediation* is a dummy variable that takes value 1 if services of a registered financial intermediary were employed during the offering

DEAL CHARACTERISTICS	**Frequency**	**%**
Security		
Debt	319	4.7%
Debt&Other	400	6.0%
Equity	4,566	68.0%
Equity&Debt	161	2.4%
Equity&Debt&Other	116	1.7%
Equity&Other	512	7.6%
Other	644	9.6%
Year		
2011	3,297	49.1%
2012	3,421	50.9%
Intermediation	290	4.3%

FIRM CHARACTERISTICS		
Legal Entity Type		
Business Trust	8	0.1%
Corporation	3,078	45.8%
General Partnership	58	0.9%
Limited Liability Company	2,985	44.4%
Limited Partnership	445	6.6%
Other	144	2.1%
Revenue Size		
$1 - $1,000,000	1,011	15.0%
$1,000,001 - $5,000,000	263	3.9%
Decline to Disclose	3,392	50.5%
No Revenues	1,835	27.3%
Not Applicable	217	3.2%
Year of Incorporation		
2009	433	6.4%
2010	1,563	23.3%
2011	2,940	43.8%
2012	1,781	26.5%

Figure 1.2: Summary Statistics: The Seed Round. Investors and Founders

(a) Distribution of total number of investors per deal as reported in Form D. The sample is restricted to filings that report the first security sale as already occurred (5,510 observations)



(b) Distribution of number of founders per firm. The status of *founder* is assigned to individuals with managerial positions in the firm at the time of its first round of funding.

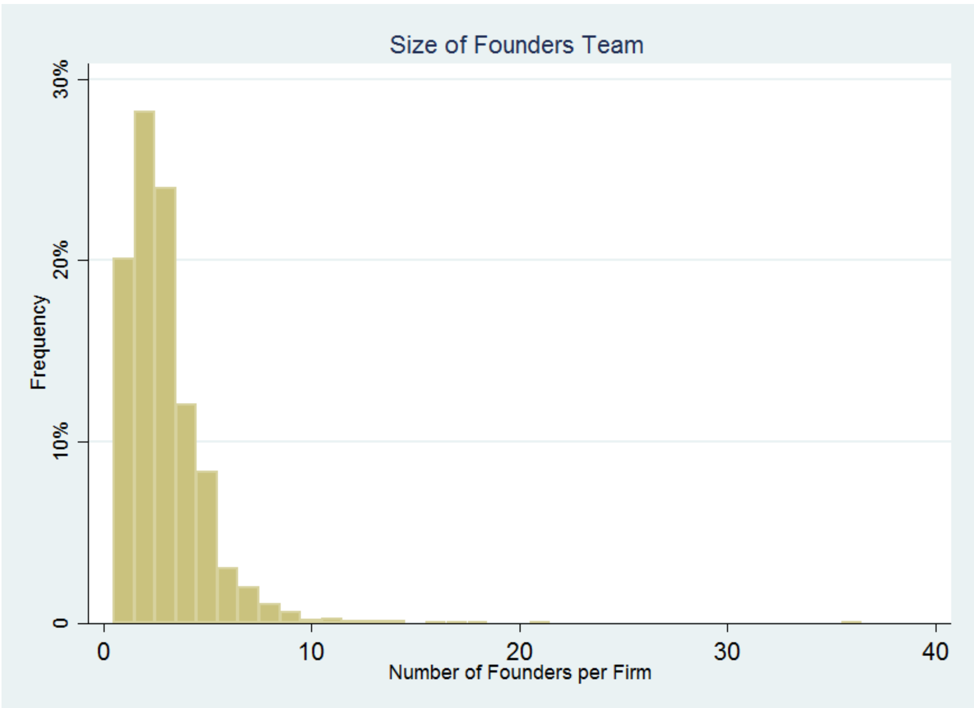


Table 1.4: Revenue Size Transition Matrix

Change in revenue size for firms that received follow-on funding (N: 1,279). Cell i,j represents the probability of having revenue size j at the time of its second offering for a firm with revenue size i at the time of the first offering.

Revenue Size (Seed Round)	**Revenue Size (Follow-on Round)** $1-$1M	$1M - $5M	Decline to Disclose	No Revenues	Not Applicable	Over $5M
$1 - $1M	73.76%	4.96%	17.02%	4.26%	0%	0%
$1M - $5M	12.50%	58.33%	25.00%	0%	4.17%	0%
Decline to Disclose	0.96%	0.12%	98.07%	0.72%	0.12%	0%
No Revenues	25.24%	2.24%	16.79%	56.34%	0%	0.37%
Not Applicable	0%	0%	18.75%	0%	81.25%	0%

Table 1.5: Seed Round Summary statistics: IF-firms vs NonIF-firms

(Non)IF-firms are firms that (did not report) reported recourse to informal finance in the seed round of funding. The status of founder is assigned to individuals with managerial positions in the firm at the time of its first round of capital raising. Follow-on Rounds are financing events that take place within 6 quarters since the seed round.

	NonIF-firms		**IF-firms**		**Full Sample**	
	Freq.	%	Freq.	%	Freq.	%
Revenue Size						
$1-$1,000,000	769	13.7%	242	21.7%	1,011	15.0%
$1,000,001 - $5,000,000	226	4.0%	37	3.3%	263	3.9%
Decline to Disclose	3,106	55.5%	286	25.6%	3,392	50.5%
No Revenues	1,349	24.1%	486	43.5%	1,835	27.3%
Not Applicable	151	2.7%	66	5.9%	217	3.2%
Year of Incorporation						
2009	374	6.7%	59	5.3%	433	6.4%
2010	1,326	23.7%	237	21.2%	1,563	23.3%
2011	2,440	43.6%	500	44.8%	2,940	43.8%
2012	1,460	26.1%	321	28.7%	1,781	26.5%
Legal Entity Type						
Business Trust	8	0.1%	0	0.0%	8	0.1%
Corporation	2,684	47.9%	394	35.3%	3,078	45.8%
General Partnership	46	0.8%	12	1.1%	58	0.9%
Limited Liability Company	2,382	42.5%	603	54.0%	2,985	44.4%
Limited Partnership	385	6.9%	60	5.4%	445	6.6%
Other	96	1.7%	48	4.3%	144	2.1%
	Mean	Median	Mean	Median	Mean	Median
Number of Founders	2.98	3	2.73	2	2.93	3
Amount Offered ($M)	1.5864	1	1.1004	0.5625	1.5056	1
Follow-on Round?	Freq.	%	Freq.	%	Freq.	%
YES	1,168	20.85%	111	9.94%	1,279	19.04%
NO	4,433	79.15%	1,006	90.06%	5,439	80.96%

Table 1.6: Ethnic/Linguistic Categories definition, founders' team mix and follow-on funding

Panel A: Ethnic/Linguistic groups are identified as in Ambekar et al. (2009). The algorithm operates via a series of classifiers assigning name strings to subgroups at each level. Level 3 is only defined for West European and Greater Asian groups.

Level 1	Level 2	Level 3
Greater European	West European	Italian
		Hispanic
		Nordic
		French
		German
	East European	*East European*
	British	*British*
	Jewish	*Jewish*
Asian	Greater East Asian	East Asian
		Japanese
	Indian	*Indian*
African	Muslim	*Muslim*
	African	*African*

Panel B: Average ethnic mix of founders' team for the full sample and for firms that access follow-on funding. On the left hand side I report average ethnic group representation in founders' teams. Standard error are in parenthesis. On the right hand side I report the proportion of firms that have more than 50% of Greater European origin founders (as by Level 1 classification above) and the proportion of firms where no ethnic group represents more than 50% of the founders.

Group (Level 2)	Full Sample	Follow-on	Ethnic Majority	Full Sample	Follow-on
African	1.3%	1.3%	European Majority	80.7%	81.2%
	(0.0775)	(0.0762)			
British	49%	50%	No Ethnic Majority	14.1%	13.7%
	(0.3701)	(0.3495)			
East European	2.9%	3.3%			
	(0.1135)	(0.1243)			
Greater East Asia	4.6%	4.6%			
	(0.1638)	(0.1485)			
Indian Subcontinent	3.3%	4.4%			
	(0.1389)	(0.1611)			
Jewish	18%	18%			
	(0.2794)	(0.2644)			
Muslim	2.1%	2.7%			
	0.1084)	(0.122)			
West European	15%	15%			
	(0.2657)	(0.25)			

Table 1.7: Small Family and Informal Finance

Estimates stem from a probit model (columns (1) and (2)) and a linear probability model (column (3)) of informal finance IF_i on the $SmallFamily$ instrument S_i and exogenous controls. IF_i is a dummy variable that takes value 1 when non-accredited investors are allowed to participate in firm i' s seed round. S_i is a dummy variable that takes value 1 when the proportion of founders in firm i with rare last names is greater than the sample average. Controls are based on FIRM, SEED ROUND and FOUNDERS characteristics, which include, but are not limited to, the number of firm's founders (Team Size), dollar amount solicited in the seed round (Amount Offered) and the Hot Deal dummy that takes value 1 if more than 80% of the amount offered was sold at the time of the filing. An interaction term between year of incorporation and quarter of seed round is also included. Column (2) shows average marginal effects for the probit specification. Standard errors in parentheses.

Dependent Variable: IF_i	(1) Probit Coefficient	(2) Probit AME	(3) LPM Coefficient
S_i	-0.254***	-0.0503***	-0.0442**
	(0.0927)	(0.0175)	(0.0185)
FOUNDERS: Team Size	0.0168	0.00347	0.00373
	(0.0131)	(0.00271)	(0.00273)
SEED ROUND: Amount Offered	-0.138***	-0.0286***	-0.0243***
	(0.0165)	(0.00339)	(0.00316)
SEED ROUND: Hot Deal	-0.325***	-0.0666***	-0.0614***
	(0.0456)	(0.00921)	(0.00937)
Year of incorporation#Quarter of Issue	Yes		Yes
FIRM	Yes		Yes
FOUNDERS	Yes		Yes
SEED ROUND	Yes		Yes
Observations	6,718		6,718
Log-Likelihood	-2,476.01		
(Pseudo)R-squared	0.1773		0.155

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

Table 1.8: Small Family and Growth

Panel A shows revenue size and size of the seed round deal for revenue disclosing firms with small combined family network ($S_i = 1$) and for the rest of the sample ($S_i = 0$). The instrument is associated with smaller revenue size, but there is no significant difference in capital raised. In Panel B I focus on firms that secured follow-on funding (1,279 observations). Change in Deal Size is computed as amount offered in seed round divided by amount offered in follow-on round. Standard errors in parentheses.

Panel A: Seed Round (Disclosed Revenues)	$S_i = 0$	$S_i = 1$	Difference
Revenue Size			
No Revenues	1,315	520	
	57.70%	62.65%	-4.95%**
	(.0103)	(.01679)	(.0197)
$1-$1M	772	239	
	33.87%	28.80%	5.1%***
	(.0099)	(.0157)	(.0186)
$1M-$5M	192	71	
	8.42%	8.55%	-0.01%
	(.0058)	(.0097)	(.0113)
Amount Offered ($ Million)			
Mean	1.38	1.45	-0.074
	(.0296)	(.0495)	(.0254)
Panel B: Follow-on vs Seed Round			
Change in Revenues			
YES	127	56	
	14.91%	13.11%	1.79%
	(.0122)	(.0163)	(.0204)
NO	852	427	
	85.1%	86.9%	-1.8%
	(.0122)	(.01633)	(.0204)
Change in Deal Size			
Mean	1.65	1.48	0.17
	(.0633)	(.0821)	(.1063)

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

Figure 1.3: Founders: Year of First Employment.

Year of first employment as reported on online CVs for the subsample of founders matched with LinkedIn members (N: 4,422)

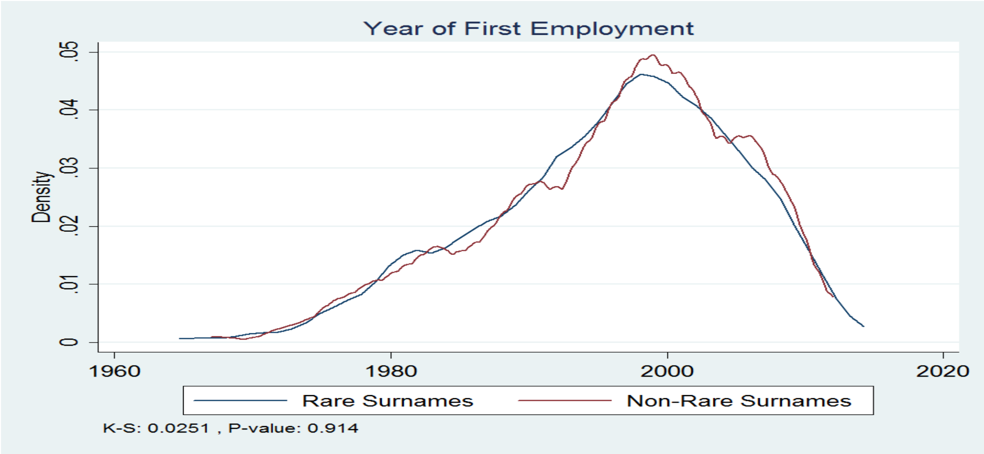


Table 1.9: Founders: Education

Highest education degree as reported on online CVs for the subsample of founders matched with LinkedIn members (N: 4,422)

	Non Rare Surnames		**Rare Surnames**	
	Freq.	%	Freq.	%
Associate	34	0.9%	5	0.8%
Bach.	1,070	28.1%	168	27.2%
J.D.	127	3.3%	23	3.7%
MBA	582	15.3%	88	14.2%
MD	66	1.7%	11	1.8%
Master	686	18.0%	120	19.4%
No data	668	17.6%	104	16.8%
Other	134	3.5%	25	4.0%
PhD	248	6.5%	39	6.3%
Private	189	5.0%	35	5.7%
Total	3804		618	

Pearson $\chi^2_{(9)} = 2.5113$, $Pr = 0.981$

Region and country of last residence	1820 to 1829	1839	1849	1859	1869	1879	1889	1899	1909	1919	1929	1939	1949	1959	1969	1979	1989	1999	2000	2001	2002	2003	2004	2005	2006	2007
Europe	77%	79%	96%	93%	90%	82%	88%	97%	92%	79%	60%	64%	55%	56%	35%	19%	11%	14%	16%	17%	17%	15%	14%	16%	13%	11%
Austria-Hungary	0%	0%	0%	0%	0%	2%	6%	14%	24%	18%	1%	2%	2%	5%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Denmark	0%	0%	0%	0%	1%	1%	2%	2%	1%	1%	1%	0%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
France	6%	7%	5%	3%	2%	3%	1%	1%	1%	1%	1%	2%	4%	2%	1%	1%	1%	0%	0%	1%	0%	0%	0%	0%	0%	0%
Germany	4%	23%	27%	35%	35%	27%	28%	16%	4%	3%	9%	17%	14%	23%	7%	2%	1%	1%	1%	2%	2%	1%	1%	1%	1%	1%
Ireland	40%	32%	46%	37%	21%	15%	13%	11%	4%	3%	5%	4%	2%	2%	1%	0%	0%	1%	0%	0%	0%	0%	0%	0%	0%	0%
Italy	0%	0%	0%	0%	0%	2%	5%	16%	24%	19%	12%	12%	6%	7%	6%	4%	1%	1%	0%	0%	0%	0%	0%	0%	0%	0%
Norway-Sweden	0%	0%	1%	1%	4%	7%	11%	9%	5%	3%	4%	2%	2%	2%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Poland	0%	0%	0%	0%	0%	0%	1%	3%	0%	0%	5%	4%	1%	0%	2%	1%	1%	2%	1%	1%	1%	2%	1%	1%	1%	1%
Portugal	0%	0%	0%	0%	0%	1%	0%	1%	1%	1%	1%	1%	1%	1%	2%	2%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Russia	0%	0%	0%	0%	0%	1%	3%	12%	18%	17%	1%	0%	0%	0%	0%	1%	1%	4%	5%	5%	5%	5%	4%	5%	5%	4%
United Kingdom	20%	14%	15%	16%	26%	21%	15%	9%	6%	6%	8%	9%	15%	8%	7%	3%	2%	2%	2%	2%	2%	2%	2%	2%	2%	2%
Yugoslavia	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%	1%	0%	0%	1%	1%	0%	1%	1%	2%	3%	1%	1%	2%	1%	1%
Asia	0%	0%	0%	1%	3%	5%	1%	2%	4%	4%	3%	3%	4%	5%	11%	33%	38%	29%	30%	32%	31%	33%	33%	34%	33%	34%
China	0%	0%	0%	1%	3%	5%	1%	0%	0%	0%	1%	1%	2%	0%	0%	0%	3%	3%	5%	5%	5%	5%	5%	6%	7%	7%
India	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%	3%	4%	4%	5%	6%	6%	7%	7%	7%	5%	5%
Korea	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%	6%	5%	2%	2%	2%	2%	2%	2%	2%	2%	2%
Philippines	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%	2%	8%	8%	5%	5%	5%	5%	6%	6%	5%	6%	7%
Taiwan	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	2%	2%	1%	1%	1%	1%	1%	1%	1%	1%	1%
Vietnam	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	3%	3%	3%	3%	3%	3%	3%	3%	3%	2%	3%
America	8%	6%	4%	3%	6%	13%	10%	1%	3%	17%	37%	33%	38%	37%	52%	45%	43%	53%	47%	44%	45%	43%	43%	39%	43%	41%
Canada and Newfoundland	2%	2%	2%	2%	6%	12%	9%	0%	2%	11%	22%	23%	19%	14%	13%	4%	3%	2%	3%	3%	3%	2%	2%	3%	2%	2%
Mexico	3%	1%	0%	0%	0%	0%	0%	0%	0%	3%	12%	5%	7%	11%	14%	15%	16%	28%	20%	19%	20%	16%	18%	14%	13%	14%
Caribbean	2%	2%	1%	0%	0%	1%	1%	1%	1%	2%	2%	3%	5%	5%	13%	17%	13%	10%	10%	9%	9%	10%	9%	8%	11%	11%
Central America	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%	2%	2%	3%	3%	5%	6%	7%	7%	6%	8%	6%	5%	6%	5%
South America	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%	1%	1%	2%	3%	8%	6%	6%	6%	7%	6%	7%	8%	7%	9%	11%	10%
Africa	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%	1%	1%	2%	2%	4%	5%	5%	5%	6%	7%	7%	9%	8%
Not Specified	15%	16%	1%	3%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	5%	0%	2%	2%	2%	1%	3%	4%	1%	4%

Figure 1.4: Immigration to U.S. 1820-2007, Source: U.S. Department of Homeland Security.
Based on records of persons obtaining permanent resident status by region and selected country of last residence. The first 18 columns until year 2000 represent decades. Starting from 2000 each column refers to single years.

Table 1.10: Ethnicity of Founders: Rare and Non Rare Surnames

Panel A: Level 2 ethnicity of founders with rare and non rare surnames. Total number of founders (excluding business entities): 18,716

	Rare Surnames	**Non Rare Surnames**
African	4.93%	0.84%
British	25.31%	55.6%
East European	10.36%	2.15%
Greater East Asian	3.74%	4.7%
Indian Subcontinent	8.13%	2.43%
Jewish	20.53%	18.58%
Muslim	6.20%	1.41%
West European	20.8%	14.29%

Panel B: Founders with first name included in the 1990 Census list of the 2,438 most common first names are classified as American while other founders are classified as Early Generation

	Rare Surnames		**Non Rare Surnames**	
	American	Early Generation	American	Early Generation
Greater European	87.65%	45.33%	93.52%	67.66%
Asian	6.12%	28.94%	4.84%	25.21%
Greater African	6.23%	25.73%	1.64%	7.13%
Observations	1,943	653	14,311	1,809
	74.85%	25.15%	88.78%	11.22%

Table 1.11: Small Family and Future Financing Events

Estimates stem from a probit model (columns (1) and (2)) and a linear probability model (column (3)) of probability of follow-on financing events Y_i on the $SmallFamily$ instrument S_i and exogenous controls. S_i is a dummy variable that takes value 1 when the proportion of founders in firm i with rare last names is greater than the sample average. Controls are based on FIRM, SEED ROUND and FOUNDERS characteristics, which include, but are not limited to, the number of firm's founders (Team Size) and dollar amount solicited in the seed round (Amount Offered). An interaction term between year of incorporation and quarter of seed round is also included. Column (2) shows average marginal effects for the probit specification. Standard errors in parentheses.

Panel A. Y_i: All Follow-on Financing Events

Dependent Variable: Y_i	(1) Probit	(2) AME	(3) LPM
S_i	0.172**	0.0407**	0.0354*
	(0.0810)	(0.0196)	(0.0197)
FOUNDERS: Team Size	0.0320***	0.00740***	0.00898***
	(0.0120)	(0.00276)	(0.00291)
SEED ROUND: Amount Offered	-0.0547***	-0.0126***	-0.0119***
	(0.0150)	(0.00346)	(0.00337)
Year of incorporation#Quarter of Issue	Yes		Yes
FIRM	Yes		Yes
FOUNDERS	Yes		Yes
SEED ROUND	Yes		Yes
Observations	6,718		6,718
Log-Likelihood	-2,756.57		
(Pseudo)R-squared	0.1514		0.137

Panel B. Y_i: Follow-on Financing with Formal Investors Only

Dependent Variable: Y_i (Formal Only)	(1) Probit	(2) AME	(3) LPM
S_i	0.182**	0.0409**	0.0355*
	(0.0828)	(0.0191)	(0.0191)
FOUNDERS: Team Size (Founders)	0.0333***	0.00730***	0.00878***
	(0.0122)	(0.00268)	(0.00283)
SEED ROUND: Amount Offered	-0.0365**	-0.00799**	-0.00792**
	(0.0152)	(0.00334)	(0.00327)
Year of incorporation#Quarter of Issue	Yes		Yes
FIRM	Yes		Yes
FOUNDERS	Yes		Yes
SEED ROUND	Yes		Yes
Observations	6,718		6,718
Log-Likelihood	-2,621.56		
(Pseudo)R-squared	0.1556		0.134

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

Table 1.12: Bivariate Probit Model: Full Sample

Estimates stem from a bivariate probit model (columns (1), (2), (5) and (6)), a 2SLS (columns (3) and (7)) and a probit model (columns (4) and (8)) of follow-on financing on informal finance IF_i. The dependent variable is an indicator function that takes value 1 if firm i receives follow-on funding within 6 quarters since the seed round. IF_i is a dummy variable that takes value 1 when non-accredited investors are allowed to participate in firm i' s seed round. The $SmallFamily$ instrument S_i is employed in the biprobit and 2SLS models. S_i is a dummy variable that takes value 1 when the proportion of founders in firm i with rare last names is greater than the sample average. Controls are based on FIRM, SEED ROUND and FOUNDERS characteristics, which include, but are not limited to, the number of firm's founders (Team Size), dollar amount solicited in the seed round (Amount Offered) and the Hot Deal dummy that takes value 1 if more than 80% of the amount offered was sold at the time of the filing. An interaction term between year of incorporation and quarter of seed round is also included. Columns (2), (4), (6) and (8) show average marginal effects for the biprobit and probit specifications. Standard errors in parentheses.

Dependent Variable:	Follow-on (Both Investors Types)				Follow-on with Formal Investors Only			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	BiProbit	BiProbit	2SLS	Probit	BiProbit	BiProbit	2SLS	Probit
	Coefficient	AME	Coefficient	AME	Coefficient	AME	Coefficient	AME
IF_i	-0.7927***	-0.1476***	-0.1956***	-0.0709***	-1.3078***	-0.1903***	-0.2322***	-0.133***
	(0.3052)	(0.046)	(0.0698)	(0.0121)	(0.3258)	(0.0336)	0.0674)	(0.00965)
FOUNDERS: Team Size	0.0406***	0.0094***	0.011***	0.00935***	0.0417***	0.0092***	0.0108***	0.00902***
	(0.0111)	(0.0026)	(0.0026)	(0.00256)	(0.0114)	(0.0025)	(0.0025)	(0.00246)
SEED ROUND: Amt Offered	-0.0703***	-0.0162***	-0.0166***	-0.0139***	-0.0591***	-0.013***	-0.0133***	-0.0103***
	(0.0164)	(0.0039)	(0.0038)	(0.00347)	(0.017)	(0.004)	(0.0037)	(0.00331)
SEED ROUND: Hot Deal	0.0413	0.0096	0.007	0.0162*	0.0289	0.0064	0.0048	0.0133
	(0.0469)	(0.0108)	(0.0109)	(0.00968)	(0.0491)	(0.0107)	(0.0105)	(0.0093)
Year of Inc.#Quarter of Issue	Yes		Yes	Yes	Yes		Yes	Yes
FIRM	Yes		Yes	Yes	Yes		Yes	Yes
FOUNDERS	Yes		Yes	Yes	Yes		Yes	Yes
SEED ROUND	Yes		Yes	Yes	Yes		Yes	Yes
Observations	6,717		6,718	6,718	6,718		6,718	6,718
Log-Likelihood	-5,219			-2,744.07	-5,039.6			-2,564.7
R-squared			0.1237				0.1303	

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

Table 1.13: Bivariate Probit Model: Disclosed Revenues

The sample is restricted to revenue disclosing firms (3,326 observations). Estimates stem from a bivariate probit model (columns (1), (2), (5) and (6)), a 2SLS (columns (3) and (7)) and a probit model (columns (4) and (8)) of follow-on financing on informal finance IF_i. The dependent variable is an indicator function that takes value 1 if firm i receives follow-on funding within 6 quarters since the seed round. IF_i is a dummy variable that takes value 1 when non-accredited investors are allowed to participate in firm i' s seed round. The $SmallFamily$ instrument S_i is employed in the biprobit and 2SLS models. S_i is a dummy variable that takes value 1 when the proportion of founders in firm i with rare last names is greater than the sample average. Controls are based on FIRM, SEED ROUND and FOUNDERS characteristics, which include, but are not limited to, the number of firm's founders (Team Size), dollar amount solicited in the seed round (Amount Offered) and the Hot Deal dummy that takes value 1 if more than 80% of the amount offered was sold at the time of the filing. An interaction term between year of incorporation and quarter of seed round is also included. Columns (2), (4), (6) and (8) show average marginal effects for the biprobit and probit specifications. Standard errors in parentheses.

Dependent Variable:	Follow-on (Both Investors Types)				Follow-on with Formal Investors Only			
	(1) BiProbit Coefficient	(2) BiProbit AME	(3) 2SLS Coefficient	(4) Probit AME	(5) BiProbit Coefficient	(6) BiProbit AME	(7) 2SLS Coefficient	(8) Probit AME
IF_i	-0.5702	-0.0877	-0.1722**	-0.0535***	-1.2098***	-0.1406***	-0.2179***	-0.0984***
	(0.4172)	(0.0579)	(0.0803)	(0.0124)	(0.4457)	(0.0471)	(0.0754)	(0.0102)
FOUNDERS: Team Size	0.0504***	0.0088***	0.0119***	0.00896**	0.06***	0.0096***	0.0127***	0.00956***
	(0.0196)	(0.0034)	(0.0036)	(0.00348)	(0.0206)	(0.0033)	(0.0034)	(0.00324)
SEED ROUND: Amt Offered	-0.0367	-0.0064	-0.00514	-0.01**	-0.0163	-0.0026	-0.0059	-0.00027
	(0.0287)	(0.0051)	(0.005)	(0.00454)	(0.031)	(0.0051)	(0.0048)	(0.00423)
SEED ROUND: Hot Deal	0.0732	0.0129	0.0085	0.0185	0.0212	0.0034	0.0021	0.0125
	(0.0885)	(0.0154)	(0.0162)	(0.0127)	(0.0985)	(0.0156)	(0.0152)	(0.012)
Year of Inc.#Quarter of Issue	Yes		Yes	Yes	Yes		Yes	Yes
FIRM	Yes		Yes	Yes	Yes		Yes	Yes
FOUNDERS	Yes		Yes	Yes	Yes		Yes	Yes
SEED ROUND	Yes		Yes	Yes	Yes		Yes	Yes
Observations	3,326		3,326	3,326	3,326		3,326	3,326
Log-Likelihood	-2,622.6			-1,049.08	-2,495.1			-921.93
R-squared			0.1335			0.1363		

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

Table 1.14: Marginal Effect of Informal Finance on the Probability of Future Financing Events

Marginal effects of informal finance on follow-on financing events conducted with all investors types (row 1)) and with formal investors only (row 2)). Estimates stem from a bivariate probit model under different specifications. In section A) the model includes only Size controls (revenue size, legal entity type and amount offered in the seed round) -column (2)- or size, location and industry controls -column (3). In section B), Instead of using the proportion of people belonging to each ethnic/linguistic group for each firm, the full model includes either a dummy variable that takes value 1 if the majority of the founders have European descent - column (4)- or a dummy variable that takes value 1 if no ethnic group represents more than 50% of the founders team -column (5). In sections C) and D) I estimate the full model restricting the sample to firms where the majority of founders have European descent and to *Hot Deals*. Standard errors are in parentheses.

	Full Model (1)	(2)	(3)	(4)	(5)	(6)	(7)
1) Y_i: Both Investors Types	-.1476***	-.164***	-.1582***	-.1582***	-.1543***	-.1541**	-.1416
	(0.046)	(0.0503)	(0.0476)	(0.0445)	(0.0454)	(0.07)	(0.0874)
2) Y_i: Formal Only	-.19***	-.1919***	-.2***	-.202***	-.1983***	-.1722***	-.1984***
	(0.0336)	(0.0421)	(0.0343)	(0.0338)	(0.0344)	(0.063)	(0.0573)
A) CONTROLS							
Size		✓	✓				
Industry and Location			✓				
B) ETHNICITY							
European Descent(>50%)				✓			
No Ethnic Majority					✓		
C)European Descent(>50%) ONLY						✓	
D)Hot Deals ONLY							✓
Observations	6,718	6,718	6,718	6,718	6,718	5,421	3,168
Log-Likelihood (Both Investors Types)	-5,219	-5,520.46	-5,351.82	-5,252.32	-5,254.05	-4,527.06	-2,383.31
Log-Likelihood (Accredited Only)	-5,039.58	-5,329.39	-5,170.02	-5,074.14	-5,076.31	-4,366.9	-2,313.34

Table 1.15: The California Subsample: Descriptive statistics and Business Entity Status (as of June 2015)

The table shows descriptive statistics and distributions by Entity Status (as of June 2015) for informally funded (IF) and non informally funded ($NonIF$) firms operating in California and matched with records from the California the Secretary of State (SoS) webpage. For the purpose of this table sectors are redefined as follows: Tech= Biotechnology,Computers,Other Technology,Telecommunications; Energy= Coal Mining,Energy Conservation,Oil and Gas,Other Energy; Health=Health Insurance, Hospitals and Physicians,Other Health Care, Pharmaceuticals; RE=Construction,Lodging and Conventions,Residential, Other RE; Service=Environmental Services,Restaurants,Tourism and Travel Services,Business Services.

	NonIF-firms	IF-firms
Descriptive Statistics		
Sector		
Health	6.2%	1.2%
Manufacturing	2.6%	3.1%
Other Sector	32.2%	36.4%
RE	7.6%	8.6%
Service	5.9%	17.9%
Energy	2.0%	1.2%
Tech	43.4%	31.5%
Revenue Size		
$1 - $1,000,000	14.2%	27.0%
$1,000,001 - $5,000,000	2.6%	2.9%
Decline to Disclose	61.5%	24.8%
No Revenues	20.5%	43.8%
Not Applicable	1.2%	1.5%
Status		
active	70.8%	71.5%
canceled	5.9%	7.3%
converted out	0.6%	1.5%
dissolved	3.0%	2.2%
forfaited/suspended	11.6%	13.1%
merged out	0.7%	0.7%
surrender	7.5%	3.6%
Total	909	137

Distributions by Status: Pearson $\chi^2_{(6)} = 4.8603$ $Prob = 0.562$

Table 1.16: Survival vs Follow-on Financing Probability

Marginal effects of informal finance (IF_i) on follow-on financing (Y_i) and survival (Y_i^S) and of Y_i on Y_i^S in the following two models: $Prob[Y_i = 1] = \Phi[X_i\beta + IF_i\lambda]$ (Columns 1 and 3) and $Prob[Y_i^S = 1] = \Phi[X_i\beta + Y_i\zeta + IF_i\lambda]$ (Columns 2 and 4). $Y_i^S = 1$ if firm i is active/merged out.

	Y_i = Financing Event, All Investors Types		Y_i = Financing Event, Accredited Only	
	(1)	(2)	(3)	(4)
	Y_i	Y_i^S	Y_i	Y_i^S
IF_i	-0.066*	0.05	-0.156***	0.06
	(0.0385)	(0.04)	(0.0295)	(0.0393)
Y_i		0.125***		0.133***
		(0.0307)		(0.0311)
Log-Likelihood	-468.24	-563.43	-434.85	-562.91
Observations	1,046	1,046	1,046	1,046

Table 1.17: Informal Finance and Control

Coefficient estimates (column (1)) and average marginal effects (column (2)) of informal finance (IF_i) and $Time$ from the probit model $Prob[E_{i,j} = 1] = \Phi[A_{i,j}\theta + IF_i\vartheta]$ where $E_{i,j} = 1$ if founder j of firm i still holds an executive position at the time of the third financing event and $A_{i,j}$ is a set of controls that includes industry, revenue size, location, number of quarters between round 1 and round 3 (*time*) and founder's ethnicity. Coefficients from a linear probability model in column (3).

	(1) **Probit**	(2) **AME**	(3) **LPM**
IF	0.541**	0.197**	0.191**
	(0.2504)	(0.0862)	(0.0946)
Time	-0.05***	-0.0183***	-0.0185***
	(0.0166)	(0.006)	(0.0063)
Log likelihood	-533.89		
Observations	846		846
R-squared			0.1054

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

Chapter 2

Private Capital Markets and Entrepreneurial Debt: Evidence from Unregistered Securities Offerings

2.1 Introduction

Despite the strong interest that entrepreneurship and its role in economic growth attracts among the general public and policy makers, there is limited empirical knowledge on the availability and use of different sources of funding for entrepreneurial firms, in particular with regard to non-bank private capital, such as funds provided by family and friends, angel investors or venture capital firms. This is due to the fragmentation of information sources commonly available, which mostly rely on surveys (Kerr et al. [2014]), self reporting investors' documentation or firms' IPO filings (Kaplan and Strömberg [2003], Tian [2011]). The current picture of entrepreneurial finance therefore may be incomplete and possibly subject to sampling and survivorship bias issues. In this paper we provide a unified empirical framework that encompasses and characterizes all stages of entrepeneurial finance, from family and friends funding to late venture capital rounds. We describe the use of private capital by U.S. non listed firms between March 2009 and October 2014. Our contribution resides in the broader evidence provided on the cross section of firms that resort to entrepreneurial finance, since all industries, locations and funding stages are represented, and on the deeper time series dimension of staged investment, as we follow start-ups' financing events over time.

More importantly, we investigate firms' choices in terms of financial contracts and document the use of non-bank private debt in entrepreneurial finance. Contrary to the common view, debt contracts are often used by start-ups for funding, although equity is the dominant source of capital. Moreover we show that, as corporate finance theory would predict, later stage funding is more likely to be conducted with debt as compared to early stage funding rounds. We provide suggestive evidence that the reason for this difference stems from cash flow uncertainty and unpredictability rather than lack of collateral.[1]

Because of market and regulatory frictions, entrepreneurial firms have limited funding sources available. While the costs of issuing publicly traded securities make this funding channel unaccessible for most start-ups, raising external capital outside of public markets, i.e. issuing unregistered securities, is typically constrained by law to protect investors from frauds. In order to overcome such restrictions and facilitate capital raising for small and young businesses, Regulation D was introduced in the U.S. in the early 80s as an exemption to Securities Laws, effectively providing entrepreneurial finance and the venture capital industry with a simplified legal framework. Regulation D allows companies to place securities in private markets, provided that the offering meets certain requirements, such as the ban on general solicitation. We use a novel dataset (Zaccaria [2015]) based on SEC filings for private placements of unregistered securities (Form Ds) conducted under Regulation D. Each Form D corresponds to a financing event in which a

[1]For a review of theories on small firms' capital structure see Chittenden et al. [1996]

firm raises funds in private markets and includes information on the firm (such as location, age, industry) and on the offering (such as amount and type of security sold). Machine readible data are available starting from 2009 when online filing was made mandatory. We collect 58,059 Form D filings for over 39,000 firms that started raising private capital in March 2009 or later. Examples of firms in our dataset include well-known companies such as Uber and Airbnb, but our records mostly comprise of ventures that operate in multiple sectors, including non-tech sectors like manufacturing or retailing, and that, after raising funds, did not reach the IPO stage or went out of business. As our data show, a very small proportion of start-ups (2%) files for public listing of their securities after raising private capital and almost half of these firms operate in technology, biotech or pharmaceutical industries, as compared to 34% in the full sample. The limelight that public offerings grant to companies may help explain why, despite a more diverse initial distribution of start-ups in terms of industries, it is common to define entrepreneurial finance as a predominantly "tech" phenomenon.

Another similarly widespread belief is that entrepreneurial funds are provided in the form of equity capital, or, in other words, that entrepreneurial finance fills the "equity gap". In this paper, we show that, contrary to this view, private non-bank debt capital is not uncommon among start-ups. In our dataset, 19% of the offerings are conducted with debt alone or in combination with other securities. We explore variation in the use of private debt through the financial growth cycle as firms move from early to late stage funding. As Berger and Udell [1998] illustrate, young and very small firms seek early stage outside funding with family, friends and angel investors and subsequently approach institutional investors such as VC firms to finance growth. Along this financing path, both firms' size and age and investors' funds and sophistication progress, potentially affecting both demand and supply of credit at different stages. Using firm and offering information contained in Form D, we define early stage funding as financing events where young firms (i.e. less than 2 years old) raise small amounts of private capital, and split our dataset accordingly in early and late stage financing events. We find that young firms are significantly less likely to use private loans. Use of debt is negatively correlated with uncertainty over future cash flows and presence on informal investors among the buyers of offered securities. Interestingly, within early stage funding, availability of collateral does not play a role in explaining variation in use of debt contracts. This holds true when we use measures of business assets collateral such as the industry long term tangible to total assets ratio and when we look at availability of personal assets collateral, proxied by MSA level elasticity of house supply (Saiz [2010]). The idea behind the latter measure is that in geographical areas where house supply is more elastic, house prices are less sensitive to local demand shocks and therefore real estate property is more suitable for being posted as collateral for loans.

In this study we present new evidence on entrepreneurial finance in its initial phases, thus connecting and complementing existing literature on entrepreneurship on one side (Evans and Jovanovic [1989], Hurst and Lusardi [2004]) and on venture capital (Da Rin et al. [2011]) on the other side. Robb and Robinson [2012] show that non-bank external capital, i.e. entrepreneurial finance, is not commonly used by newly established firms. Only 4% of the new firms in the Kauffman Firm Survey (KFS) database access this form of funding during the first year of operations. Firms that use "outsider equity", however, look very different from the rest of the KFS sample. In particular the size of their financial assets is between 5 and 20 times larger, which suggests larger early stage investments and more aggressive business plans, or simply that these firms operate in sectors where fast growth is essential for success. This is not surprising: evidence on the more "mature" investment stage of the entrepreneurial finance spectrum shows that VC funding is usually provided to firms with high growth ambitions and innovative business models, which are more likely to be "transformational" rather than "substistence" ventures (Schoar [2010]). We know however that VC funded firms often embark in the private capital raising process well before the VC phase, raising funds with family and friends, angels, seed-firms, incubators, peer to peer lenders. In Robb and Robinson [2012], non-VC (early stage) capital is used by more than 87% of firms that rely on outsider equity. Little is known about the "dawn" of these high-growth, transformational start-ups, despite the fact that these are the biggest potential contributors to employment and innovation. We provide novel evidence on characteristics, financing choices and funding history of these firms, which can constitute the basis for future empirical work.

The remainder of the chapter is organized as follows. Section 2 describes the data . Section 3 focuses on use of private debt and its determinants. Section 4 concludes.

2.2 Entrepreneurial Finance, Regulation D and Private Capital Markets

Entrepreneurial finance can be widely defined as the process of allocating financial resources for new ventures. Compared to listed or long established companies, start-ups undoubtedly have a limited range of funding source. Raising capital with a public offering is usually not a viable financing option for small businesses because of the costs involved in the registration procedure and the degree of information disclosure required by regulatory authorities. In the absence of a public market for their financial claims, new ventures must raise funds for projects from investors in private capital markets. Sale of securities outside supervised markets, however, is typically restricted by law in order to protect investors from frauds. In the United States, the legal framework in which entrepreneurial finance operates is defined by Regulation D, the private placement exemption to the Securities Laws (1933, 1934) that was enacted in 1982 to facilitate capital raising for small businesses.[2] Under certain restrictions, such as the ban on public advertisment

[2]Other exemptions exist, such as the ones offered in Section 4(a)(2), but are claimed with far less

of the offerings, Regulation D allows firms to raise funds by issuing unregistered securities that are exempt from authorization and periodic disclosure requireme nts. Securities can take any contractual form, such as pure debt, preferred stocks or convertible notes. As in Ivanov and Bauguess [2013], we refer to the collections of financing events conducted in compliance with Regulation D as private capital markets.[3] When making their investments, founders' family and friends, angel investors, venture capital (VC) and private equity firms effectively purchase unregistered securities in private capital markets. Thus, private capital markets include all stages of entrepreneurial finance as defined by the industry and the academic literature, from seed funding to the latest rounds of capital raising before an IPO.

Regulation D requires firms that sell securities in a private placement to file a notification form (Form D) with the SEC, providing information on the firm (including location, industry and name of directors) and on the offering (including security used and dollar amount offered and sold) . Online filing was made mandatory since March 2009. In order to explore and characterize the full spectrum of entrepreneurial finance we collect and process Form Ds for private non-financial firms that started raising private capital after March 2009 (see Zaccaria [2015]). Our dataset consists of 58,059 private placements, conducted by 39,230 firms before October 2014. In what follows, we present some descriptive statistics and stylized facts on our private capital markets sample.

Figure 2.1 shows number of deals and total amount sold for each calendar year covered by our dataset. The majority of the deals are first rounds, namely financing events of firms that tap private capital markets for the first time since incorporation. Most offerings are conducted by young firms (less than 3 years from incorporation) with less than 4 different investors (Table 2.1). Figure 2.2 shows the time series for median and mean round size. With a mean value that exceeds that of the median by a factor of 7 on average, the skewness of the round size distribution sig-

frequency, as showed by Ivanov and Bauguess [2013]

[3]Regulation D also applies to listed firms' private placements and investment funds' sale of shares. We exclude these financing events from our analysis.

nals that a large portion of the dataset comprises small deals, where firms raised less than 1$ million . Unsurprisingly, Technology (27%), Energy and Utilities (9%), Health Care (9%), and BioTech&Pharma (7%) dominate the industry breakdown, but also the Commercial (7%), Real Estate (7%), Manufacturing (4%) and Services sectors are represented (Table 2.2).

A key feature of Regulation D is the ban on general solicitation, i.e. firms cannot freely advertise the offering via, for example, a website or a fund raising event. During the observation period and until March 2015, U.S. legislation did not allow for crowdfunding at the federal level, since sales of financial claims to the general public on internet-based matching platforms were in violation of Securities Laws.[4] In 2012 however, a new chapter of Regulation D, Rule 506(c), was introduced that allows for general solicitation provided that all investors are *accredited*, namely either financial institutions or high net worth individuals.[5] Our data show that Rule 506(c) was not popular: only 4% of the financing events after 2012 were conducted under this exemption.[6] Since the vast majority of the offerings, both before and after the reform, were conducted with accredited investors only, it is possible that lack of success of this new form of restricted crowdfunding is partly due to the disclosure of information that advertising inevitably involves.[7] Firms with innovative business models may be reluctant to publicly disclose their business plan

[4]There is no violation of the Securities Laws if claims are sold with an in-kind repayment promise, as these claims do not qualify as securities. This is the case for famous crowdfunding platforms such as Kickstarter or Indiegogo. Federal laws on crowdfunding that allow for public sale of securities with no restrictions on the sophistication of the investors have been introduced by the JOBS Act (2012) and enacted by the SEC with the so called Regulation A+ in March 2015.

[5] Individuals with an annual income greater than 200,000$ or net worth above 1$ milion qualify as accredited.

[6]The most commonly used chapter of Regulation D is Rule 506(b), which, together with the ban on general solicitation, imposes limits to non-accredited investors' participation. This limit is set to 35 per offering but it does not appear to be binding in practice for our sample as more than 90% of the completed offerings are conducted with less than 20 investors in total. Private offerings in exemption of securities laws can be conducted also under Rule 504, Rule 505 and, since the end of year 2012, Rule 506(c). Rules 504 and 505 are applicable to smaller issuances ($1 million or $5 million) and, under certain circumstances, they relax constraints on non-accred ited investors participation . However, only Rule 506(b) exempts from Blue Sky law registration. This seems to be the reason why Rule 506(b) is used for almost the totality of the private placements. See Ivanov and Bauguess [2013]

[7]Another potential explanation is related to the fact that under Rule 506(c) the burden of the proof of investors' accredited status is born by the issuer instead of the investors themselves.

and may prefer to illustrate the details of the venture privately only to interested investors. Table 2.3 supports this interpretation and shows that the new restricted crowdfunding option was less common among highly innovative industries, such as technology and biotech.[8]

US based firms conducted 54,249 offerings in our dataset and the majority of them (85%) are located in metropolitan areas (MSAs). About half of the financing events takes place in only 10 of the 327 MSAs in our sample, with the Silicon Valley hosting 13% of the recorded deals (Table 2.4).[9] Foreign located firms represent 7% of the whole dataset. Geographic proximity and strong cultural ties seem to drive foreign participation in US private capital markets. Foreign firms are mostly located in Canada (78%) followed by UK (5%), Australia (3%), Cayman Islands (2%), Israel (2%) and Mexico (1%). Interestingly, only 3% of the offerings conducted by foreign firms are located in continental Europe, despite the fact that this economic area is substantially larger in terms of population and GDP as compared to the first 6 countries in Panel B of Table 2.4 combined.

Since IPOs are common exit options for investors, in an attempt to provide a measure of success for companies in our dataset we collect information on whether firms filed form S-1, the SEC filing used to register securities by companies that plan to go public. As of March 2016, only 2,5% of the offerings in our dataset were conducted by firms that subsequently filed for public listing of their securities. Public listings are more common among BioTech&Pharma firms (26%) and firms located in the Silicon Valley (18%) (see Table 2.5 and 2.6).

Tangent to this private capital markets overview, the question arises of the extent to which firms actually comply with the Form D filing requirement. Although failing to file the form D does not result in the loss of the federal registration exemption, the SEC can seek to have the issuer enjoined from future use of Regulation

[8]This evidence highlights the possible limitations of crowdfunding in supporting and promoting business innovation.

[9]We indicate as Silicon Valley the combined MSAs of San Francisco-Oakland-Fremont and San Jose-Sunnyvale-Santa Clara.

D under rule 507. Enforcement of this requirement may be weak, but firms that have access to basic legal advice and that intend to access private or public capital markets are reasonably likely to comply. There are no filing fees and the "estimated average burden hours per response" is 4, as stated on the form. We compare our records with deals included in the widely used proprietary dataset VentureExpert (VE) . 60% of firms that started raising VC in 2009 according to VE are also included in our dataset. On the other hand, our dataset contains over 30,000 deals more than VE over the relevant years, suggesting that a large portion of financing events are not tracked by commonly used datasets. This is not surprising, since most observations seem to match Berger and Udell [1998] description of early stage funding, with very young firms raising relatively modest amounts of capital. These financing operations are typically supported by small and non-institutional investors, who are unlikely to report their investments to data collection companies.

2.3 Entrepreneurial Debt

Entrepreneurial finance is often said to fill the "equity gap" for small and young firms. Corporate finance theory predicts that low, negative or uncertain cash flows and lack of tangible assets can prevent newly established ventures from borrowing. Investors with lower risk aversion and less regulatory requirements than traditional bank lenders, such as angels or venture capital firms, provide equity to support new businesses. At the same time, empirical studies show that debt contracts are not uncommon in start-ups' capital structures, whether in the form of bank loans (Robb and Robinson [2012]) or venture debt (Ibrahim [2010]). This holds true even for firms at the very beginning of their business operations. This paper can contribute to this literature by virtue of the detailed information contained in Form D filings. Regulation D requires issuers to specify the type of security used in the offering. This can be equity, debt, other security (e.g. options, warrants, mineral property security) or a combination of them. In our dataset, debt (alone or in combination with other securities) is used in 19% of the total private placement deals, with this proportion oscillating between a maximum of 22% in 2009 and a minimum of 17% in 2011.

In order to investigate heterogeneity in financing contracts among start-ups we further characterize financing events as early and late stage rounds. In doing so, we also provide novel evidence on the least explored side of entrepreneurial finance spectrum, namely the pre-VC stage.

2.3.1 Early vs Late Stage

Start-ups early stage funding phase usually involves family and friends, angels, seed firms or peer to peer lenders as investors and very young, small firms issuing securities. Lacking any conventional definition and in the absence of information on the exact identity of investors in our data, we identify early stage rounds as private placements conducted by firms that are less than 2 years old and that aim at raising less than $6M. The first criterion is intuitive. The second is based on industry reports on the average size of a VC Series A funding round and it is meant to rid the early stage group from deals conducted by firms that, although young, already reached a mature stage at the time of the financing event.[10] This can happen for example with firms that originated from spin-offs of established businesses or that undergo extremely fast growth right after incorporation. There is a considerable overlap between the group identified with the first criterion and the one identified with first and second : 48% of the total deals satisfy the age requirement and 42% satisfy both age and round size rules. Of course, our criteria merely attempt to draw quantitative boundaries around a finance concept, that of early stage funding, which is itself hard to define numerically. Seed capital is the amount of money needed to start off a business, but ventures' investment schedules are very firm, industry and time specific.

[10] Average Series A VC deal size was $6.2 milion, $6.5 milion and $8.6milion in years 2012, 2013 and in the first three quarters of 2014 respectively, according to Prequin Venture Capital Deals report October 2014.

We split the dataset according to our definition into early and late stage financing events. Only 13% of deals in the VE dataset match financing events classified as early stage in this paper. Therefore our records include a vast sample of pre-VC funding rounds we only had a glimpse at so far via survey data (see for example Kerr et al. [2014] or Lerner et al. [2015]). Tables 2.7 and 2.8 juxtapose early and late stage financing events along various dimensions. Early stage rounds are smaller, conducted with less investors and more likely subscribed by family and friends of the firms' founders.[11]

Firms raising early stage capital have smaller revenues and fewer board members and are more likely to operate in commercial, services and real estate industries. Figures 2.3a and 2.3b present the time series of median round size by sector and funding stage. The amount of capital raised varies considerably across sectors both in early and late stage deals (biotech&pharma offerings, for example, are consistently larger than health care or energy offerings) but no pronounced trends are detectable within sectors over time.

Seed capital is often seen as the "stepping stone" for reaching VC funding. 4,650 deals classified as late stage are conducted by firms that had previously raised early funding. Transitions to late stage funding, however, are not common. Only 12% of firms involved in early stage deals reach the late stage within our observation period. Transitions are more common in the technology, biotech&pharma and health care sectors and less frequent in commercial and real estate industries.

Early and late stage deals differ substantially in terms of securities used and there is a large heterogeneity in this variation across sectors (Table 2.9). For example, while technology and telecommunication firms use more debt in early rather than late stage, the opposite is true for all other sectors, with airlines, commercial and utility firms increasing reliance on debt by 20% or more in late stages. We investi-

[11] As in Zaccaria 2015, we use the information on presence of non-accredited individuals among an offering's investors as the indicator that family and friends of the entrepreneurs participated in the deal.

gate entrepreneurs' choices on sources of funding further in the next section.

2.3.2 Determinants of Private Debt

We show that use of different financial contracts is related to the financing stages in which the offering takes place. Pure equity is more commonly used by firms in early funding stages while use of debt is associated with late stage financing events. Specifically, late stage rounds are 3% more likely to be conducted with debt contracts, after controlling for industry, revenue size and location (Table 2.10).

In order to examine the determinants of such difference in the use of debt in private capital markets, we estimate two separate probit models for the probability of an offering to be conducted with debt in early and late stage, and compare the estimated coefficients for several factors (Table 2.11). Uncertainty over future cash flows due to lack of any track record on profitability is a strong predictor for use of debt. Offerings of firms in the pre-revenue phase are 4% less likely to be conducted with debt contracts in both early and late stage deals. The number of directors, which can be interpreted as a proxy for firm size, has opposite impact for early (negative) and late (positive) stage deals, but the magnitude of the marginal effect is below 1% in both cases. While the number of investors that participated in the offering has a negligible effect, the proportion of amount offered already subscribed by the filing date is strongly correlated with the probability of debt being used. In other words, deals that are "closed" faster are less likely to be conducted with debt, and the intensity and significance of this variable is independent of the financing stage. The presence of non-accredited investors participating in the offering is negatively correlated with use of debt, with the effect being stronger in late stage deals (-5%) as compared to early stage ones (-2%). Interestingly, in late stage deals, firms that previously received outside capital from private investors, i.e. transitioned firms, are no more likely to raise debt. Thus, presence of existing outside investors that may help reduce information asymmetry does not seem to drive the larger use of debt in late stages.

The major difference between the two estimated models resides in the role of collateral for debt financing. We use the industry long term ratio of tangible assets over total assets for S&P500 companies as a proxy for collateral availability. It is reasonable to assume that in case of bankruptcy of the borrower, it would be easier for the lender to seize a (tangible) piece of machinery rather than an (intangible) algorithm. The proportion of tangible assets on balance sheet plays a relevant role in late stage debt financing, while it has no significant impact in seed funding. This result is robust to different model specifications and in particular it persists when we restrict the sample to revenue generating firms. This evidence suggests that while both cash flow uncertainty and lack of collateral affect firms' debt capacity in late stages of entrepreneurial finance, only the former explanation may be valid for start-ups at the very beginning of the funding process.[12]

It can be argued, however, that start-ups founders use personal rather than business assets as collateral for business loans in order to start of their ventures. This would explain why use of debt is unrelated to industry specific tangible assets ratios, without ruling out the collateral channel. In order to verify this hypothesis, we use local elasticity of house supply (Saiz [2010]) as a proxy for availability of personal collateral assets (see Robb and Robinson [2012]).[13] The idea is that in areas where house supply is more elastic, house prices are less sensitive to local demand shocks and therefore real estate property is more suitable for being posted as collateral for loans. This can make borrowing a more accessible source of funding for entrepreneurs. Table 2.12 shows that house supply elasticity has no significant effect on debt, suggesting that personal collateral does not help explain variation in the use of different financial contracts in early stage financing.

[12]The sample is restricted to exclude firms that operate in Other sectors, for which the ratio of tangible versus total assets cannot be computed. We obtained analogous results when including the Other sector and estimating the tangible to total assets ratio as an average of all other sectors.

[13]Due to changes in the definition of MSA by the Office of Management and Budget, we were only able to exactly match only 141 out of the 327 in the dataset.

Finally, we examine the effect of state-level bankruptcy exemptions (Cerqueiro and Penas [2014], Robb and Robinson [2012]). Higher protection on personal assets in bankruptcy laws is typically associated with higher denial of personal loans. If debt is raised in private capital markets as a substitute for personal credit then the (exogenous) variation in state-level bankruptcy exemptions should affect use of debt via an "indirect" collateral channel. This conjecture is not supported by our data, as showed in Table 2.12.

The evidence we present suggests that collateral does not play a major role in early stage debt financing. One explanation for this result is that early stage firms in our sample are too young for credit markets as they had not yet developed an adequate asset base. Previous studies show, however, that bank debt is a very common feature of firms' capital structure in the very first year of operations and across sectors. This debt is usually collateralized with either firms' assets (possibly purchased with the liquidity provided by the loan itself) or with personal assets of the entrepreneurs. Use of early stage private debt, instead, is unrelated to availability of business or personal collateral. This may be due to the specific characteristics of seed capital providers in private markets. Small early stage investors, such as family, friends or angels, may be unable to seize collateral in an efficient way, for example because of legal and opportunity costs of bankruptcy liquidation procedures. The use of private early stage debt and the result on irrelevance of collateral can be reconciled by arguing that borrowers may pledge *social* rather than tangible collateral, relying on reputation built from personal connections (Stiglitz [1990], Besley and Coate [1995]). This is possible in the context of private markets because of the direct and non-intermediated nature of the relationship between very young firms and small early stage capital providers (Bernstein et al. [2015]).

2.4 Conclusions

Corporate finance theory predicts that young firms face financial constraints during the initial years of operation. In particular, lack of an adequate asset base to serve as collateral is considered the main impediment in raising capital with debt contracts. We explore financing decision of young firms in the context of private capital markets, i.e. funding provided by individuals (family , friends, angel investors) or unsupervised financial intermediaries (e.g. VC firms and peer-to-peer lending platforms). We show that, contrary to various theoretical predictions, debt is a recurrent source of entrepreneurial funding. Almost 20% of the financing events in our dataset involve debt securities.

We further explore heterogeneity in financing contracts and document a significantly lower occurrence of debt contracts in early stage financing events, i.e. funding rounds smaller than 6$ M conducted by firms that are less than 2 years old. Interestingly, while uncertainty over future cash flows is significantly correlated with use of debt, availability of collateral, in terms of both business and personal assets, is irrelevant. This result is in contrast with evidence provided in previous research on the determinants of bank credit for start-ups. The evidence that collateral does not play a significant role in private debt markets, especially in early stages, can be related to the peculiar nature of early stage investors and their personal connection with the entrepreneurs. On one hand liquidation costs may be too high for such small investors and on the other hand entrepreneurs may pledge social rather than tangible collateral.

We use a novel dataset based on SEC Form D filings for private placements. This allows us to provide a complete picture of private capital markets for unlisted firms, for example in terms of industry, location, management team, financing needs and funding stage and to follow firms' access to this market over time.

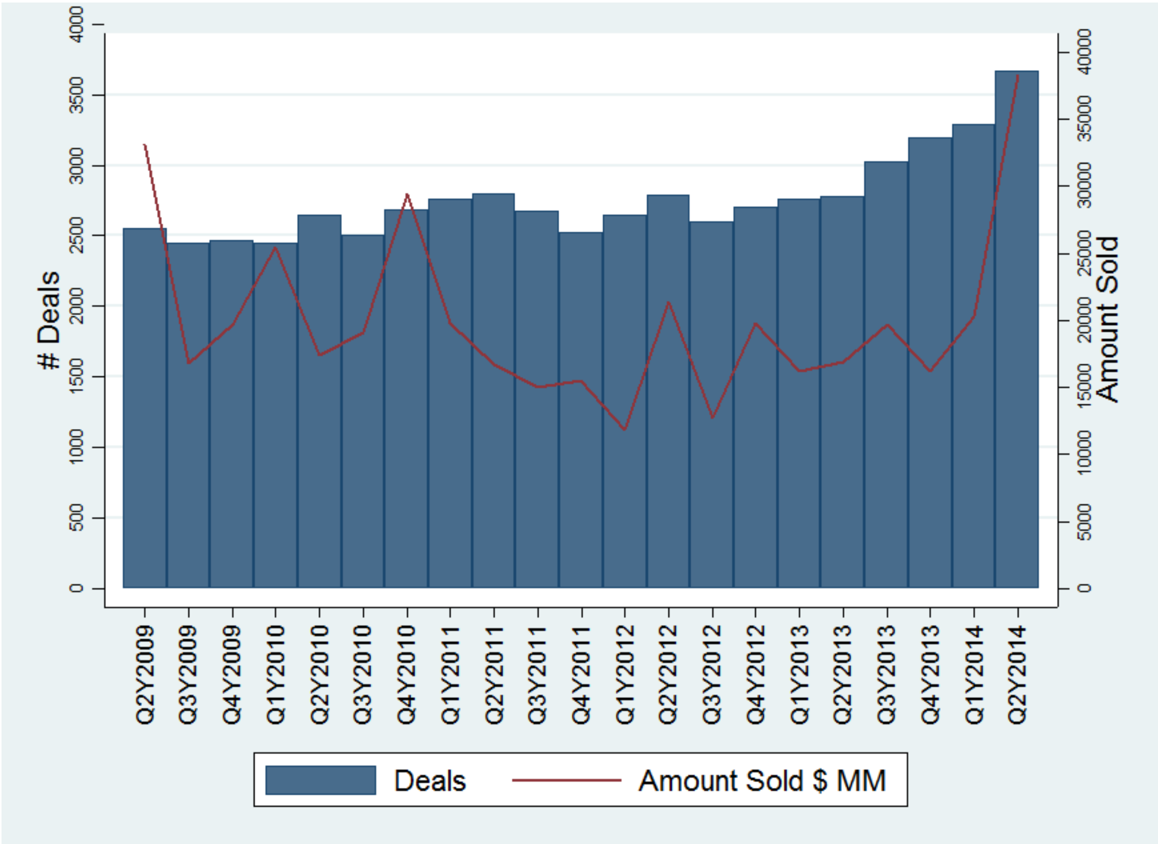


Figure 2.1: Number of Offerings and Amounts Sold by Quarter

Table 2.1: Deal and Firm Characteristics

	Freq.	Percent	Cum.
Round			
1st	39,230	68%	68%
2nd	9,560	16%	84%
3rd	4,224	7%	91%
4th or later	5,045	9%	100%
Firm Age (yrs)			
0	11,962	21%	21%
1	9,839	17%	38%
2	6,215	11%	48%
3	4,744	8%	56%
4 or more	20,866	36%	92%
NA	4,433	8%	100%
Investors			
4 or less	28,792	50%	50%
5 to 10	12,970	22%	72%
11 to 35	13,128	23%	95%
more than 35	3,169	5%	100%
Firm Revenues Size			
No Revenues	10,071	17%	17%
$1 - $1,000,000	7,262	13%	30%
$1,000,001 - $5,000,000	2,655	5%	34%
$5,000,001 - $25,000,000	1,376	2%	37%
$25,000,001 - $100,000,000	439	1%	38%
Over $100,000,000	390	1%	38%
Decline to Disclose	34,869	60%	98%
Not Applicable	997	2%	100%
Directors			
1 to 3	28,310	49%	49%
4 to 6	18,305	32%	80%
7 or more	11,444	20%	100%
Total	58,059		

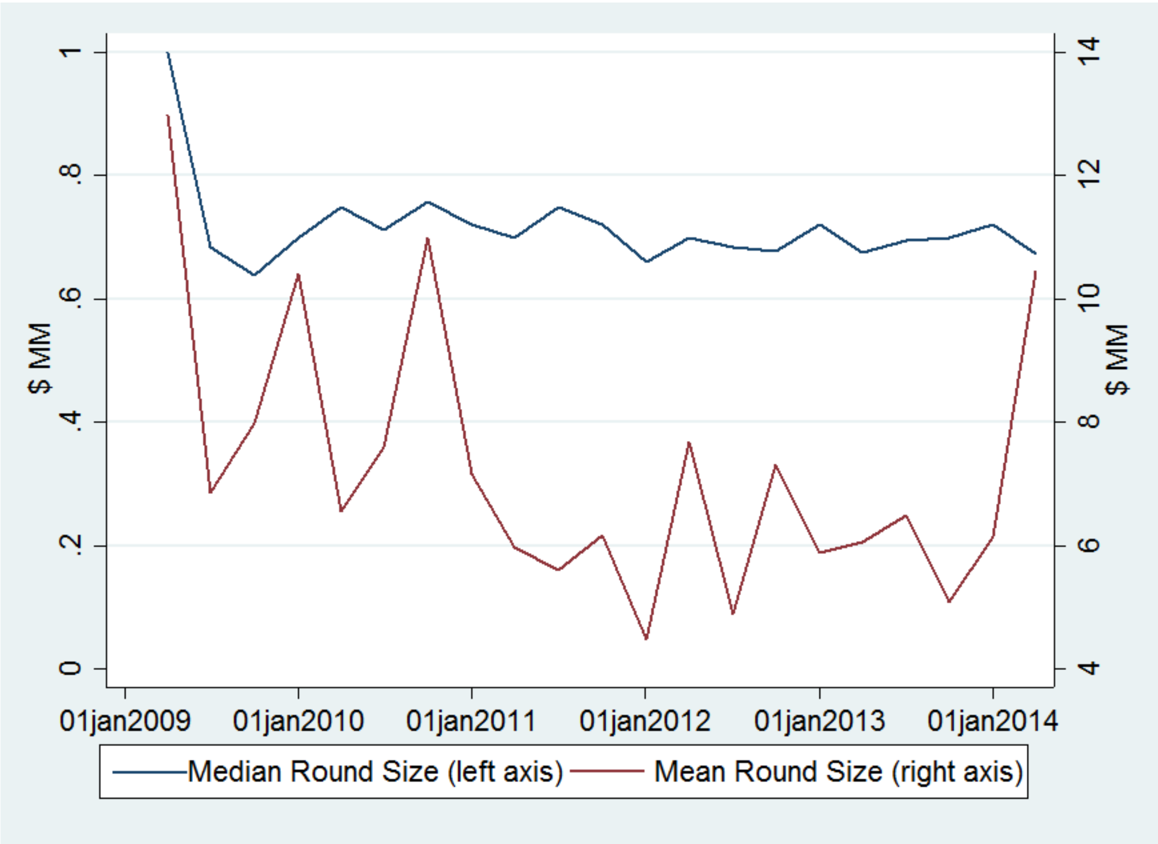


Figure 2.2: Median and Mean Dollar Amount Sold per Offering

Table 2.2: Total Offerings by Industry

	Freq.	Percent	Cum.
Industry			
Technology[a]	15,760	27.1%	27.1%
Other	14,096	24.3%	51.4%
Energy[b]	5,249	9.0%	60.5%
Health Care[c]	4,947	8.5%	69.0%
Real Estate[d]	4,075	7.0%	76.0%
BioTech&Pharma [e]	3,967	6.8%	82.8%
Commercial	3,963	6.8%	89.7%
Manufacturing	2,167	3.7%	93.4%
Business Services	1,081	1.9%	95.3%
Restaurants	964	1.7%	96.9%
Telecommunications	898	1.6%	98.5%
Agriculture	371	0.6%	99.1%
Travel	211	0.4%	99.5%
Environmental Services	164	0.3%	99.8%
Electric Utilities	110	0.2%	99.9%
Airlines and Airports	36	0.1%	100.0%
Total	58,059		

a) Includes Computer and Other Technology

b) Includes Coal Mines, Oil and Gas and Other Energy

c) Includes Hospital and Physicians, Health Insurance and Other Health Care

d) Includes Constructions, Residential, Lodging and Conventions and Other Real Estate

e) Includes Biotechnology and Pharmaceutical

Table 2.3: Industry Breakdown and the General Solicitation Exemption

	Rule 506 (c)		Other Exemptions	
	Freq.	**Percent**	**Freq.**	**Percent**
Industry				
Agriculture	11	1.6%	125	0.7%
Airlines and Airports	1	0.1%	9	0.1%
BioTech&Pharma	28	4.0%	1,185	6.6%
Business Services	22	3.2%	301	1.7%
Commercial	52	7.5%	1,284	7.1%
Electric Utilities	0	0.0%	13	0.1%
Energy	80	11.5%	1,318	7.3%
Environmental Services	1	0.1%	52	0.3%
Health Care	39	5.6%	1,474	8.2%
Manufacturing	34	4.9%	650	3.6%
Other	165	23.8%	4,389	24.4%
Real Estate	83	12.0%	1,575	8.7%
Restaurants	12	1.7%	315	1.8%
Technology	152	21.9%	5,087	28.2%
Telecommunications	8	1.2%	194	1.1%
Travel	6	0.9%	51	0.3%
Total	694		18,022	

Deals conducted under Rule 506(c) benefit from the lift on the ban on general solicitation, provided that all investors qualify as accredited.
This table refers to deals conducted after January 2013

Table 2.4: Location: U.S. and Non-U.S. Firms

Panel A: US Firms. Obs.: 54,249			
	Freq.	**Percent**	**Cum.**
State			
California	12,265	22.6%	22.6%
Texas	5,210	9.6%	32.2%
New York	4,469	8.2%	40.5%
Massachusetts	3,213	5.9%	46.4%
Washington	2,388	4.4%	50.8%
Colorado	2,202	4.1%	54.8%
Florida	2,145	4.0%	58.8%
Illinois	1,748	3.2%	62.0%
Pennsylvania	1,627	3.0%	65.0%
North Carolina	1,379	2.5%	67.6%
MSA			
San Francisco-Oakland-Fremont	4,168	8.7%	8.7%
New York-Northern New Jersey-Long Island	4,059	8.5%	17.2%
Los Angeles-Long Beach-Santa Ana	3,169	6.6%	23.8%
Dallas-Fort Worth-Arlington	2,515	5.3%	29.1%
San Jose-Sunnyvale-Santa Clara	2,193	4.6%	33.7%
Seattle-Tacoma-Bellevue	2,045	4.3%	38.0%
Chicago-Naperville-Joliet	1,631	3.4%	41.4%
San Diego-Carlsbad-San Marcos	1,386	2.9%	44.3%
Denver-Aurora	1,324	2.8%	47.0%
Washington-Arlington-Alexandria	1,279	2.7%	49.7%

Panel B: Non-US Firms. Obs.: 3,805			
COUNTRY			
CANADA	2,960	77.8%	77.8%
UNITED KINGDOM	194	5.1%	82.9%
AUSTRALIA	125	3.3%	86.2%
CAYMAN ISLANDS	71	1.9%	88.0%
ISRAEL	59	1.6%	89.6%
MEXICO	41	1.1%	90.7%
CHINA	36	0.9%	91.6%
VIRGIN ISLANDS, BRITISH	21	0.6%	92.2%
HONG KONG	20	0.5%	92.7%
BERMUDA	18	0.5%	93.2%

Panel A shows top 10 most frequent location states and MSAs for deals conducted by U.S. firms. Panel B shows top 10 most frequent location countries deals conducted by Non-U.S. firms.

Table 2.5: Public Listings and Industry

	S-1 Filing: Y *		S-1 Filing: N *	
	Freq.	**Percent**	**Freq.**	**Percent**
Industry				
Technology	135	18.5%	9,087	23.6%
Other	156	21.4%	9,704	25.2%
Energy	53	7.3%	3,293	8.6%
Health Care	49	6.7%	3,014	7.8%
Real Estate	56	7.7%	3,662	9.5%
BioTech&Pharma	189	25.9%	1,909	5.0%
Commercial	23	3.2%	3,532	9.2%
Manufacturing	16	2.2%	1,479	3.8%
Business Services	22	3.0%	798	2.1%
Restaurants	3	0.4%	843	2.2%
Telecommunications	11	1.5%	503	1.3%
Agriculture	6	0.8%	282	0.7%
Travel	8	1.1%	144	0.4%
Environmental Services	1	0.1%	118	0.3%
Electric Utilities	2	0.3%	100	0.3%
Airlines and Airports	0	0.0%	32	0.1%
Total	730		38,500	

* S-1 Filing: Y (N) denotes firms that filed (did not file) form S-1 to register securities with the SEC after raising private capital.

Table 2.6: Public Listings and Location

S-1 Filing: Y		
	Freq.	**Percent**
MSA		
San Francisco-Oakland-Fremont	75	12.5%
Houston-Sugar Land-Baytown	60	10.0%
New York-Northern New Jersey-Long Island	41	6.8%
Los Angeles-Long Beach-Santa Ana	35	5.8%
San Jose-Sunnyvale-Santa Clara	33	5.5%
Miami-Fort Lauderdale-Pompano Beach	30	5.0%
San Diego-Carlsbad-San Marcos	29	4.8%
Dallas-Fort Worth-Arlington	25	4.2%
Las Vegas-Paradise	17	2.8%
Philadelphia-Camden-Wilmington	17	2.8%

S-1 Filing: N		
MSA		
New York-Northern New Jersey-Long Island	2,780	8.6%
San Francisco-Oakland-Fremont	2,461	7.6%
Los Angeles-Long Beach-Santa Ana	2,228	6.9%
Dallas-Fort Worth-Arlington	1,728	5.4%
Seattle-Tacoma-Bellevue	1,281	4.0%
Chicago-Naperville-Joliet	1,203	3.7%
San Jose-Sunnyvale-Santa Clara	1,186	3.7%
Washington-Arlington-Alexandria	853	2.6%
Denver-Aurora	844	2.6%
San Diego-Carlsbad-San Marcos	837	2.6%

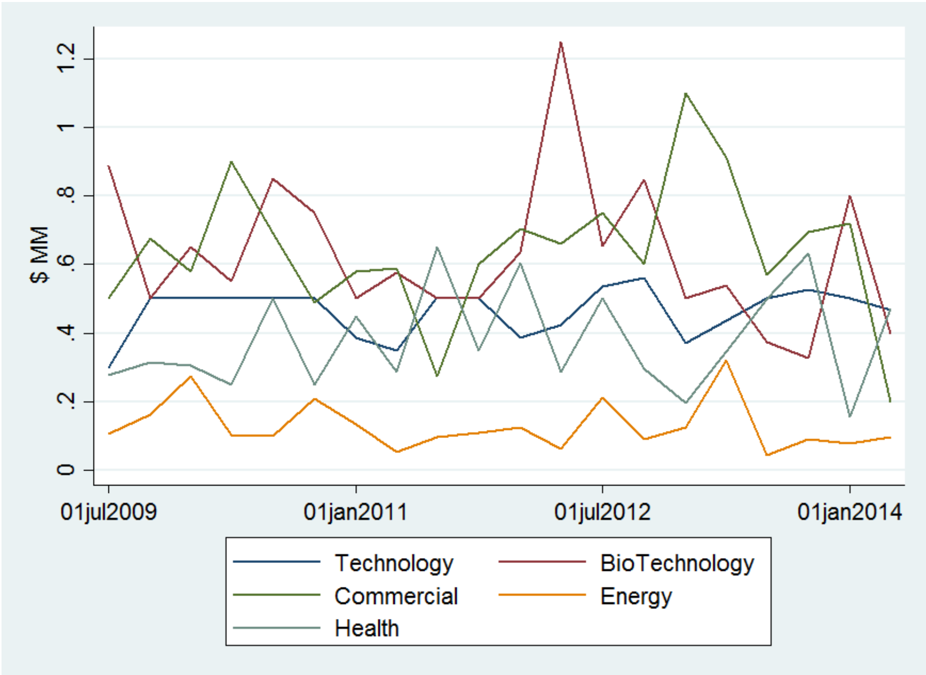
Top 10 most frequent MSA locations for firms that filed (S-1 Filing: Y) and did not file (S-1 Filing: N) form S-1 to register securities with the SEC after raising private capital

Table 2.7: Early vs Late Stage Deals: Descriptive Statistics

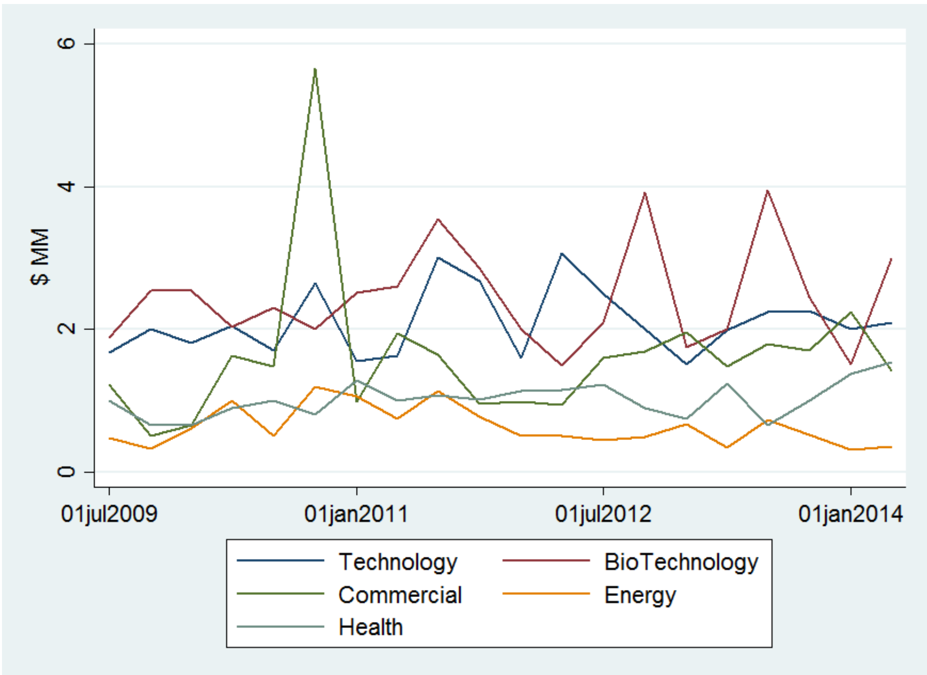
	Early Stage		Late Stage	
	Freq.	**Percent**	**Freq.**	**Percent**
Round				
1st	20,044	82%	19,186	57%
2nd	3,093	13%	6,467	19%
3rd	805	3%	3,419	10%
4th or later	538	2%	4,507	5%
Investors				
4 or less	13,278	54%	15,514	46%
5 to 10	5,116	21%	7,854	23%
11 to 35	5,148	21%	7,980	24%
more than 35	938	4%	2,231	7%
Non-accredited investors	3,346	14%	3,133	9%
Firm Revenues Size				
No Revenues	6,163	25%	3,908	12%
$1 - $1,000,000	3,432	14%	3,830	11%
$1,000,001 - $5,000,000	938	4%	1,717	5%
$5,000,001 - $25,000,000	324	1%	1,052	3%
$25,000,001 - $100,000,000	51	0%	388	1%
Over $100,000,000	23	0%	367	1%
Decline to Disclose	12,978	53%	21,891	65%
Not Applicable	571	2%	426	1%
Directors				
1 to 3	16,050	66%	12,260	37%
4 to 6	6,711	27%	11,594	35%
7 or more	1,719	7%	9,725	29%
	Mean	**Median**	**Mean**	**Median**
Round Size ($ Thousands)	969	350	11,852	1,335

Table 2.8: Early vs Late Stage Deals: Industry Breakdown

Industry	**Early Stage**	**Late Stage**	**Total**
Agriculture	151	220	371
%	0.62	0.66	0.64
Airlines and Airports	17	19	36
%	0.07	0.06	0.06
BioTech&Pharma	998	2,969	3,967
%	4.08	8.84	6.83
Business Services	534	547	1,081
%	2.18	1.63	1.86
Commercial	2,024	1,939	3,963
%	8.27	5.77	6.83
Electric Utilities	61	49	110
%	0.25	0.15	0.19
Energy	2,217	3,032	5,249
%	9.06	9.03	9.04
Environmental Services	64	100	164
%	0.26	0.3	0.28
Health Care	1,659	3,288	4,947
%	6.78	9.79	8.52
Manufacturing	843	1,324	2,167
%	3.44	3.94	3.73
Other	5,994	8,102	14,096
%	24.49	24.13	24.28
Real Estate	2,311	1,764	4,075
%	9.44	5.25	7.02
Restaurants	573	391	964
%	2.34	1.16	1.66
Technology	6,690	9,070	15,760
%	27.33	27.01	27.14
Telecommunications	254	644	898
%	1.04	1.92	1.55
Travel	90	121	211
%	0.37	0.36	0.36
Total	24,480	33,579	58,059



(a) Early Stage Median Round Size. Selected Industries



(b) Late Stage Median Round Size. Selected Industries

Table 2.9: Securities Issued and Use of Debt

Panel A: Securities Issued by Funding Stage

Security	Early Stage	Late Stage	Total
Debt&Other	3,010	5,232	8,242
%	12.3	15.58	14.2
Equity&Debt	572	799	1,371
%	2.34	2.38	2.36
Equity&Debt&Other	424	713	1,137
%	1.73	2.12	1.96
Equity&Other	18,221	24,251	42,472
%	74.43	72.22	73.15
Other Security	2,253	2,584	4,837
%	9.2	7.7	8.33

Panel B: Use of Debt by Industry and Funding Stage

	Early Stage		Late Stage	
Industry	**Debt***	**Total**	**Debt***	**Total**
Agriculture	24	151	49	220
%	15.89		22.27	
Airlines and Airports	3	17	8	19
%	17.65		42.11	
BioTech&Pharma	201	998	785	2969
%	20.14		26.44	
Business Services	78	534	116	547
%	14.61		21.21	
Commercial	151	2024	521	1939
%	7.46		26.87	
Electric Utilities	11	61	19	49
%	18.03		38.78	
Energy	170	2217	427	3032
%	7.67		14.08	
Environmental Services	10	64	17	100
%	15.63		17	
Health Care	248	1659	656	3288
%	14.95		19.95	
Manufacturing	168	843	368	1324
%	19.93		27.79	
Other	932	5994	1263	8102
%	15.55		15.59	
Real Estate	226	2311	362	1764
%	9.78		20.52	
Restaurants	60	573	53	391
%	10.47		13.55	
Tech	1643	6690	1933	9070
%	24.56		21.31	
Telecommunications	63	254	146	644
%	24.8		22.67	
Travel	18	90	21	121
%	20		17.36	

* For each sector, the first row indicates the number of offerings conducted with debt (alone or in combination with other securities),the second row indicates the frequency of such offerings within the sector

Table 2.10: Use of Debt in Private Capital Markets

Estimates stem from a probit model $Pr(Y_i = 1) = X_i + \epsilon_i$ where the dependent variable is a dichotomous indicator that takes value 1 if debt securities are issued in offering i. *Late Stage* is a categorical variable that equals 1 if the offering is classified as Late Stage. *Non Accredited* is a categorical variable that equals 1 if the securities are offered to non-accredited investors. Variables *Directors* and *Investors* indicate the number of firm's directors and offering's investors. The table shows both coefficients and average marginal effects for each regressor.

	Coefficient		**AME**	
Late Stage	0.09204***	0.09028***	0.02988***	0.0225***
	(0.01313)	(0.01408)	(0.003315)	(0.00349)
Non Accredited		-0.12818***		-0.03076***
		(0.02288)		(0.00524)
Directors		0.00433*		0.00108*
		(0.00242)		(0.00061)
Investors		-0.00126***		-0.00031***
		(0.00037)		(0.00009)
Amount Sold		0.00016		0.00004
		(0.00016)		(0.00004)
Amount Sold/Amount Offered		-0.30306***		-0.07593***
		(0.01798)		(0.00448)
Industry FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Revenue Size FE	Y	Y	Y	Y
Entity Type FE	N	Y	N	Y
Obs.	58,059	58,059		
Pseudo R-squared	0.0437	0.0626		
LR^2 (df)	2426.59 (110)	3325.52 (117)		

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

Table 2.11: Use of Debt: Early and Late Stage Deals

Estimates stem from a probit model $Pr(Y_i = 1) = X_i + \epsilon_i$ where the dependent variable is a dichotomous indicator that takes value 1 if debt securities are issued in offering i. The model is estimated separately for Early and Late Stage deals. The table shows both coefficients and average marginal effects for each regressor.

	Early Stage		**Late Stage**	
	Coefficient	**AME**	**Coefficient**	**AME**
Pre Revenue	-0.18847***	-0.04109***	-0.16176***	-0.04239***
	(0.03030)	(0.0063)	(0.03492)	(0.00866)
Tangible Assets	0.34257	0.07798	0.71136*	0.19608*
	(0.41895)	(0.09536)	(0.39416)	(0.10863)
Transition			-0.0382	-0.01053
			(0.02673)	(0.00737)
Non Accredited	-0.08093**	-0.01794**	-0.19235***	-0.04982***
	(0.03901)	(0.00841)	(0.03675)	(0.00889)
Directors	-0.02227***	-0.00507***	0.02746***	0.00757***
	(0.00627)	(0.00143)	(0.00314)	(0.00086)
Investors	-0.00199*	-0.00045*	-0.00043	-0.00012
	(0.00113)	(0.00026)	(0.00044)	(0.00012)
Amount Sold/Amount Offered	-0.26847***	-0.06111***	-0.22666***	-0.06248***
	(0.03489)	(0.00792)	(0.02685)	(0.00738)
Industry FE	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Entity Type FE	Y	Y	Y	Y
Obs.	17,531		24,217	
Pseudo R-squared	0.0938		0.0558	
LR^2 (df)	1,484.36 (83)		1,408.46 (89)	

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

Table 2.12: Use of Debt in Early Stage and Collateral Availability

Estimates stem from a probit model $Pr(Y_i = 1) = X_i + \epsilon_i$ where the dependent variable is a dichotomous indicator that takes value 1 if debt securities are issued in offering i. *Pre Revenue* is a categorical variable that equals 1 if the offering is conducted by a firm that is not generating revenues. *House Supply Elasticity* is a measure of MSA specific house supply elasticity computed by Saiz(2010). *Home Exemption* is the state-year level maximum exemption to personal bankruptcy as in Cerqueiro and Penas (2014). The table shows both coefficients and average marginal effects for each regressor.

Pre Revenue		-0.13443*		-0.18505***	-0.17042**
		(0.07811)		(0.02646)	(0.07210)
House Supply Elasticity	-0.1007	-0.08843			-0.08863
	(0.06977)	(0.07553)			(0.06991)
Home Exemption			0.0114438	0.01402	-0.04072
			(0.03053)	(0.03205)	(0.1154)
Industry FE	Y	Y	Y		Y
State FE	Y	Y	Y		Y
Entity Type FE	N	Y	N		N
Revenue Size FE	Y	N	Y		N
Deal-Firm Controls	N	Y	N		N
Obs.	2,586	2,586	23,629	23,629	2,586
Pseudo R-squared	0.07	0.1061	0.0499	0.0862	0.0673
LR^2 (df)	155.69 (50)	219.3 (51)	1,058.07 (67)	1,749.62 (71)	147.03 (44)

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

Chapter 3

Discipline in the Securitization Market

3.1 Introduction

The expansion of securitized credit in the years preceding the recent financial crisis suggests a strong link between securitization practices and increases in default rates on loans. A popular explanation among academics, policy makers and the general public hinges on an argument based on banks' moral hazard and lax screening standards . Consequently, emphasis has been placed on the need for stricter regulatory requirements for banks, involving, for example, mandatory information disclosure. On the other hand, little attention has been paid to the impact of the "buy side" of securitization transactions on loan performance. Yet, it seems natural to conjecture that skills and incentives of buyers can potentially affect originators' behaviour. In this paper, I examine the effects of investors' sophistication on screening standards and credit quality. In doing so, I propose a definition of market discipline in the securitization market context based on investors' ability to induce sound origination practices. More specifically, according to the formalization provided, Buy Side sophistication is optimal in a market discipline sense if it preserves efficient risk allocation and credit expansion achieved by securitization but prevents screening standards from deteriorating. My results show that sophistication can be excessive and discourage safe lending and that high risk free rates and low volatility contribute to discipline enforcement.

The ability of screening and monitoring loans in an efficient manner has been identified as one of the reasons for bank lending to firms and households (Diamond [1984]): over time, banks can increase lending profitability by developing specific knowledge on their customer base, spotting sound investment opportunities and collecting (soft) information, which is not available to other capital providers. However, incentives to carry out proper due diligence on loan applications may be distorted by loan selling and securitization practices. Moral hazard behaviour can arise when banks offload credit risk onto outside investors leading to increases in default rates (Petersen and Rajan [2002]). Thus, poor lending practices are a likely outcome when secutitization is motivated by risk-sharing purposes.[1] Risk-sharing as the rational for trade has been proposed by Dewatripont and Tirole [1994] , Chemla and Hennessy [2010] and Malherbe [2010] and supported by many policy makers : risk averse banks trade loans with risk neutral investors in order to decrease the volatility of their payoffs or to diverify their holdings. This paper relies on this same mechanism as the rational for banks to sell the loans they originate, but introduces heterogeneity among financial intermediaries in terms of risk aversion, thus generating heterogeneity in the optimal insurance levels chosen by each institution.

As due diligence is assumed to be not observable for loan buyers, the equilibrium level of monitoring and screening may be lower than if loans were not sold (Pennacchi [1988]), even when the optimal loan sale contract is designed to preserve

[1] Pennacchi [1988]and Acharya et al. [2013] provide both theoretical and empirical support for an alternative explanation based on regulatory capital arbitrage

bank's monitoring/screening incentives. Empirical evidence suggests that credit standards have been significantly loosened in the last few years before the crisis (Keys et al. [2010]). However, from the Seventies the mid years 2000 securitization kept expanding at a solid pace and without major disruptions, despite it being remarkably prone to adverse-selection type market failure. One possible explanation has been proposed by Gorton and Pennacchi [1995] : during the years, investors have become more and more able to acquire and process information (thanks to the new information technology , regulation on transparency and rating agencies) , thereby significantly reducing asymmetries. In my model, hard information (i.e. all loan characteristics) is completely shared between originators and buyers, while the only uncertainty left concerns the unobservable screening action. Importantly, I assume that investors can process hard information by combining it with a signal they privately receive on the state of the economy. The precision of the signal defines investors' sophistication. This assumption is made to capture the institutional nature of the securitization market, where buyers are professional investors with (presumably) better forecasting skills than other agents. It follows that, in this framework, the deterioration of credit quality induced by securitization can be mitigated by investors' sophistication. This intuition leads to the idea of market discipline.

According to Flannery [2001], the concept of market discipline refers to the ability of the investors to judge a bank's behaviour towards risk and to their actions' impact (influence) on that behaviour. This interpretation mirrors the definition of market discipline proposed by regulatory authorities (Basel II) as one of the three pillars of the prudential supervisory architecture. The intuition for market discipline is that if the investor has sufficient means to verify her counterparty risk attitude and if she has the proper incentive to behave consequently (punishing the bank for excessive risk taking), the bank will take into account investor's actions and engage in more investor-friendly activities (such us monitoring and screening). Not surprisingly, most of the regulators' attention concerning market discipline was focused on information disclosure and transparency. Information availability alone, however, may not be enough to prevent risk build up : also relevant are costs and ability of processing information and investor's incentives to adopt disciplining behaviour. Theoretical literature on market discipline is quite exiguous. The most relevant contribution (for this discussion) is Malherbe [2010] characterization of market discipline, which links the ratio of observable but not verifiable information to the influence on agents' behaviour arising from the prospect of observing the information.

This paper expands the existent literature on securitization by emphasizing the impact of loan buyers on credit generation outcomes, rather than focussing on banks or borrowers as in most of previous research. As investors ability to influence financial intermediaries is considered crucial for market discipline enforcement, a novel formalization of Basel's "Third Pillar" arises naturally from this framework and illustrates the interactions between investors skills (sophistication), origination practices, borrowing and loan performances.

In order to simplify the analysis, securitization transactions are modeled in their primitive form as loan sales, i.e. I abstract from loan pooling and tranching practices as, in my framework, no further insight would be added to the main results[2]

This paper proceeds as follows. The model is described in Section 2 and solved in Section 3. I discuss the results in Section 4. Section 5 concludes.

[2]The set up of the model allows for a disciplining mechanism that is economically equivalent to retaining the equity tranch in the originator's balance sheet as skin in the game. On the other hand, the possibility of catering a segmented market with multiple tranches of the same loan pool doesn't qualitatively affect my findings.

3.2 Model Set Up

The Banks

There is a continuum $[0,1]$ of banks . Each bank is indexed by x and is risk averse, with utility function as follows : $U(C) = E(C^{1-x})$. Risk aversion coefficient is banks' private information: this assumption is meant to capture the idea that at any given point in time , banks privately observe the quality of their assets on balance sheet, their liquidity position or ability to fulfill regulatory capital requirements, and these features determine their risk capacity.

Each bank is endowed with one unit of cash, which can be invested in a risk-free asset or can be used to finance a project.

The Project

Each bank has access to a pool of projects and all pools have the same ex-ante characteristics. All projects require one unit of cash to be implemented and have a payoff X equal to $R > 2$ if they are successful and 0 if they fail. Success probability depends on the state of the world $\omega \in \{G, B\}$, with $Prob(\omega = G) = Prob(\omega = B)$. Define the average success probability as θ^{ω} .

I will further assume that θ^{ω} is higher in the good state of the world ($\theta^G > \theta^B$) and that the net present value of the average project is positive in the good state and negative in the bad state of the world ($\theta^G > \frac{1}{2}$, $\theta^B R < 1$).

In the analysis I will make use of the following definitions

$\theta^G - \theta^B \equiv \Delta$

$E(\theta) \equiv \bar{\theta}$

Screening

When issuing a loan, banks can pick a project randomly within their pool, or they can choose to invest c (non monetary), screen the pool and improve the quality of their investment loan by selecting the best project, thus shifting probability mass from the failure to the success outcome. In particular, if banks screen, the project will return R with probability $\theta^{\omega} + \epsilon$, where

$\epsilon < 1 - \theta^{G}$

$\bar{\theta} + \epsilon > \frac{1}{2}$

$c < \frac{\epsilon}{2}$

Define action $a \in \{S, NS\}$: banks' utility function rewrites

$$U\left(C, x, c(a)\right) = E\left(C^{1-x}\right) - c(a)$$

with $c\left(NS\right) = 0$ and $c\left(S\right) = c$.

The screening technology is efficient as $c < \epsilon R$, i.e. the investment cost is lower than the extra expected return that it generates. Moreover , with "traditional banking", i.e. in the absence of a secondary market for loans, every bank that chooses to invest in the project will screen as

$$\left(\bar{\theta} + \epsilon\right) R^{(1-x)} - c > \bar{\theta} R^{(1-x)}$$

$\forall x \in [0, 1]$

Finally, action a is not observable to outside investors.

The Risk-Free Asset

A risk-free asset is available to both investors and banks. Its return r is exogenously fixed . I'll assume

$1 \leq 1 + r < \bar{\theta} R$

Thus, the return on the risk free asset is weakly positive and always lower than the expected return on the risky asset.

Time Line and Negotiation

In this two-periods model, at time $t = 0$ each bank decides whether to invest in the risk-free asset or in the project. If a bank invests in a project it attempts to sell it on the market and trade occurs by random matching : each bank is paired with one investor from a pool of measure $I \geq 1$ (the "Buy Side").

The bank sets price P and makes a take-it-or-leave-it offer to the investor. If the investor rejects the offer the loan will be held on balance sheet until payoffs are realised. If the investor accepts the offer, the bank invests the cash received in the transaction at the risk-free rate. Renegotiation costs (associated for example with reputational concerns) are assumed to be high enough to prevent multiple rounds of bargaining.

This trading protocol is intended to mimick a common practice in the market place where banks usually approache the market with a sale proposal and a price guidance for the deal, if the demand meets the offer the deal closes (with little, if any, revision to the price guidance), otherwise the issuance fails.

Payoffs realise at $t = 1$.

The Buy Side

Each risk-neutral, deep-pocketed investor in the Buy Side receives a signal $y \in \{H, L\}$ on ω with the following characteristics

$$Prob\,(y = H \mid \omega = G) = Prob\,(y = L \mid \omega = B) = k$$

Parameter $k \in \left[\frac{1}{2}, 1\right]$ is the precision of signal y and identifies investors' sophistication. This theoretical framework is applicable to securitization deals where hard information is completely shared between originators and buyers, and the loan performance depends both on screening (privately chosen by banks) and on macroeconomic variables, such as real estate prices, on which institutional investors may have specific forecasting skills.

Based on signal y and price P , investors choose action i, that is they decide whether to buy the loan or invest in the risk-free asset (i.e. $i \in \{B, NB\}$).

3.3 Solving the Model

In what follows, I'll first solve for the equilibrium in the securitization subgame, and then superimpose the participation constraint given by the utility gained by banks investing in the risk free rate. The mass of banks choosing to invest in a project and to undertake the efficient screening ation is a feature of final equilibria. The extent to which investor sophistication can affect this quantity imposing discipline to the banking sector is the main focus of the analysis.

Securitization Equilibrium Definition

According to the negotiation protocol , when a bank invests in the project, it will choose whether to screen and which price to "show" to the market. Upon receiving a sale proposal and after observing her signal, the investor will pick her action. Thus, strategies are defined by

$\sigma_B : x \to \mathbb{R}^+ \times A$

$\sigma_i : (y, P) \to I$

with

$A \equiv \{S, NS\}$

$P \in \mathbb{R}^+$

$I \equiv \{B, NB\}$

Importantly, a is payoff-relevant for the investor and the price asked by the bank is the only potentially informative signal on a. The investor will form a belief

$$\mu = Prob\,(a = S \mid P)$$

SECURITIZATION EQUILIBRIUM. The equilibrium in the securitization subgame is defined by $[\sigma_B^*, \sigma_i^*]$ *and* $\mu^* = Prob\,(a^* = S \mid P^*)$ *such that :*

$\sigma_B^* : (P^*(x), a^*(x)) = \underset{P,a}{argmax}\; U\,(P, c\,(a), x, \sigma_i^*)$

$\sigma_i^* : i^*(y, P) = \underset{i}{argmax}\; u\,(i, y, P^*, \mu^*)$

With $U\,(\cdot)$ *and* $u\,(\cdot)$ *being the expected utility functions for the bank and the investor respectively.*

Solving the Securitization Game

Define investors belief on $\omega = G$, updated upon receiving y , as

$$\Phi^y \equiv Prob\,(\omega = G \mid y)$$

The investor will buy the securitized asset offered at price P if its net expected return is greater than the net return on the risk-free security, so

$i^*\,(y, P) = B$ if $\left(\Phi^y \Delta + \theta^B + \mu\epsilon\right) R - P > rP$

or, equivalently, if

$\Phi^y > \frac{P(1+r)}{\Delta R} - \frac{\theta^B + \mu\epsilon}{\Delta} \equiv \bar{\Phi}\,(P)$

when $\Phi^y = \bar{\Phi}\,(P)$, I will allow investors to randomly select their strategy : $Prob\left[i^* = B \mid \Phi^y = \bar{\Phi}\right.$
$q \in [0, 1]$.

Investor optimal strategy depends on her belief on the state of the economy Φ^y and on (a function of) the price asked for the loan. Everything else equal, investors are more likely to buy when they are more optimistic about general economic conditions. The effect of prices, instead, is less clear-cut: high prices reduce returns but may signal better loan quality and higher expected payoffs.

Notice that, given precision k and since $Prob\,(\omega = G) = Prob\,(\omega = B) = \frac{1}{2}$, Φ^y can only take values $\{1-k, k\}$ both with ex-ante probability $\frac{1}{2}$[3] .

Hence, given the Buy Side's optimal investment rule, from the bank's perspective the probability of selling the loan at price P is

[3] $Prob\,(y = H) = Prob\,(y = L) = \frac{1}{2}k + (1-k)\,\frac{1}{2} = \frac{1}{2}$; $\Phi^H = \frac{Prob(y=H|\omega=G)Prob(\omega=G)}{Prob(y=H)} = \frac{\frac{1}{2}k}{\frac{1}{2}} = k$;$\Phi^L = 1-k$

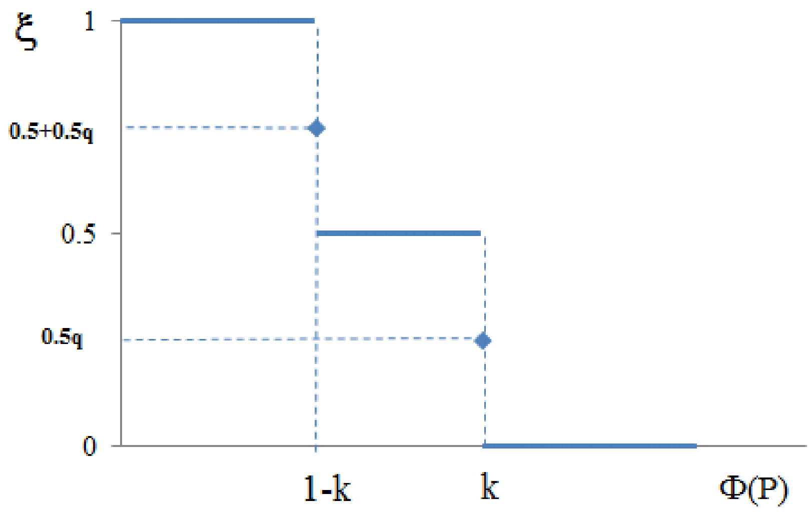


Figure 3.1: Probability of loan transaction
$Prob\left(i^{*}=B\mid P\right)$

$$\xi \equiv Prob\left(i^{*}=B\mid P\right)=\begin{cases}1 & \bar{\Phi}\left(P\right)<1-k\\ \frac{1}{2}\left(1+q\right) & \bar{\Phi}\left(P\right)=1-k\\ \frac{1}{2} & 1-k<\bar{\Phi}\left(P\right)<k\\ \frac{1}{2}q & \bar{\Phi}\left(P\right)=k\\ 0 & \bar{\Phi}\left(P\right)>k\end{cases}$$

as illustrated in Figure 1

Recall that P belongs to the banks' strategy set. It's easy to see that no equilibrium can be reached when $\xi = 1$ or $\xi = \frac{1}{2}$, as banks' utility is increasing in P. On the other hand, $\xi = 0$ overlaps with a "traditional banking" equilibrium, and investors' choices and sophistication have no effect on credit generation. Thus, in a securitization equilibrium, investors will be pushed to indifference and ξ can either be $\frac{1}{2}\left(1+q\right)$ or $\frac{1}{2}q$, or equivalently, $\bar{\Phi}\left(P\right)\in\left\{1-k,k\right\}$.

As $\bar{\Phi}\left(P\right)$ is increasing in P , the statement above implies that banks will choose either a "high" price or a "low" price : the higher the price, the higher the profits if trade occurs but the lower the probability of trade occurring. Intuitively, more (less) risk averse banks will opt for the lower (higher) but less (more) uncertain payoff. Finally, the likelihood of trading will drive the choice of action a . Since banks' optimal action will depend on investors' mixing strategies, it is useful to split the support for q in 4 regions as follows:

1. $q \in [\bar{q}, 1]$ (Region 1)
2. $q \in \left(\underline{q}, \bar{q}\right)$ (Region 2)
3. $q \in \left(0, \underline{q}\right]$ (Region 3)
4. $q = 0$

where $\bar{q} = 1 - \frac{2c}{\epsilon R}$ and $\underline{q} = 1 - \frac{2c}{\epsilon}$.

PROPOSITION 1

Suppose $q \in [\bar{q}, 1]$ *. There exists* x^* *such that*

- *if* $x \geq x^*$ *:* $[(P^* = P^0, a^* = NS), i^*(H, P^0) = B, Prob[i^*(L, P^0) = B] = q]$ ***and*** $\mu^* \mid P^0 = 0$
- *if* $x < x^*$ *:* $[(P^* = P^1, a^* = S), Prob[i^*(H, P^1) = B] = q, i^*(L, P^1) = NB]$ ***and*** $\mu^* \mid P^1 = 1$

When q is high enough, less (more) risk averse banks will ask a high (low) price for the loan and will (not) screen available projects. Upon observing a high signal on

ω, investors will buy at the low (high) price with probability 1 (q). Upon observing a low signal on ω, investors will only buy at the low price, with probability q. Prices are fully revealing of banks screening strategies.

Since I established that equilibria can only be achieved in $\bar{\Phi}(P) \in \{1-k, k\}$, I will provide a proof of the proposition above by deriving the optimal startegies in the two cases $\bar{\Phi}(P) = 1-k$ and $\bar{\Phi}(P) = k$. The final equilibrium result is obtained by maximising banks' utilities, according to their risk aversion coefficients.

Case $\bar{\Phi}(P) = 1-k$

In this case, the probability of $i^* = B$ ($i^* = NB$) is $\frac{1}{2}(1+q)$ ($\frac{1}{2}(1-q)$). The payoff to the bank if the investor buys the loan is $P(1+r)$. If the investor doesn't buy the loan, the bank will receive either R or zero and the success probability will be updated, based on the informational content of investors' optimal action:

$Prob\,(X = R \mid i^* = NB, a = S) = \theta^G + \epsilon - k\Delta$

$Prob\,(X = R \mid i^* = NB, a = NS) = \theta^G - k\Delta$

It follows that the bank's utility with $a = S$:

$$\frac{1}{2}(1+q)\,(P\,(1+r))^{(1-x)} + \frac{1}{2}(1-q)\left(\theta^G + \epsilon - k\Delta\right)R^{(1-x)} - c$$

while the bank's utility with $a = NS$:

$$\frac{1}{2}(1+q)\,(P\,(1+r))^{(1-x)} + \frac{1}{2}(1-q)\left(\theta^G - k\Delta\right)R^{(1-x)}$$

Implying $a^* = NS$ if

$$x \geq 1 - \frac{ln\left(\frac{2c}{(1-q)\epsilon}\right)}{ln\,(R)} \tag{3.1}$$

which holds $\forall x \in [0,1]$.

Since $a^* = NS$ for all banks in the continuum, $\mu^* = 0$ and $P^* = \left((1-k) + \frac{\theta^B}{\Delta}\right)\frac{\Delta R}{1+r} \equiv P^0$. Moreover , the bank's utility wil be

$$\frac{1}{2}(1+q)\left(P^0(1+r)\right)^{(1-x)} + \frac{1}{2}(1-q)\left(\theta^G - k\Delta\right)R^{(1-x)} =$$

$$= \frac{1}{2}(1+q)\left(\left(\theta^G - k\Delta\right)R\right)^{(1-x)} + \frac{1}{2}(1-q)\left(\theta^G - k\Delta\right)R^{(1-x)} \equiv U^0(k,x)$$

with $\frac{\partial U^0}{\partial k} < 0$

With $\bar{\Phi}(P) = 1-k$, the optimal strategy is $(P = P^0, a = NS)$ for any $x \in [0,1]$

Case $\bar{\Phi}(P) = k$

In this case, the probability of $i^* = B$ ($i^* = NB$) is $\frac{1}{2}q$ ($(1-\frac{1}{2}q)$). Payoffs and success probability are same as above.

Bank's utility with $a = S$:

$$\frac{1}{2}q\,(P(1+r))^{(1-x)} + \left(1 - \frac{1}{2}q\right)\left(\theta^G + \epsilon - k\Delta\right)R^{(1-x)} - c$$

Bank's utility with $a = NS$:

$$\frac{1}{2}q\,(P(1+r))^{(1-x)} + \left(1 - \frac{1}{2}q\right)\left(\theta^G - k\Delta\right)R^{(1-x)}$$

Implying $a^* = S$ if

$$\left(1 - \frac{1}{2}q\right)\epsilon R^{(1-x)} > c \tag{3.2}$$

Condition 3.2) holds $\forall x \in [0,1]$ as $c < \frac{\epsilon}{2}$. It follows that $\mu^* = 1$ and $P^* = \left(k + \frac{\theta^B + \epsilon}{\Delta}\right)\frac{\Delta R}{1+r} \equiv P^1$. Moreover , the bank's utility will be

$$\frac{1}{2}q\left(\left(k\Delta + \theta^B + \epsilon\right)R\right)^{(1-x)} + \left(1 - \frac{1}{2}q\right)\left(\theta^G + \epsilon - k\Delta\right)R^{(1-x)} - c \equiv U^1\left(k, x\right)$$

with $\frac{\partial U^1}{\partial k} < 0$ (See Appendix A).

With $\bar{\Phi}\left(P\right) = k$, the optimal strategy is $\left(P = P^1, a = S\right)$ for any $x \in [0,1]$

Each bank will choose P^0 or P^1, based on its own risk aversion coefficient x. Equilibrium utility is

$$U^E_{Sec}\left(k, x\right) = max\left[U^1\left(k, x\right), U^0\left(k, x\right)\right]$$

Define the function

$$F\left(k, x\right) = U^1\left(k, x\right) - U^0\left(k, x\right)$$

$F\left(\cdot\right)$ is continuous in $x \in [0,1]$ and observe that

$F\left(k, 0\right) = R\left[q\Delta\left(k - \frac{1}{2}\right) + \epsilon\right] - c > 0$

$F\left(k, 1\right) = \epsilon\left(1 - \frac{1}{2}q\right) - \frac{k\Delta}{2} - c - \frac{1-\theta^G}{2} < 0$

This implies that there exists $x^*\left(k\right) \in [0,1]$ such that $F\left(k, x^*\left(k\right)\right) = 0$ and confirms the existence of the proposed equilibrium (pictured in Figure 2)[4].

When indifferent investors are relatively more likely to buy the loan (i.e. q is high), more risk averse banks will offer a lower price in order to increase the chances

[4]Uniqueness can be proven by showing that $\frac{\partial F}{\partial x}$ is continuous in x and $\frac{\partial F}{\partial x} = 0$ has at most one solution in $x \in [0,1]$

of their offer being accepted and of risk being transferred. Such high level of insurance is only compatible with no screening, as the bank is highly unlikely to internalize the benefits of screening. Effectively, banks with risk aversion coefficient to the right of the threshold x^* act as pure credit brokers. Banks with $x < x^*$ are less concerned with carrying risk on balance sheet and they are only willing to sell the loan for a higher price, even though the probability of receiving the certain payoff is lower. This low level of insurance ensures they use the efficient screening technology. Notice that these results mirror standard optimal contracting solutions for moral hazard problems: a lower degree of protection in a risk-sharing driven transaction is cheaper for the risk-averse agent and induces higher effort. Furthermore, when risk aversion coefficient is below the threshold x^*risk is more likely to be born by relatively more risk averse agents (as compared to investors) : the efficient action $a = S$ occurs at the expenses of the efficient allocation of the asset.

Finally notice that the difference between the two equilibrium prices is increasing in investors' sophistication. Even though more sophistication reduces the gains from trade for all banks, this effect is mitigated by a higher price (P^1) for the relatively less risk averse ones.

PROPOSITION 2

Suppose $q \in \left(0, \underline{q}\right]$ *. There exists* x^* *such that*

- ***if*** $x \geq x^*$ ***:*** $\left[\left(P^* = P', a^* = S\right), i^*\left(H, P'\right) = B, Prob\left[i^*\left(L, P'\right) = B\right] = q\right]$ ***and*** $\mu^* \mid P' = 1$
- ***if*** $x < x^*$ ***:*** $\left[\left(P^* = P^1, a^* = S\right), Prob\left[i^*\left(H, P^1\right) = B\right] = q, i^*\left(L, P^1\right) = NB\right]$ ***and*** $\mu^* \mid P^1 = 1$

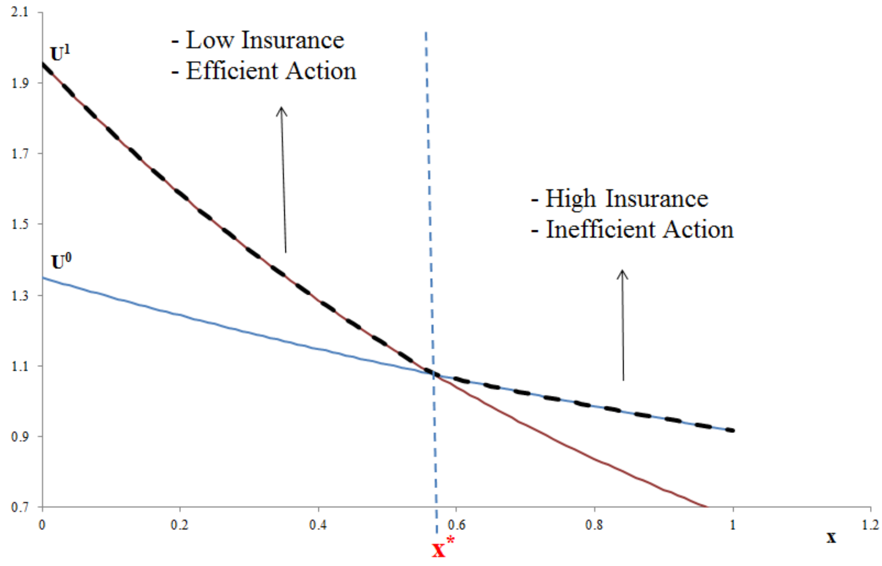


Figure 3.2: Equilibrium 1

$k = 0,6$, $q = 0,7$, $R = 3$, $\theta^G = 0,75$, $\theta^B = 0,25$, $\epsilon = 0,2$, $c = 0,1$

This equilibrium can be easly proven by following the same reasoning as proposition 1. In particular , notice that equation 3.1) never holds when $q < \underline{q}$, implying $a^* = S$ and $P^* = \left((1-k) + \frac{\theta^B+\epsilon}{\Delta}\right)\frac{\Delta R}{1+r} \equiv P'$ when $\bar{\Phi}(P) = 1-k$.

Condition 3.2) holds *a fortiori* with $q < \underline{q}$. Define $U(P', x, S) \equiv U'(x)$. Banks' utility in equilibrium is $U^E_{Sec} = max\left[U^1(x), U'(x)\right]$, with $U^1(x) > U(x)$ for $x < x^*$. This equilibrium is illustrated is Figure 3.

When indifferent investors are less likely to buy the loan, the insurance protection that banks can get, even with the low price, is not high enough to make them forgo the efficient screening technology : all banks will screen, and the most risk averse ones will offer a lower price in order to improve the odds of risk sharing.

PROPOSITION 3

Suppose $q \in (\underline{q}, \bar{q})$. *If an equilibrium exists, it will be either of the type described in proposition 1 or there will exist* x'' *and* x^* *such that*

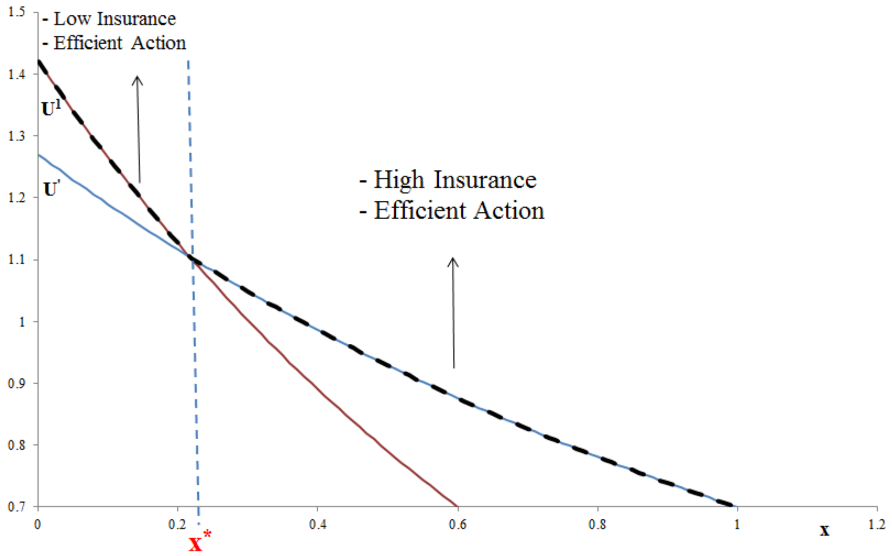


Figure 3.3: Equilibrium 2

$k = 1$, $q = 0,2$, $R = 3$, $\theta^G = 0,75$, $\theta^B = 0,25$, $\epsilon = 0,2$, $c = 0,1$

- *if* $x \geq x^*$: $\left[\left(P^* = P'', a^* = NS\right), i^*\left(H, P''\right) = B, Prob\left[i^*\left(L, P''\right) = B\right] = q\right]$ ***and*** $\mu^* \mid P'' \in (0, 1)$
- *if* $x'' < x < x^*$: $\left[\left(P^* = P'', a^* = S\right), i^*\left(H, P''\right) = B, Prob\left[i^*\left(L, P''\right) = B\right] = q\right]$ ***and*** $\mu^* \mid P'' \in (0, 1)$
- *if* $x \leq x''$: $\left[\left(P^* = P^1, a^* = S\right), Prob\left[i^*\left(H, P^1\right) = B\right] = q, i^*\left(L, P^1\right) = NB\right]$ ***and*** $\mu^* \mid P^1 = 1$

See Appendix B.

The equilibrium in Proposition 3 differs from the previous ones because relatively more risk averse banks may pool at price P'' (with $\bar{\Phi}\left(P''\right) = 1 - k$), provided that a consistent belief can be formed on $Prob\left(a^* = S \mid P''\right)$. Since risk aversion coefficient x is banks private information, price P'' is not fully revealing of each bank's optimal strategy a^*. Notice however that in this case the mass of banks choosing $a^* = S$ is

$$x^* = 1 - \frac{ln\left(\frac{2c}{(1-q)\epsilon}\right)}{ln\left(R\right)}$$

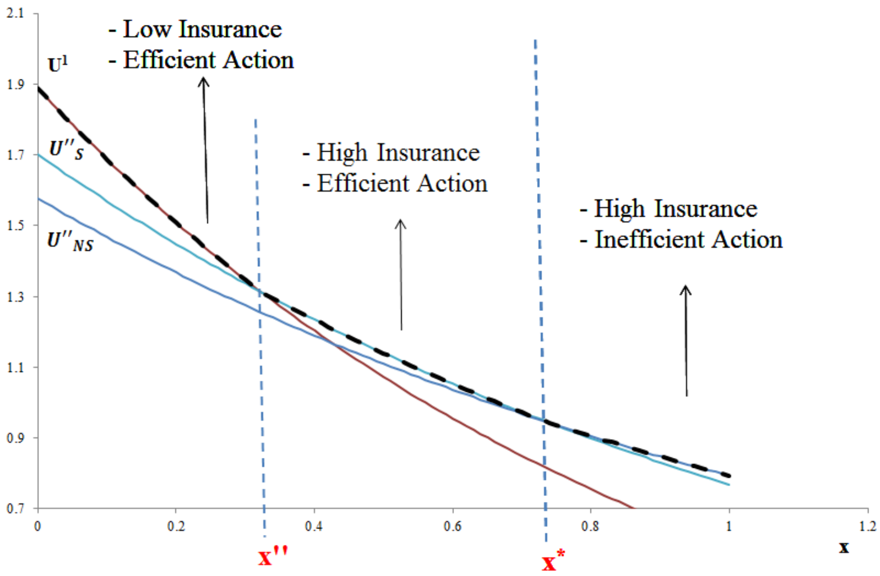


Figure 3.4: Equilibrium 3

$k = 0,6$, $q = 0,25$, $R = 3$, $\theta^G = 0,75$, $\theta^B = 0,25$, $\epsilon = 0,2$, $c = 0,1$, $\mu^* = 0.6$

which does not depend on sophistication k . An example of such equilibrium is illustrated in Figure 4.

Finally, no securitization equilibrium exists when $q = 0$.

The existence of a securitization market amplifies credit generation as it allows risk averse agents who have access to projects to share risks held on their balance sheet. Credit expansion however potentially comes at the expenses of credit quality and efficiency, as not all banks choose to properly select the loans they issue (as opposite to the traditional banking case). Next, I will show how the Buy Side sophistication can avoid the loss in efficiency associated with the securitization process, while retaining the benefits of additional borrowing.

Equilibrium and Market Discipline

According to the Basel Committee on Banking Supervision (2001), "market discipline imposes strong incentives on banks to conduct their business in a safe, sound and efficient manner". This definition can be easily rephrased within the framework of this model : the Buy Side imposes discipline on banks if it induces the majority of them to perform a proper due diligence on financed loans. Notice that this definition abstracts from welfare considerations within the model. In this sense, I am assuming that Market Discipline is part of the social planner's optimization problem because of positive externalities arising from screening efficiency. In order to relate our previous results on securitization to market discipline, I will proceed as follows. I will first impose the bank's participation constraint $PC(x) = (1+r)^{(1-x)}$ on the securitization equilibrium. Each bank will choose between investing in the risk free asset or financing the loan (and trying to sell it on the market) . Once the participation constraint is introduced, it is possible to identify three distinct and exhaustive subsets in the continuum of banks, on the basis of their investment decision and optimal actions. Specifically, one subset of banks will finance the project and screen, one subset of banks will finance the project and will not screen and the last subset will invest in the risk free asset. Finally, I will investigate the effect of investors' sophistication on the size of the subset of banks that undertake the efficient action (screening). Investors' sophistication will implement market discipline if it induces the maximum possible mass of banks to choose $a^* = S$. This comparative statics exercise will be conducted for equilibria arising in the different regions of q , as identified in the previous section.

Region 1 : $q \in [\bar{q}, 1]$**.**

Define $\hat{x}$ as the coefficient that satisfies $U^1(k, \hat{x}) = PC(\hat{x})$ and x^S as

$$x^S \equiv min\left[\hat{x}(k), x^*(k)\right]$$

where $x^*(k)$ is defined as in proposition 1. Suppose $\hat{x}(k) < x^*(k)$: all banks with

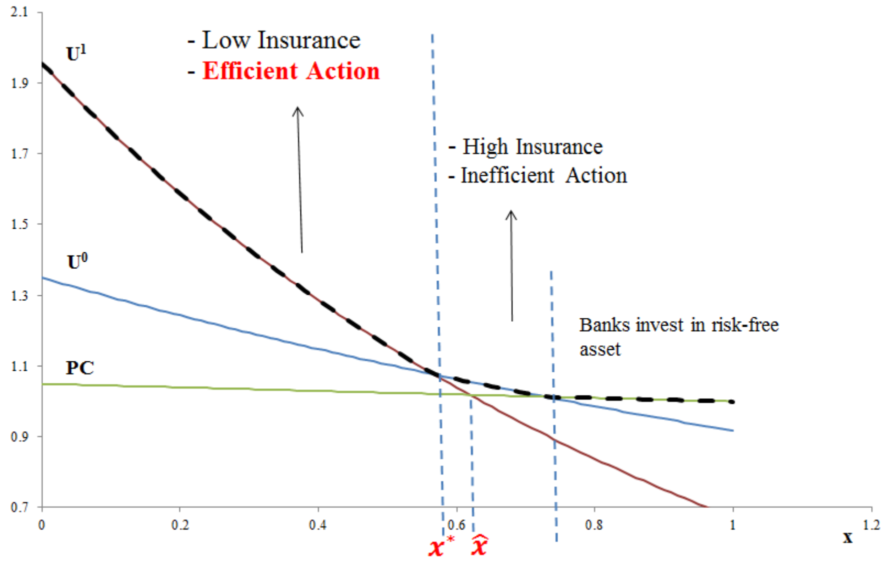


Figure 3.5: Equilibrium and market discipline
$k = 0,6$, $q = 0,7$, $R = 3$, $\theta^G = 0,75$, $\theta^B = 0,25$, $\epsilon = 0,2$, $c = 0,1$, $r = 5\%$

$x < \hat{x}(k)$ will finance the project and choose $\sigma_B^* = (P^1, a = S)$, while the remaining ones will invest in the risk-free assets[5]. Suppose instead $\hat{x}(k) > x^*(k)$: banks with $x < x^*(k)$will finance the project and choose $\sigma_B^* = (P^1, a = S)$, while the remaining ones will either finance the project and choose $\sigma_B^* = (P^0, a = NS)$or will invest in the risk-free asset.

Thus , x^S represents the mass of banks that performed "due diligence" on the originated loan , or , loosely speaking , the quantity of "good credit" generated (see Figure 5)

Market discipline is defined by the following statement :

Market discipline is achieved when x^S is maximized .

Suppose $x^*(k)$ is increasing in k (in Appendix C, I provide a set of restrictions on the parameters that ensures this condition is met) . It is immediate to see that , for any $x \in [0, 1]$

[5] as $PC(x) > U^0(k, x)$ for $x > \hat{x}$

$$PC(x) = (1+r)^{(1-x)} > \frac{1}{2}(1+q)\left(\theta^B R\right)^{(1-x)} + \frac{1}{2}(1-q)\,\theta^B R^{(1-x)} = U^0(1,x)$$

as $\theta^B R < 1$ and $1+r \geq 1$, implying that market discipline cannot be achieved at $k=1$. A perfectly informed Buy Side would impose too much discipline, preventing some banks (the ones in the "middle" of the risk aversion range) from investing in positive NPV projects. Sophistication will improve market discipline up to the threshold level k^* satisfying

$$U^1(k^*,x) = U^0(k^*,x) \tag{3.3}$$

$$U^0(k^*,x) = PC(x) \tag{3.4}$$

or, equivalently, the optimal k is $k^* = argmax\left[x^S(k)\right]$, implying $\hat{x}(k^*) = x^*(k^*)$[6]. An analytic solution for k^* cannot be computed for a generic q (a numerical simulation is provided in Figure 6).

Since k^* is increasing in q when $\frac{\partial x^*}{\partial k} > 0$ (see Appendix D), $k^*(q=1)$ will serve as an upper bound for the more general case of $1 - \frac{2c}{\epsilon R} \leq q \leq 1$.

When $q=1$, conditions 3.3) and 3.4) hold simultaneously for

$$k^* = 1 - \frac{1+r-\theta^B R}{R\Delta} \equiv k_1^* \tag{3.5}$$

That is, the maximum value of k that achieves market discipline is $k = k_1^* < 1$, with k_1^* decreasing in r and increasing in Δ.

Finally, if $x^*(k)$ is decreasing in k then, trivially, $k^* = \frac{1}{2}$.

[6] We assumed $\frac{\partial x^*}{\partial k} > 0$. Since $\frac{\partial U^1}{\partial k} < 0$, then $\frac{\partial \hat{x}}{\partial k} < 0$. This implies that $x^S(k)$ is maximized when $\hat{x}(k^*) = x^*(k^*)$

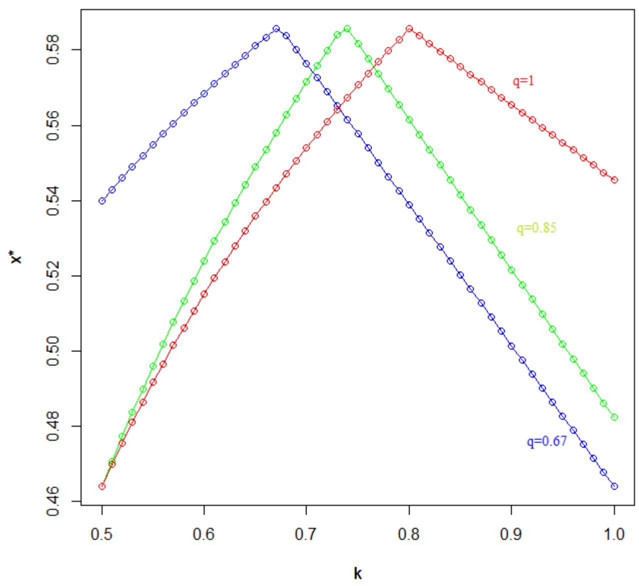


Figure 3.6: Market discipline and credit generation: numerical simulation
$R = 3$, $\theta^G = 0,75$, $\theta^B = 0,25$, $\epsilon = 0,2$, $c = 0,1$, $r = 5\%$

Region 2 $q \in \left(\underline{q}, \bar{q}\right)$.

Once the participation constraint is imposed, the support of the conditional distribution of $x \mid P''$ changes: the upper bound will be $\bar{x} < 1$, with $\bar{x}$ defined by $PC\left(\bar{x}\right) = U^E_{Sec}\left(\bar{x}\right)$. An equilibrium exists if a consistent belief $\mu^* \mid P''$ can be found in $[0,1]$. As noted in the previous section however, the mass of banks choosing $a^* = S$ does not depend on k. In this region, the Buy Side cannot impose discipline on the banking sector.

Region 3 $q \in \left(0, \underline{q}\right]$

Since all the banks that invest in the project choose to screen (see proposition 2), the mass of banks with $a^* = S$ is $\bar{x}$, as defined by $PC\left(\bar{x}\right) = U^E_{Sec}\left(\bar{x}\right)$. As banks' utility is decreasing in k, market discipline is achieved when $k = \frac{1}{2}$.

Optimal precision k^* is the level of sophistication that clears the most risk averse banks off the securitization market, while preserving incentives for the rest of the originators to issue and screen loans.

It emerges from the analysis above that the solution k^* to the market discipline maximization problem belongs to the set $K^* \equiv \left[\frac{1}{2}, k_1^*\right]$, with $k_1^* < 1$. It is never optimal to have a perfectly informed Buy Side participating to the securitization market. Moreover, the upper bound of K^*approaches the lower bound $\frac{1}{2}$when the risk free rate increases and the volatility in the real sector (Δ) decreases. Market discipline is easier to implement (i.e. lower investors' sophistication is needed) when risk free rates are high and banks have less incentive to share risk.

3.4 Discussion

The first result illustrated above ($k^* < 1$) states that market can impose too much discipline and constrain good quality credit expansion. The intuition behind is that high levels of sophistication increase the difference in the expected values of the payoffs from securitization for banks that choose to screen. As a result, securitization becomes relatively too risky for these agents as compared to investing in the risk free rate and their resources will be subtracted from the credit market. On the other hand, comparative statics on k_1^*highlight the complementarity between sophistication and risk free rates: market discipline can be achieved with little investors' sophistication provided that interest rates are high enough. Furthermore, monetary policy is shown to affect both quantity and quality of credit : for any given level of sophistication, "too low" risk free rates increase the amount of loan issued but decrease their average expected returns.

The analysis presented in the previous section allows investors to randomly select a pure strategy, with q being the probability of $i = B$ being selected. An alternative interpretation of the results, based on market sentiment, can be provided. Suppose that all investors are risk neutral and homogeneous in terms of sophistication, but differ in their tie-breaking rule. When indifferent, optimists buy the risky assets, while pessimists buy the risk-free asset. By setting q as the observable proportion of optimists over pessimists among investors, it can be easily interpreted as an indicator of market sentiment, and the analysis goes through unchanged. The optimal sophistication required to obtain market discipline, under this interpretation, is increasing in market sentiment.

Finally, the model relies on the assumption that hard information is common knowledge. This is compatible with a highly standardized origination process where a limited amount of information is collected, which is easy to be transferred to investors. An example may be house mortgages: few indicators (such as LTV, DTI ratios or appraisal value) are used in order to process the loan application and such figures are typically shared with the buyers. On the other hand, the model seems less applicable to more complex, project-specific lending. Also, overcollateralized lending may distort screening incentives, regardless of subsequent securitization (Manove et al. [2001]): market discipline (as defined in this paper) can't play a role in such context.

3.5 Conclusion

The goal of this paper is to examine how investors' sophistication can affect efficiency and credit quality by inducing a subset of participants in the banking sector to choose screening over not screening. A definition of market discipline, that echoes the one used by regulators, is provided along these lines. Investors' sophistication implements market discipline if it induces the largest possible mass of banks to perform proper due diligence on the loans issued.

I present a model that builds on the standard argument of the trade-off between risk sharing and moral hazard in loan sale or securitization transactions : risk averse agents (banks) are willing to sell risky assets to outside buyers, but by doing so they lose incentives to efficiently conduct proper due diligence (screening) and improve expected returns. Two novel features are added to this framework. First, the profitability of the projects depends not only on the banks' choices in terms of screening, but also on general macroeconomic conditions. I allow for outside investors to receive a signal on the aggregate state of the economy, which guides their investment decisions. The precision of this signal defines the Buy Side sophistication . Furthermore, I introduce heterogeneity in banks' utility functions thus generating heterogeneity in the equilibrium optimal screening decisions: the amount of risk sold to investors depends on each bank's risk aversion coefficient and will ultimately drive the (unobservable) action choice.

My results show that it is never optimal (in a market-discipline sense) to have a perfectly informed Buy Side participating in the securitization market, as it would constrain high quality credit expansion. A strong informational advantage allows buyers to extract too much rent from sellers, inducing some banks to resort to the safe investment option. For high levels of sophistication, even relatively less risk averse originators (who are more likely to screen projects) switch to the risk-free asset.

Furthermore, optimal sophistication is (weakly) decreasing in the risk free rate and (weakly) increasing in the volatility of the real sector. In other words, market discipline is easier to achieve (i.e. lower investors' sophistication is needed) when risk free rates are high and when loans' payoffs are less volatile.

Appendix A

$$\frac{\partial U^1}{\partial k} = (1-x)\,\frac{1}{2}q\left(k\Delta + \theta^B + \epsilon\right)^{-x} R^{(1-x)}\Delta - \left(1 - \frac{1}{2}q\right)\Delta R^{(1-x)} \tag{3.6}$$

Expression 3.6) is negative if

$$(1-x)\left(k\Delta+\theta^{B}+\epsilon\right)^{-x}<\frac{2-q}{q}$$

or

$$Max\left[(1-x)\left(k\Delta+\theta^{B}+\epsilon\right)^{-x}\right]=(1-x)\,2^{x}<1=Min\left[\frac{2-q}{q}\right] \tag{3.7}$$

and 3.7) always holds $\forall x \in [0,1]$

Appendix B

Case $\bar{\Phi}(P)=k$. See proposition 1.

Case $\bar{\Phi}(P)=1-k$. Suppose equilibrium price is P''. Optimal bank's action is

- $a^{*}=S$ if $x<1-\frac{ln\left(\frac{2c}{(1-q)\epsilon}\right)}{ln(R)}\equiv x^{*}$. $U\left(P'',x,S\right)\equiv U_{S}''(x)$
- $a^{*}=NS$ otherwise. $U\left(P'',x,NS\right)\equiv U_{NS}''(x)$

Define x'' as the solution to $U^{1}(x)=U_{S}''(x)$and notice that x'' depends on P''. Furthermore P'' must satisfy $\frac{P(1+r)}{\Delta R}-\frac{\theta^{B}+\mu\epsilon}{\Delta}=1-k$. An equilibrium exists if there exists a solution in $[0,1]$ to the following fixed point problem

$Prob\left(a^{*}=S\mid P''\right)=\mu^{*}=\frac{x^{*}-x''(\mu^{*})}{1-x''(\mu^{*})}$

and the banks equilibrium utility is $U_{Sec}^{E}(x)=max\left[U^{1}(x),U_{S}''(x),U_{NS}''(x)\right]$.

Finally, if $U^{1}(x^{*})\geq U_{S}''(x)$ for any $\mu\in[0,1]$ then the equilibrium will be the same as the one described in proposition 1.

Appendix C

Suppose $\Delta > \frac{1}{R-\frac{2c}{\epsilon}}$ and $\theta^B R > e^{-2}$. Then the following conditions are satisfied

1. $\frac{\partial F(k,0)}{\partial k}\left[F\left(k,0\right)-F\left(k,1\right)\right]-F\left(k,0\right)>0$

2. $q\left(k\Delta+\theta^B+\epsilon\right)^{-x} ln\left(k\Delta+\theta^B+\epsilon\right)\left[(1-x)\, ln\left(\left(k\Delta+\theta^B+\epsilon\right)R\right)+2\right]+(1+q)\left((1-k)\Delta+\theta\right.$
   $\left(ln\left(R\right)\right)^2<0 \Rightarrow \frac{\left(\frac{\partial^2 F}{\partial x^2}\right)}{\partial k}<0$

Condition 1. ensures that the intercept with the x-axis of the chord that connects $F\left(k,0\right)$ and $F\left(k,1\right)$ is increasing in k. Condition 2. implies that the convexity of the function $F\left(k,x\right)$ decreases in k . Hence, Conditions 1. and 2. imply $\frac{\partial x^*}{\partial k}>0$

Appendix D

Recall $F\left(\cdot\right)=U^1\left(\cdot\right)-U^0\left(\cdot\right)$ and $F\left(x^*\right)=0$. Observe that

$\frac{\partial F}{\partial q}<0$ if $A\left(x\right)\equiv\left(\theta^B+\epsilon+k\Delta\right)^{1-x}-\left(\theta^B+\left(1-k\right)\Delta\right)^{1-x}-\epsilon<0$.

Since

$A\left(0\right)>0$

$A\left(1\right)<0$

$A\left(x\right)$ is continuous in x and $A\left(x\right)=0$ has a unique solution in $x\in[0,1]$ (as $\frac{\partial A}{\partial x}=0$ admits at most one solution in $x\in[0,1]$)

there exists x^Asuch that

$\frac{\partial F}{\partial q}<0$ for $x>x^A$ and $\frac{\partial F}{\partial q}>0$ otherwise.

Notice that $F(\cdot)$ can be written as

$\frac{1}{2}q\left[\left(\theta^{B}+\epsilon+k\Delta\right)^{1-x}-\left(\theta^{B}+(1-k)\,\Delta\right)^{1-x}-\epsilon\right]+\frac{1}{2}\left(\theta^{G}-k\Delta\right)+\epsilon-\frac{c}{R^{1-x}}$ or

$\frac{1}{2}q\left[A(x)\right]+\frac{1}{2}\left(\theta^{G}-k\Delta\right)+\epsilon-\frac{c}{R^{1-x}}$

which, evaluated at x^{A} yields

$\frac{1}{2}\left(\theta^{G}-k\Delta\right)+\epsilon-\frac{c}{R^{1-x}}>0$, as $\theta^{G}-k\Delta>0$ and $\epsilon R^{1-x}>c$ by assumption.

This implies

$x^{A}<x^{*}$, or equivalently $\frac{\partial x^{*}}{\partial q}<0$

as $F(x)$ is monotonic and decreasing in x .

The market discipline optimal k is defined by

$x^{*}\left(q,k^{*}(q)\right)=\hat{x}\left(q,k^{*}(q)\right)$

hence

$\frac{\partial x^{*}}{\partial q}+\frac{\partial x^{*}}{\partial k^{*}}\frac{\partial k^{*}}{\partial q}=\frac{\partial \hat{x}^{*}}{\partial q}+\frac{\partial \hat{x}}{\partial k^{*}}\frac{\partial k^{*}}{\partial q}$

Rearranging

$\frac{\partial k^{*}}{\partial q}\left(\frac{\partial x^{*}}{\partial k^{*}}-\frac{\partial \hat{x}}{\partial k^{*}}\right)=\frac{\partial \hat{x}}{\partial q}-\frac{\partial x^{*}}{\partial q}$

Since $\frac{\partial U^{1}}{\partial k}<0$ and $\frac{\partial U^{1}}{\partial q}>0$, then $\frac{\partial \hat{x}}{\partial k^{*}}<0$ and $\frac{\partial \hat{x}}{\partial q}>0$

Assuming $\frac{\partial x^{*}}{\partial k^{*}}>0$, we have

$\frac{\partial x^{*}}{\partial k^{*}}>0.$

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