Essays in Entrepreneurial Finance

Financing new firms and innovations

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Till Mamma och Pappa

Foreword

This volume is the result of a research project carried out at the Department of Finance at the Stockholm School of Economics (SSE).

This volume is submitted as a doctoral thesis at SSE. In keeping with the policies of SSE, the author has been entirely free to conduct and present her research in the manner of her choosing as an expression of her own ideas.

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Copenhagen, February 28, 2023
Katarina Warg

Contents

Introduction

This doctoral thesis consists of three independent essays within the field of entrepreneurial finance. The first two essays are closely related and complementary, studying the role of venture capital (VC) markets in shaping startup firms' innovation trajectories. The first is an empirical study, and the second provides a theoretical perspective. The third essay is an empirical investigation of business angels.

The first chapter **VC Exits and Startup Innovations** employs a textual analysis approach to study the role VC markets play in shaping startups' innovation incentives and, ultimately, the trajectory of their innovation output. The paper develops new measures suitable for studying the direction and complementarity of startups' innovation output inspired by Hoberg and Phillips (2010). These new measures outline the innovation network of the startups —capturing the relationship between startups' innovation portfolio and incumbent firms' innovation assets. The evolution of this network describes the technological innovation path and the commercialization of innovations by startups. By analyzing both trademark and patent data, it is possible to study both technological (patented) innovations, the commercialization of such inventions, and the commercialization of a large share of non-patented innovations. Many innovations that enhance productivity and create value are not patentable, either for secrecy reasons or because the innovation (e.g., a novel business model, a process innovation, or product enhancement) needs to meet the patent criteria. While previous literature has primarily focused on patentable innovations, this paper expands the scope by studying the commercialization decisions of a more representative fraction of the innovation efforts in the startup economy. As such, the first chapter makes two empirical methodology contributions: introducing a text-based approach to construct novel measures suitable for studying the direction of innovation efforts and expanding the scope of innovations studied in the literature by complementing patent data with trademark data.

By utilizing these measures and the innovation network, the paper documents that startups gravitate toward innovation areas with more active exit markets, suggesting that startups focus more innovation efforts on projects that increase the likelihood of a successful and timely exit. Motivated by the theory developed in the second chapter—**Capital market (VC) competition and startup catering incentives**— the paper exploits the fact that as inflows into local VC markets increase following a regulatory change, the startups' catering incentives shift. When venture capital (VC) supply exogenously increases and VC competition increases, startups' commercialized innovations become less similar to incumbent firms' innovation assets. The trajectory of patentable innovations adjusts, and startups cater less to attractive acquisition markets.

VC plays a key role in the entrepreneurial ecosystem by channeling institutional capital into new firms, with unique skill in screening, supporting and financing startups (e.g., Kaplan and Strömberg, 2001), and private equity markets have become increasingly larger over the past decades. Previous literature has shown that the availability of capital and startups' financing constraints directly impact the quantity and quality of innovation output (e.g., Brown et al., 2009; Kortum and Lerner, 2000). Additionally, VC industry inflows determine the bargaining relationship between the entrepreneur and investors with implications for contracting, allocation of cash flow rights, and control rights (e.g., Chen and Ewens, 2021; Gompers and Lerner, 2000). The two chapters build on the insight from the previous literature and exploit two crucial features of the VC industry: the importance of a timely exit and VCs' monitoring and advisory role. These combined insights allow for investigating VC's role in shaping the direction of innovation efforts.

The availability of external capital to finance innovative and productive new firms is crucial for economic growth. VC is an established and powerful source of financing; however, VC financing does not fit all types of businesses, firm life-cycle stages, and projects. The third chapter—**Who becomes a business angel?** studies a different segment of the private equity markets and entrepreneurial ecosystem—business angels. Unlike VCs, business angels invest their personal wealth into small, new, and unproven firms. The population of business angels is a heterogenous group with diverse objectives. The informal nature of angel financing has constrained empirical studies of these individuals' role in and contribution to the entrepreneurial ecosystem, financial markets, and the economy, and several key questions remain unanswered. How prevalent are business angels, and is there sufficient angel capital to fill the VC gap? What determines whether an individual becomes a business angel? What are the implications for effective policy design? The third chapter exploits rich data, combining Swedish administrative registers and a new dataset on equity-related investments in Swedish firms, constructed by us authors, to study the angel population. The paper provides insights into the prevalence and importance of business angels and the characteristics of the angel population, ultimately providing insights with implications for designing effective policies encouraging the financing of early-stage ventures.

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Chapter 1

VC Exits and Startup Innovations

Abstract

This paper studies the direction of startups' innovation efforts, particularly the role of venture capital in shaping the trajectory of startups' innovation output. New text-based measures, constructed from patent and trademark data, outline the innovation network of the startups—informing about both the technological innovation path and the commercialization of innovations. The results show that startups gravitate toward innovation areas with more active exit markets. When venture capital (VC) supply exogenously increases and VC competition increases, startups' commercialized innovations become less similar to incumbent firms' innovation assets. The trajectory of patentable innovations adjusts, and startups cater less to attractive acquisition markets.

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1.1. Introduction

It has, for many decades, been the consensus that well-functioning financial markets play a key role in allocating capital toward the most promising and productive projects in the economy, thus driving economic and productivity growth as well as innovation (e.g., King and Levine, 1993a,b; Schumpeter, 1942). The availability of capital can have a first-order effect on both the quantity and quality of innovation output. Brown et al. (2009) argue that the surge in R&D spending in the US in 1994-2004 was primarily finance driven. Banking deregulations improving access to bank credit has been shown to boost small firm innovation output (e.g., Chava et al., 2013; Cornaggia et al., 2015), and increasing venture capital (VC) activity increases innovation output (e.g., Kortum and Lerner, 2000).

Small, new firms—such as the startups studied in this paper—play a distinct role in innovation production. They contribute disproportionately to novel, radical innovations (e.g., Akcigit and Kerr, 2018; Kerr et al., 2014) and face a different financing environment than mature, established firms. Startups are inherently explorative and experimental; they do not yet have the built-up capabilities, existing assets, or infrastructure to guide or constrain the path going forward. Thus investments in startups share many features with investments directly into innovations—they are characterized by uncertainty about both probability of outcomes and the possible outcomes themselves. The projects are challenging to evaluate as risk levels are high or difficult to assess, and returns are highly skewed. The difficulty in evaluating the potential of investments, and startups' lack of access to public equity markets and debt financing, create a funding need that alternative financial intermediaries such as VC funds have filled.

VC is an established, potent, and essential source of financing for new firms, particularly for innovative startups, and has been the subject of most empirical work on startup financing. One key feature of the VC market is the importance of the exit event, most commonly through an initial public offering (IPO) or trade sale. The importance of the exit event is driven by the VC funds' fixed investment horizons and the lack of liquidity in secondary markets. Despite the significant contributions of VC-financed firms to innovation output and the importance of the exit event in determining the entrepreneurs' and investors' payoffs, research on the role of exit markets in shaping the path of innovation is scarce, with some exceptions.

This paper studies how the exit market motives shape the *trajectory* of VC-financed startups' innovations. Specifically, this paper does not study the quality or quantity of startups' innovations but how changing financial market conditions affect the type of innovation projects pursued. By studying a sample of startups that received VC financing, this paper shows that the state of exit markets plays a crucial role in determining the focus of startups' innovation efforts. I construct novel text-based measures suitable for measuring the *direction* and *distinctiveness* of a startup's innovations efforts. For each startup, I compute the similarity of i) their recent innovations and ii) their innovation portfolio to the existing innovation assets of incumbent firms. These innovation similarity scores outline the startups' innovation network. Studying the evolution of this network as financing conditions change makes it possible to learn how VC markets influence the trajectory of startups' innovations.

Startups focus more innovation efforts in directions associated with more active exit markets, both active acquisition markets and where IPO activity has been high. The increased innovation efforts expand the startups' scope within the innovation area. This first finding extends to technological innovations, measured using the text of patent applications, and commercialized innovations, studied by using the information in trademark applications defining the products and services introduced to the marketplace by the firm. The magnitudes vary across the two samples studied. However, the general intuition is similar— attractive exit opportunities are essential for all investors, and the type of innovation projects that startups pursue correlates with the more attractive exit markets.

These findings are robust to controlling for all possible startup characteristics that influence the entrepreneurs' and investors' incentives to cater to future attractive exit opportunities, including characteristics that vary over time and the firms' early life cycles. However, if demand for a given type of asset increases, positive NPV investment opportunities arise—stimulating both startup entry and innovation investments and driving IPO and acquisition activity. In particular, past IPO activity is not predictive of future IPO activity but rather represents other startups' ability to commercialize their products and innovations successfully. The second empirical section addresses concerns of a demand-driven story.

I exploit another feature of the startup and VC market to address this concern—that an increase in the supply of capital increases the ability to fund more experimental projects but also changes the bargaining relationship between the entrepreneur and the VC. The experimental nature of investments into startups and innovation projects, as well as the information asymmetries and agency issues that characterize the relationship between the entrepreneur and the investor, have made the staging of investments standard practice within the VC market. Staging allows the investors to monitor the progress effectively and abandon non-profitable projects at an early stage, but also exposes the firms to financing risk, making it more difficult to pursue more explorative and experimental projects (see, e.g., Nanda and Rhodes-Kropf, 2013, 2017). Staging also transfers control from the insiders to the external investors. When capital is scarce, investors can negotiate more control, and the investors' preferences become more influential.[1]

[1]Gompers and Lerner (2000) show that increasing valuation flows increases demand for attractive investments and pushes up valuations. More recently, Chen and Ewens (2021) studied the effects on VC funds and their investments following a contraction of inflows into VC funds and found that the decrease in capital supply affects the composition of startups funded and the contractual terms of the deals. Aggarwal et al. (2022) show that increasing supply and VC market competition affects contractual outcomes between entrepreneurs and investors, looking primarily at the prevalence of dual-class stocks in VC-backed IPOs.

Many papers have documented the increased quantity of innovation output as startups become less capital constrained. This literature also provides evidence that the "quality" of patent output increases, typically measured using forward patent citations.[2] The second set of empirical results provides evidence in line with prior literature, using a plausibly exogenous variation in local capital inflows. Startups' new products become less similar to incumbent firms' existing product portfolios, and this effect is robust to any demand-driven concerns. These results suggest that startups focus less on incremental improvements ("new-to-the-firm") and instead forge their own path—introducing novel products to the area ("new-to-the world"). The results are slightly different within the patent sample; patent output becomes significantly less similar to incumbent firms' assets following the increase in capital supply. However, the result is not robust to controlling for factors associated with the specific product area. This observation suggests that patenting startups' response could be more nuanced, possibly due to longer lead times, more path dependence, and higher adjustment costs associated with R&D that leads to successful patent outcomes.

While the results support the findings in the previous literature, they are also more nuanced. First, this is the first paper that documents this finding looking specifically at the similarity of commercialized products *and* technological innovations. Second, the evidence applies to adjustments in the innovation strategies *within* firms—startups' innovation trajectory in their early life responds quickly to changes in the financing environment. Third, technologically intensive firms with patentable innovations respond to these changes nuancedly.

In the last set of results, I show that patenting firms primarily decrease innovation efforts directed at attractive acquisition markets, suggesting that patenting firms are less likely to innovate to be acquired when financing constraints are alleviated. The catering story of Wang (2018), that attractive acquisition markets stimulate entrepreneurial entry and that startups cater more to potential acquirers in larger and more fragmented markets, is consistent with these results. This paper, however, shows that the influence of the catering motive on startups' innovation trajectory also depends on the startups' ability to fund their independent journey. As such, it combines the catering story of Wang (2018) with the findings of Cornaggia et al. (2015), who argue that when startups are less financially constrained, they are less likely to sell out to incumbent firms, which results in an increase in small firms' innovation output increases while large firms' innovation output decreases.

This paper contributes to understanding how VC markets influence the trajectory of startups' innovations. Previous research has primarily used patent counts and citation-based measures (e.g., forward and backward citation counts), which are informative

[2]E.g., Kortum and Lerner (2000), Nanda and Rhodes-Kropf (2017), and Samila and Sorenson (2011) for evidence in the VC markets. Chava et al. (2013) and Cornaggia et al. (2015) look specifically at bank financing.

about the effectiveness and impact of a firm's innovation strategy. However, they offer limited insight into the direction and content of innovations and their relation to other firms' assets. Other patent-based measures that look at cross-citations or other proxies of overlap can be informative about the relation of a startup's technological innovations to incumbent firms' assets. However, many novelties and innovations introduced by startup firms are not patentable. A firm's innovations encompass many activities, including technological innovations and product enhancements, process improvements, and new business models. The trademark data widens the scope of innovative activities—new firms are often innovative along dimensions not captured by patents and thus complement the patent data. This paper shows that using trademark data makes it possible to study the innovation output of a larger fraction of the economy.[3]

The literature on the role of exit markets in shaping the direction of innovation among startup firms is limited, but a related area of the literature studies innovation as a determinant of exit outcomes (e.g., Bayar and Chemmanur, 2011; Bowen III et al., 2022). Other research has focused on the role of innovation assets in motivating merger and acquisition activity (e.g., Bena and Li, 2014; Hoberg and Phillips, 2010). This paper instead highlights the importance of expectations regarding exit markets in shaping the ex-ante innovation decisions of new firms. Thus, while past innovation activity shapes exit outcomes, the types of innovations that eventually reach the market are determined by entrepreneurs' and investors' expectations regarding financing and exit conditions. Schwienbacher (2008) theoretically studies the role of the exit event in shaping innovation output but focuses on the agency conflict between the VC and entrepreneur, their different exit preferences, and the contracting issues that arise.

The paper is also related to the literature on the boundaries of the firm, with a focus on innovation activities. Incomplete contracting motivates putting complementary assets under shared control (e.g., Grossman and Hart, 1986; Hart and Moore, 1990). The results in this paper indirectly relate to alternative financing and contractual agreements such as strategic alliances and corporate VC. Through catering, new firms maximize the acquisition option by incorporating the innovation incentives of the incumbent firms, suggesting that incumbent firms partially outsource their innovation activities. A similar mechanism is documented by Phillips and Zhdanov (2013), who show how the prospects of selling out to a larger firm incentivize smaller firms to innovate more, while larger firms optimally decrease R&D spending in favor of acquiring smaller firms. However, they do not study the direction or the type of innovations, only public firms' spending on R&D,

[3]For example, the biotechnology and electrical component industries are patent-intensive, while many innovations in the retail and computer software sector are not patentable. This paper shows that the sample of firms with a trademark is more representative of the full sample of VC-financed firms. About 55% of firms in the sample have at least one trademark, while only 22% have a patent. Among firms with a patent, more than 80% have at least one trademark.

and not the inherent trade-off between the two exit routes that are important for the type of innovations startup firms produce that are the focus of this paper.

This paper also introduces a novel application of patent and trademark descriptions within the context of startup firms. The general principle, that text-based similarity measures can inform about inter-firm product market relations has been exploited by e.g., Hoberg and Phillips (2010). This paper is not the first to apply textual analysis tools to understand firms' innovation output. Bena, Erel, et al. (2021) study the post-merger changes in the specificity of merging firms' patent output using text-based similarity measures of patents; the measures are distinct but similar to those developed in this paper and more apt for capturing asset specificity. The innovation measures and the construction of the innovation network developed in this paper are particularly suitable for understanding the direction of startup innovation efforts and the novelty and uniqueness of a startup innovation output similar to the use of the text-based measures developed in Kelly et al. (2021).[4] Text-based tools can be informative about many additional dimensions of innovation activity. The interpretation of the measures crucially depends on the textual input and the specifics of constructing the quantitative measures. The similarity measures and empirical methodology employed in this paper are suitable for understanding the trajectory of innovation and the relationship to the innovation assets of other firms in the economy.

[4] Both Bena, Erel, et al. (2021) and Kelly et al. (2021) compute the cosine similarity of a weighted vector representation of two patents. They use a term-frequency-inverse-document-frequency (TF-IDF) scheme similar to Kelly et al. (2021). More weight is assigned to words that are less common in other patents, reflecting the shared "specificity" of the expression. The TF-IDF weighting depends on what patents are included for comparison (e.g., what time horizon).

1.2. Firm sample and innovation data

Startup firms The sample of startup firms is obtained from Venturexpert and consists of 33, 435 firms (see table 1.1), all based in the US and founded in 1980 or later. The sample consists of firms that received VC financing after 1980, where the founding date and first date of investment are not missing, and where the first investment occurs after the founding date.[5] VC-financed firms comprise a significant fraction of high-growth firms that contribute disproportionately to economic growth and innovation output, though only a small fraction of the total number of new firms in the economy. The sample is not representative of the population of new firms but is likely a representative sample of the group of firms that are suitable targets for VCs. A comparison of all venture-financed firms in the CapitalIQ database to the Venturexpert sample suggests that Venturexpert has good coverage in the period 1980-2010; however, newly founded firms increased substantially in the CapitalIQ database but remain relatively stable in Venturexpert, indicating some incompleteness in the latest part of the sample.

Firms exit the sample when they go public, are acquired, fail, or go through some other exit event, as indicated by the current situation of the firm obtained from Venturexpert. Not all firms exit the sample and remain unresolved for the time studied in this paper. If more than ten years pass between the last observed round or deal, including also non-VC-deals (e.g., PE deals, debt financing), the firm exits the sample with exit code "failed". The data also covers the firm's industry, the timing of financing rounds and financing stage, and occasionally round amount, valuation, and other round-related information. Lastly, Venturexpert also provides VC fund data, including the closing date of each fund, preferred investment type and focus, fund size and sequence number, firm, and some information on the funds' investments.

Table 1.1 presents the exit outcomes for the startup sample, and Figure 1.1 shows the distribution of the founding years and years of first investment. The full sample includes all firms that match the above criteria, and the other samples contain the subsets of startups with trademarks or patents. More than half of the startups in the full sample have at least one trademark, while only about a quarter have a patent. By using trademarks, it is thus possible to study a larger fraction of innovation activity in the economy, particularly the kind of innovation that is not technological. The bulk of startups in the sample was founded between 1995-2015.

Potential acquirers The sample of potential acquirers consists of all listed US firms obtained from the Compustat universe of US firms, and each firm is included in the potential acquirer sample a few years prior to their IPO. Some firms in the startup sample

[5]A significant number of firms in Venturexpert are missing the founding date variable. By matching the name, state, and approximate financing rounds to CapitalIQ and filling in the missing founding date variable, fewer firms are excluded due to missing founding dates.

eventually enter the potential acquirer sample. Thus, a firm can be in the set of potential acquirers for other startup firms while still being a part of the sample but not among its own set of potential acquirers while still in the startup sample.

The true sample of potential acquirers most likely extends beyond this sample and includes other private and foreign firms. However, the scope of non-US firms' innovative assets is unlikely to be fully represented by the USPTO datasets, and private firm data is scarce. The empirical design accommodates that the potential acquirers are not fully representative of the true acquirers of the startup firms and further discussed in sections 1.4 and 1.5.

Patent data The first set of innovation measures builds on patent data, specifically patent data from the USPTO Bulk Data Storage (BDS) and PatentsView. Patents describe technological innovations well and are the most commonly used information source when studying firms' innovation output and assets. The dataset covers nearly all patent grants from 1976 through today and most patent applications from 2001 onward. The patent-based innovation measures in this paper derive from only granted patents as the coverage and information are better over the sample period.

The information includes general patent and application information, such as application date, grant date, and assignees (owners), including reassignments and citations. Most importantly, it contains the full text from the claims section of granted patents, which describes the new technology and should fully characterize the scope of the innovation and its distinguishing features.[6] The claim determines the scope of the patent holder's rights and is also where the applicant defines what makes the innovation unique.

A firm's patent portfolio consists of all patents assigned to the startup or potential acquirer by matching the patent assignee information to the two samples based on name (standardized using reclink2, see, Wasi and Flaaen 2015) and state while requiring that the firm's founding date occurs before the assignment date. A patent remains in the portfolio until it expires, approximately 20 years after the filing date. This procedure may underestimate the true innovation activity of firms (false negatives), but it is unlikely it overestimates innovation activity by introducing false matches.

Trademark data Patents describe technological innovations well, but they do not capture other innovation activities commonly associated with innovative startups, including novel business models, process innovations, and product enhancements. Therefore, the second set of innovation measures uses the USPTO Trademark case file dataset to extend the scope of innovative activity studied.

[6] The claim(s) of a patent "shall define the matter for which protection is sought" (PCT Article 6, `https://www.uspto.gov/web/offices/pac/mpep/s1824.html`).

The trademark dataset has near complete coverage of all trademark applications and publications after 1982 and includes general information such as application and publication date, ownership assignment, and a statement. The applicant must outline for which goods and services (products) protection is sought in the statement section, and trademark protection only extends to those goods and services listed in this section. The text is somewhat standardized and easily understandable but does not outline what makes the firm's products unique.[7] The description of the goods and services reflects the scope of the firm's product offering rather than the level of differentiation within a specific product-market category.

The applicant must also provide proof of use in commerce before the trademark grants the owner any protection, and the dataset covers the date of first use and the date of first commercial use of the listed goods and services. These dates better reflect the true introduction patterns by the firm than application or publication dates. Therefore, it is possible to observe the evolution of the goods and services the firm offers its customers and from which point these goods and services are commercialized. The applicant can amend the scope of the goods and services section later, and firms can file a trademark based on intent to use. Trademarks remain in the firms' portfolio for as long as they are "live".

Patent and trademark activity About 55% of the startups in the sample have applied for trademark protection, and 22% for patents. A smaller fraction has introductions spanning more than one year (about 33% and 16%), as shown in table 1.1. The sample of innovative firms is more representative of the startup economy when using patents and trademarks. Firms with patents are very likely also to have trademarks, but the reverse does not hold, and patenting is more common in some industries.

Compared to the underlying sample, patenting firms have a relatively higher representation in the biotechnology, medical/health, and semiconductor/electrical components industry, as shown in figure 1.2. In contrast, the industry distribution of firms with trademarks aligns well with the full sample of VC-financed firms. Moreover, sample firms with patents and trademarks are likelier to have had a successful exit (IPO or acquisition). Part of this might reflect that older firms have had more time to file for patents and trademarks and to exit. However, the failure rate is also lower among this subset of firms indicating that firms that successfully apply for intellectual property (IP) protection have a higher success rate. Receiving IP protection implies successful development (patents) and commercial launch (trademark), essential milestones in the startup lifecycle. The trademark and patent samples are thus likely to exhibit some survivorship bias.

[7] "The language used [...] should be understandable to the average person" (US Patent and Trademark Office, 2020).

Patent and trademark firms raise more financing rounds than the average VC-financed firm. Table 1.2 presents the timing of new patents and trademarks across the different samples. In general, it appears that patenting activity precedes trademarking activity, as firms are, on average, younger at the time of the first patent application when comparing the trademark sample to the patent sample and within the sample of firms with both patents and trademarks. Patenting activity slightly precedes the first VC financing round, while trademarks, if anything, follow the first investments. It is worth noting that trademarking requires proof of commerce, e.g., a launched product. Patenting firms also appear to go through more financing rounds than those with trademarks. These observations further support the notion that firms that successfully apply for IP protection are, on average, more successful than other firms. Moreover, they also suggest that by using trademarks, it is possible to study a distinct and larger subset of firms whose innovation activities and business projects are fundamentally different from firms that patent their innovations.

Lastly, the sample's number of new patents and trademarks is highly skewed, with the mean significantly larger than the median. However, this pattern is less prevalent for the number of patent-year or trademark-year observations.

1.3. The innovation network

1.3.1. Similarity scores

Cosine similarity is the cosine of the angle between two N-dimensional vectors and a commonly used measure of similarity between two text corpora; it simply describes the similarity between the two text bodies, and the interpretation of the measures ultimately depends on the type of texts used. Hoberg and Phillips (2010) use cosine similarity measures to study the role of product market synergies in acquisitions as well as in a series of subsequent papers. For example, a similar approach underlies the dynamic industry definitions developed to study the competitive environment in various product markets in Hoberg and Phillips (2016). Other papers use similarity scores to analyze the evolution in a time series of texts, for example to capture novelty, trends, or trend breaks (see e.g., Kelly et al., 2021).

This paper uses similarity scores constructed from trademark and patent text representing the startups' intellectual property, compared to similar text bodies from larger incumbent firms or "potential acquirers". The current patents and live trademarks belonging to a firm—startup or potential acquirer—are referred to as the firm's *portfolio* of innovation assets. The portfolio is the firm's stock of innovations and represents the cumulative innovation efforts of the firm since its inception. New additions to the firm's portfolio represent the inflow of innovations. This flow is the output of the firm's recent innovation efforts and are in this paper referred to as *introductions*.

Specifically, the similarity scores are the pairwise (normalized) cosine similarity of the cleaned text representing the two firms' innovation portfolios or introductions. Cleaning the text involves removing commonly used words and transforming the text into a vector representation, "word indicator vectors", $I_{i,t}$. The vector indicates whether a word is used in the (cleaned) text it represents; element n of firm i's vector is 1 if the corresponding word is used in the text, and 0 otherwise. When using indicator vectors, the cosine similarity measure can be rewritten as a function of word counts, see equation 1.1, greatly reducing the computational efforts. The goods and services section in the trademarks must follow a specific structure that requires word repetition. Similarly, the nature of the claims section imposes word repetition. These words are not assigned more weight when using the indicator vectors.

$$S_{ij,t} = \frac{I_{i,t} \cdot I_{j,t}}{||I_{i,t}||\,||I_{j,t}||} = \frac{\text{Common words}_{ij,t}}{\sqrt{\text{Distinct words}_{i,t} \cdot \text{Distinct words}_{j,t}}} \tag{1.1}$$

The similarity scores are informative about the novelty and uniqueness of startup innovations. However, motivated by the large literature on the determinants of the probability and success of merger and acquisition activity, they should also be informative about the value of the startups' innovation portfolio in the event of an acquisition. One strand of this literature suggests mergers are primarily motivated by complementarities; asset complementarities determine incidence and value of acquisition (e.g., Rhodes-Kropf and Robinson, 2008) and the property rights theory suggests these synergies are most effectively realized when assets are under shared control (e.g., Grossman and Hart, 1986; Hart and Moore, 1990). Complementarities arising from innovation activities as determinants of acquisitions have been documented by, e.g., Hoberg and Phillips (2010) and Bena and Li (2014). A different view emphasizes the incumbent firms' incentives to escape competition and increase market power (e.g., Baker and Bresnahan, 1985; Cunningham et al., 2021). While both motives are likely to be present in the data; both also suggest some degree of overlap between the targets' and the acquirers' innovation activities, e.g., firms buy similar firms. Thus, in addition to informing about the uniqueness and distinctiveness of a startup's innovation output, the innovation scores also capture the similarity or overlap in innovation activities that motivate acquisitions, regardless of whether acquisitions are driven primarily by complementary or anticompetitive motives.

1.3.2. The innovation network

The best visualization of the data set of innovation scores is a network with two types of nodes - *startups* and *potential acquirers* or new firms and incumbents. The score represents the strength of the connection, or the proximity, between a startup's and an acquirer's innovation portfolios. As firms introduce new trademarks or patents, the network evolves, and the firms move closer or further away from each other. The complete set of innovation scores comprises each startup-potential acquirer pair similarity score in all years that the two firms are members of the respective samples. The complete network is large; the set of observations amounts to 254,902×319,720—more than 80 billion—times the number of different innovation scores computed for the trademark sample only.[8]

Only a subset of the pairwise observations is "relevant"; most companies have zero or minimal overlap in their innovation activities, and it is necessary to restrict attention to the informative scores. For this reason, most of the analysis focuses on *relatively close pairs*, specifically the ten potential acquirers with the highest similarity score the year before the startup made any changes.[9]

Moreover, the primary interest in this paper is how the exit and financing environment affect what innovation projects the startups undertake. The construction of the two scores used in this paper, the introduction score and the portfolio score, mitigate

[8]The number of startup years in which the startups have live trademarks times the number of potential acquirer years with trademarks.

[9]In some cases, when some startup-acquirer pairs have the same rank score, more than ten pairs associated with one startup-year observation are included. Similarly, if there are fewer than ten potential acquirers with any overlap with the startup, the number of pairs could be less than ten. Moreover, alternative criteria, such as the top five closest potential acquirers or the potential acquirers with a similarity score above a specific threshold, yield similar results.

the concern that the evolution of the network captured in the analysis is driven primarily by the actions of the potential acquirers. First, the analysis is limited to years when the startup introduces an addition to its innovation portfolio. Second, comparing the startup's innovations to the lagged innovation portfolio of the potential acquirer ensures that any changes in the network structure are known to the startup's agents at the time of the introduction.

This paper uses the *introduction score* and the *portfolio score*. The introduction score computes the similarity score between the text corpus of all trademarks or patents introduced by a startup during a year relative to the potential acquirer's portfolio at the beginning of the year. The introduction score compares the startup's innovation flow to the potential acquirer's stock of innovations. It thus quantifies whether the startup has focused its most recent innovation efforts in the direction of the potential acquirer. The portfolio score instead compares the startup's portfolio at the end of the year, after any trademark or patent additions, to the potential acquirer's portfolio at the beginning of the year. This score quantifies the scope of the startup's innovation activities. An increase in the portfolio score implies that the new additions increase the startup's scope in the innovation area defined by the potential acquirer. The introduction score can be high, while the portfolio score simultaneously decreases. Such an observation would imply that the startup has focused its most recent innovation efforts in the direction of the innovation area defined by the potential acquirer. At the same time, the startup ultimately adds more variety and differentiation relative to the innovation area.

Figure 1.3 illustrates one startup-year observation, Kilopass Technologies, in 2003 from the patent sample. The portfolio score at the beginning of the year (figure a) determines the relevant potential acquirer directions. The introduction scores (figure b) are positive for all ten potential acquirer directions and vary from 27-39. A high pair-wise introduction score does not necessarily imply an increase in the portfolio score (figure c); three of the pair-wise portfolio scores decreased relative to the portfolio scores at the beginning of the year. The introduction score relative to Quality Semiconductor Inc. was the second highest, 35.5, but led to a 5.5-point decrease in the portfolio score. The change in the portfolio score and the introduction score are not necessarily strongly positively correlated.[10] A startup can put significant efforts into innovation spaces overlapping with a potential acquirer's innovation portfolio without any material impact on the overlap in scope, resulting in a simultaneously high introduction score and a negligible shift, from possibly low levels, in the portfolio score. The post-introduction portfolio score can decrease, even when the introduction score is high.

Panel A and B of table 1.3 show that the introduction score is, on average, lower than the portfolio scores and that the mean is slightly higher than the median for all types of

[10]The correlation between the introduction score and the difference between beginning of year score and the portfolio score is 0.127 in the trademark sample and 0.061 in the patent sample.

scores. Some startup-potential acquirer pair scores are perfectly similar, with a score of 100, while this never occurs in the patent sample. The format of the patent claims section follows a specific structure, but the “writer” has discretion in terms of length, detail, and word choice. On average, the trademark goods and services descriptions are shorter, and word choices are standardized and subject to approval. There is also a substantial variation within each startup-year observation.

1.4. Direction of startups innovation efforts

Table 1.3 shows substantial variation in the level of the beginning-of-year portfolio score and across the introduction and portfolio scores. There is also considerable variation within startup-year observations. Table 1.4 provides further insight into the evolution of the networks. Only 64% and 69% of the closest potential acquirers remain among the startups' top 10 closest by the beginning of the following year, suggesting substantial turnover. The turnover is slightly lower when isolating the actions by the startup, 70%, and 75% for the trademark and patent sample, as captured by the portfolio score comparing the startup's portfolio at the end of the year to the potential acquirer portfolio at the beginning of the year. These observations motivate using the portfolio and introduction score instead of the level and changes in the end-of-the-year score. The two scores isolate the actions taken by the startup and relate the startup's innovation activities to information known to the startup at the time of the innovation activity, and the difference is substantial.

The score construction has further implications for the interpretation of the scores. They do not measure the relative similarity with the given potential acquirer firms but rather the similarity of the startup's innovation output to the innovation area as defined by the portfolio of the potential acquirer—are the startups' innovations more similar to the innovation area defined by potential acquirer *A* or *B*? Does the direction of the innovation efforts relate to the exit conditions for startups in the given area? Are startups more likely to innovate toward more favorable exit markets? Table 1.4 also displays summary statistics of the startup exit outcomes associated with the area defined by the potential acquirer. The acquisition and IPO activity variables are constructed at the acquirer level and from exits by the sample startups. The variables are the lagged three-year average of the number of acquisitions of, or IPOs by, startups with the potential acquirer among its closest potential acquirers that exited in the given year. Startups with exits that constitute the basis for the measure have consequently exited the sample before the year of observation. The variables' lower bound and modal outcome is zero across both exit types and samples. In the patent sample, 61% and 68% of startup-potential acquirer year observations are zero for IPOs and acquisitions, respectively, and 73% and 77% in the trademark sample. However, within each startup observation, there is generally variation. Among the already close potential acquirers, having IPO exits are slightly more common than acquisitions.

The estimation of equation 1.2 sheds light on the relationship between exit markets and the direction of startups' innovation efforts. The variables of interest are *3-year Acq* and *3-year IPO*, the exit activity variables in table 1.4. Table 1.5 presents the estimation results with the introduction and portfolio score as the dependent variables. Odd-numbered columns (1, 3, and 5) include separate fixed effects for startups and years, while even-numbered columns (2, 4, and 6) employ the more exhaustive set of interacted startup-year fixed effects, thus removing any time-varying differences in startup characteristics. The last two specifications include the beginning of year portfolio scores as a control, effectively changing the interpretation of the specification to the change in portfolio scope following the introduction of new innovations by the startup. The interpretation of the coefficient is slightly different depending on the dependent variables.[11]

$$\begin{aligned}\text{Score}_{iat} = {} & \beta_1\text{3-year Acq}_{at} + \beta_2\text{3-year IPO}_{at} + \beta_3\text{BoY portfolio score}_{iat} \\ & + \text{Startup/year fixed effects} + \varepsilon_{iat}\end{aligned} \tag{1.2}$$

In columns 1 and 2, the dependent variable is the introduction score, and the results suggest that past successful exits are strongly correlated with future innovation activity by other startups. The introduction score captures the most recent innovation efforts by the startup, and positive and significant coefficients on the two exit market variables suggest that the startup is more likely to innovate in directions with more favorable exit market conditions. The results show a robust positive relationship between acquisition and innovation activity across all specifications and in both samples. Within the trademark sample, these coefficient estimates correspond to approximately a 1%-1.5% increase in the introduction score relative to the sample mean if there has been one more acquisition in the past three years.[12] Within the patent sample, the estimates are statistically significant but smaller in magnitude—only 0.3%. The coefficient on IPO activity is, within the trademark sample, smaller in magnitude but remains positively correlated with the direction of innovation activity. The same is not valid in the patent sample, where the sign on the coefficient flips after introducing interacted startup-year fixed effects.

The portfolio score is the dependent variable in columns 3 through 6, comparing the startups' portfolios at the end of the year, including all additions to the portfolio, to the potential acquirer portfolios at the beginning of the year. The portfolio score measures the scope of the startups' cumulative innovation efforts, and when including the beginning of the year portfolio score as a control variable, the interpretation of the coefficient estimates changes. First, there appears to be no clear correlation between the startups' level of portfolio scores and past acquisition activity, and if anything, the relationship is negative. On the other hand, the results suggest that startups' portfolios are negatively associated with high past IPO activity. The estimates suggest the portfolio score decreases by about 1.5% relative to the mean if there has been one additional successful IPO in the past three years in the patent sample and by 0.7% in the trademark sample. These results do, however, not imply that the change in startups' scope is unrelated or negatively associated with past exit market activity. Columns 5 and 6 show that higher past acquisition activity is

[11] Appendix tables 1.10 and 1.11 present results from similar specifications that complement the results in table 1.5, including only the acquisition activity measure, only the IPO measure, or both. The coefficient estimates are relatively stable across these different specifications.

[12] One more acquisition in the past three years corresponds to an increase of the acquisition activity score of 0.33 ($0.33 \cdot 1.102/26.4 \approx 1.4\%$). Such an increase is similar in magnitude to the within-sample standard deviations of the acquisition activity score: 0.37 in the patent sample and 0.27 in the trademark sample(table 1.4).

associated with an increase in the startups' scope. Within both samples, the coefficient on past IPO activity is large in magnitude and statistically significant across all specifications and both samples. The magnitude of the acquisition activity coefficient is smaller and not statistically significant in the trademark sample.

To summarize, these results suggest that startups direct significant innovation efforts toward more attractive acquisition markets, and these efforts often translate into an increased scope within the associated innovation areas. However, this does not translate into a turnover of the startups' innovation portfolios as the startups' cumulative innovation efforts are not strongly associated with active acquisition markets—nor IPO markets. On the other hand, while startups focus some innovation efforts in the direction of active IPO markets, though not as much as toward active acquisition markets, the change in scope is more significant within these markets. The startup and year fixed effects address concerns of biased estimates arising from omitted factors, varying across startups and time. However, it does not address concerns that other omitted factors might be correlated with exit market outcomes. In particular, high demand for a given type of asset should stimulate startup entry, incentivize innovation, and drive IPO and acquisition activity. Section 1.5 addresses this concern by introducing a natural experiment affecting the availability of financing with a set-up such that it is possible to control for additional omitted variables.

1.5. Startups' innovation trajectories

1.5.1. The availability of capital

The previous section established that startups direct more innovation efforts toward more active exit markets. This section instead aspires to investigate whether startups are more or less likely to cater when the availability of capital increases. The empirical strategy exploits a legislative change that increased the inflow to venture capital funds at the state level, specifically the implementation of the Prudent Person Rule (PPR) across US states.

The implementation of the PPR was staggered across US states following the Uniform Prudent Investor Act (UPIA) adoption in 1994 by the Uniform Law Commission. The PPR impacted all state pension funds not affected by the Employee Retirement Security Act implemented in 1979 and redefined the trustee's fiduciary duties. Prior to the PPR, the prudence of an investor was evaluated at the level of an individual investment, rendering certain types of investments inherently imprudent. The implementation of the PPR redefined prudence by emphasizing diversification and bringing the policy in line with modern portfolio theory. The "prudence" of risky individual investments, such as private equity (including VC), is then evaluated for its contribution to the overall portfolio. The policy enabled local state pension funds to extend their investment activities into alternative asset classes such as private equity, including VC. Illinois was the first state to implement the PPR in 1992, notably before the UPIA adoption, followed by Florida in 1993. The last state to implement the legislation within the sample was Montana in 2013.[13] The implementation of the PPR as an exogenous increase in VC capital inflows has been used previously in the literature. For example, González-Uribe (2020) exploits the staggered adoption to estimate the probability of a given firm joining a VC's portfolio, with the ultimate objective to assess the exchange of innovation resources among portfolio firms. González-Uribe (2020) also provides evidence that implementing the PPR increased capital inflows from local pension funds into local private equity funds, including VC and buyout funds. These results are consistent with the findings of Hochberg and Rauh (2013), who document a significant home bias in US public pension funds' private equity investments.

Previous literature has shown that the availability of financing affects the amount and type of innovations produced by both mature firms and startups. Increased availability of capital is associated with increases in R&D spending and innovation output. For example, Brown et al. (2009) argue that the hot stock markets in the late 1990s were the main driver of the US's contemporaneous and subsequent R&D boom. Not just the quantity but also the quality of innovation output and type of innovation projects pursued are, on aggregate,

[13]The appendix provides more details about the timing of the implementation across different US states and how this feeds into the cohorts. Specifically, appendix table 1.12 provides an overview of the staggered implementation.

affected by the availability of financing. Nanda and Nicholas (2014) take a historical perspective and provide evidence that firms located in states more negatively affected by the bank suspensions during the Great Depression had lower innovation output but also focused on less explorative innovation projects. Within the VC and startup space, the literature has provided evidence that startups founded in "hot" VC markets engage in riskier and potentially more rewarding innovation projects of a more explorative and radical nature (e.g., Nanda and Rhodes-Kropf, 2013). The first specification, in equation 1.3 estimates the change in the average similarity of the startups' innovations to the innovation assets of incumbents and potential acquirers. A decrease in the similarity with existing innovations suggests that startups are pursuing more independent innovation trajectories. A decrease in the innovation scores following the adoption of the PPR is consistent with the results from the previous literature of a decrease in exploitative, incremental innovations toward more explorative innovation activities following a decrease in the availability of capital.

$$Score_{iact} = \beta(\text{Post}_{ct} \cdot \text{PPR}_{ic}) + \text{Startup FE}_c + \text{Year FE}_c + {}_{iact} \tag{1.3}$$

The specification outlined in equation 1.3 is akin to a stacked difference-in-differences model, exploiting the staggered roll-out of the PPR legislation. A cohort consists of "treated" startups and a "control group". The treated group within the cohort consists of startups (i) located in states that implemented the PPR in the "cohort year" (c). The control group consists of firms within similar industries to the treated group but located in states that did not implement the PPR within a five- or seven-year window around the cohort year. The cohort only includes startups with innovation output (i.e., patent or trademark applications depending on the sample) in the five years before the cohort-specific event year *and* in the five years after the event year.[14] This construction ensures the possibility of the inclusion of startup-cohort fixed effects, and the coefficient estimates reflect changes over time within a given startup's innovation activities. The startup fixed effects address any concerns that differences across startups' innate characteristics, driven, for example, by financing conditions at the time of entry, are driving the results. The year fixed effects control for any time-varying factors that affect all startups within the cohort similarly. The startup and year fixed effects are cohort-specific.

The specification differs from a "standard" stacked difference-in-differences specification in two key ways; there is no proper time series in the cohort dataset, and each

[14] Appendix tables 1.13 and 1.14 show which states are represented in the "treated" and "control" groups for each cohort in the patent and trademark sample respectively. The tables apply the less restrictive 5-year window criteria.

startup-year observation translates into (approximately) ten startup-potential acquirer-year observations.[15] First, the data only includes years in which the startups have introduced a new innovation. For most startups in the cohort data, there is only one observation before the cohort-specific PPR adoption year and one after. Effectively, it is similar to having one pre-period and one post-period. Second, for the purposes of the specification in equation 1.3, the interpretation of the coefficient instead becomes an "average" across all already close potential acquirers.

Columns one and two of tables 1.6 (patent sample) and 1.7 (trademark sample) presents the results from the estimation of equation 1.3 when varying the window for inclusion into the control group from five to seven years. The results suggest that an increase in the availability of capital causes startups to engage less in innovation efforts that are more similar to incumbent firms' assets (Panel A). Startups' innovations become less incremental and exploitative and possibly more explorative and radical in the innovation strategy. These results are in line with results in previous literature studying the effects of financing markets on innovation. For example, Chava et al. (2013) show that (in particular) small firms' innovation output increased following bank deregulations that increased competition in the banking industry. They further provide evidence suggesting that the affected firms pursued more high-risk innovation projects. Nanda and Rhodes-Kropf (2013) argue that hot VC markets, when capital is abundant, promote increased innovation activity, particularly more explorative and radical innovation projects. However, the results in this paper build on these results. First, this paper exploits an exogenous shock to the availability of equity financing, specifically venture and other private equity capital. At some point, all firms in the sample receive VC financing and are arguably constrained from accessing credit markets and bank financing. Second, this paper demonstrates that already-founded firms adjust their innovation strategy over time in response to changes in the local financing environment, thus suggesting that the trajectory of a firm depends critically on the environment in which it is established. However, the results from the same specification, but with the portfolio score as the dependent variable, are generally not statistically significant. Thus, these results suggest that an exogenous shock to the financing environment affects current innovation efforts—the novelty of startups' current innovation efforts—but does not fundamentally change the scope or breadth of the firms' innovation assets.

Columns three and four of tables 1.6 and 1.7 extend the specification in equation 1.3 by adding potential acquirer-year fixed effects, effectively removing any factors affecting

[15] Baker, Larcker, et al. (2022) discuss the "standard" stacked difference-in-differences model in the context of staggered difference-in-differences specifications. They review the recent advances and suggested solutions in the econometric literature to address the specification issues arising from heterogenous treatment effects in the standard two-way fixed effects difference-in-differences estimator (see e.g., Athey and Imbens, 2022; Callaway and Sant'Anna, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021). The alternative approaches are not suitable for this setting due to the nature of the data.

all startup firms with the potential acquirer among its closest incumbents similarly. In particular, it controls for any innovation efforts primarily driven by increased demand but also for other factors correlated with the specific innovation area at a given time. Interestingly, startups decrease their similarity across all possible innovation areas within the trademark sample (columns 3 and 4 of table 1.7) but not within the patent sample (columns 3 and 4 of table 1.6). The trademark sample studies commercialized products, and these results thus suggest that startups introduce more novel products and pursue more unique business models when the availability of financing increases. However, the behavior of patenting firms appears to be more nuanced, suggesting that they adjust their innovation strategies in specific directions, a behavior further studied in 1.5.2.

1.5.2. Catering strategies

The specification outlined in equation 1.4 allows further investigation into how changing financing conditions affect the trajectory of startups' innovation strategy. The set-up builds on the specification in 1.3 and is estimated using the same cohort dataset but has some main differences. First, the usual difference-in-differences variables are interacted with the exit market variables from section 1.4: acquisition activity and IPO activity. Second, the specification includes startup-year fixed effects and potential acquirer-year fixed effects. The potential acquirer-year fixed effects serve the same purpose as in the estimation discussed in the last paragraph of section 1.5.1. They address concerns of a demand-driven story—that demand for specific assets is driving "all" startups to innovate in a similar direction. The interacted startup-year fixed effects remove the first-order effects estimated in 1.3, and only relative differences across the possible directions of the startup firm at the given point in time remain. Specifically, are startups that experienced an increase in capital supply more or less likely to engage in innovation activities related to more active exit markets? A positive β_1 or β_2 suggests that startups within the treated group responded differently to exit market incentives prior to the PPR introduction within their state relative to the control group. On the other hand, a positive β_3 or β_4 implies that startups affected by the PPR implementation increased their responsiveness to different exit market outlooks or, similarly, reduced their responsiveness given a negative coefficient estimate.

$$\begin{aligned} Score_{iact} = {} & \beta_1(\mathrm{PPR}_{ic} \cdot \text{3-year Acq}_{act}) + \beta_2(\mathrm{PPR}_{ic} \cdot \text{3-year IPO}_{at}) + \\ & \beta_3(\mathrm{Post}_{ct} \cdot \mathrm{PPR}_{ic} \cdot \text{3-year Acq}_{act}) + \beta_4(\mathrm{Post}_{ct} \cdot \mathrm{PPR}_{ic} \cdot \text{3-year IPO}_{at}) + \\ & \text{Startup-year FE}_c + \text{Acquirer-year FE}_c + {}_{iact} \end{aligned} \tag{1.4}$$

Table 1.8 presents the results estimated within the patent sample. The pre-PPR implementation coefficient estimates (rows 1 and 2) are statistically insignificant, suggesting that startups in the "treated" and the control group did not respond differently to exit market incentives leading up to the PPR implementation. There is no evidence suggesting the startups adjusted their behavior with respect to active IPO markets after the implementation. However, the recent innovation efforts of the patenting startups appear to be less directed toward active acquisition markets after the increase in VC capital availability, as suggested by the negative and statistically significant β_3 estimates in columns 1 and 2. These results carry over to a lower scope similarity (columns 3 and 4) but do not translate into a measurable effect on the change in scope (columns 5 and 6). Although not statistically measurable, the coefficient estimates are consistently negative.

These results are consistent with the catering story proposed by Wang (2018) and reminiscent of the proposed explanation for the reallocation of innovation output from public to private firms following an increase in banking competition in Cornaggia et al. (2015). Wang (2018) documents the increasing importance of entrepreneurial exit through strategic acquisition and the importance of market structure among incumbent firms for the entrepreneurial entry decision, arguing that more fragmented markets promote entry. However, conditional on entry, startups appear to cater more to potential acquirers in larger and more fragmented markets. The results presented in table 1.8 document a change in the catering behavior of a similar sample of startup firms following an increase in the local supply of capital. The results suggest that patenting startups decrease their innovation activities in directions of more attractive acquisition markets—startups cater less to potential acquirers following the implementation of the PPR. This effect is also measurable when controlling for time-varying startup-year characteristics, including how startup firms have different incentives to cater, conditional on the market they entered and their current capital-raising needs. This implies that the incentives to cater depend not only on incumbent firms' market structure and attractiveness of a potential acquisition but also on a startup's ability to fund its journey as an independent entity.

Moreover, the results are congruent with the explanation proposed by Cornaggia et al. (2015). The authors first document that the quality and quantity of innovation output increase among private firms and decrease among public firms following banking deregulation, promoting increased banking competition—consistent with Chava et al. (2013). Small, private firms are generally more bank dependent, and therefore, these firms were more financially constrained before deregulation. The improved ability to raise capital for investments into innovation activities also enabled startups to remain independent and not sell out to larger (public) firms—which results in lower innovation output among public firms. The results in 1.8 complement prior literature by suggesting that startups patenting output also become more independent of potential acquirers' innovation trajectories. The same story can, however, not be documented when studying the innovation trajectories of firms using trademark data. Table 1.9 presents the estimates using the trademark sample. First, there is no consistently negative β_3 estimate. Instead, the β_4 estimate is negative. However, these results are inconclusive, as the β_2 estimates are clearly positive, suggesting that the firms in the "treated" group responded differently to exit market incentives before the PPR implementation event.

1.6. Conclusion

High uncertainty about future outcomes and high risk characterize investments in startups and innovative ventures. The entrepreneur-investor relationship is characterized by high information asymmetries, similar to those between inventors and investors. VC is an established and essential source of capital specialized in investing in such projects. A large and active literature has studied VCs, their investments, and their contribution to economic output. An influential paper by Kortum and Lerner (2000) provides evidence that VC capital efficiently boosts innovation activity, showing that patent output is three or four times as high per VC dollar invested in R&D compared to traditional corporate R&D investments. Subsequent papers have confirmed the positive effect of VC capital in stimulating both the quantity and quality of innovation output.

This paper contributes to the literature on how VCs influence startup innovations by focusing specifically on the trajectory of startup innovations and the role of the exit motive. Intense monitoring and the importance of a timely exit are two key features of the VC-startup relationship. The importance of the exit follows from the VC funds' fixed investment horizon and lack of liquidity in secondary markets, and intense monitoring addresses the information asymmetries and agency issues that characterize the investments. However, when capital supply increases and VC competition increases, VC influence over startups decreases. A large literature studies the role of VC monitoring in shaping startup innovation output, e.g., Bernstein et al. (2016) document positive effects on innovation output and exit outcomes, as direct involvement with portfolio firms becomes less costly.

The results in this paper suggest that exit motives drive the trajectory of startups' innovations, showing that startups gravitate toward innovation areas associated with more active exit markets. Using a staggered policy shift that increased the local supply of capital, this paper also shows that the startups gravitate less toward all related innovation areas when capital supply increases. When capital becomes more abundant, startups' innovation trajectories become more independent of incumbent firms' innovation paths. This effect is particularly prevalent when studying the commercialization process of startup innovations and applies to all directions.

When studying startups with a more technological innovation process—firms with patentable inventions—the evidence suggests that the innovation efforts are primarily shifted *away* from directions with more active acquisition markets. These results suggest that when VCs can exert more influence over startup firms, the catering motive is more influential in determining the startups' innovation trajectory. Recently, the high acquisition activity of young, small firms by large technological incumbents has been under regulatory scrutiny. Antitrust authorities' scrutiny of merger and acquisition activity primarily focuses on the competitive implication of such activity; this paper instead documents the implications on startup firms' ex-ante innovation decisions and VCs' role.

1.7. Figures

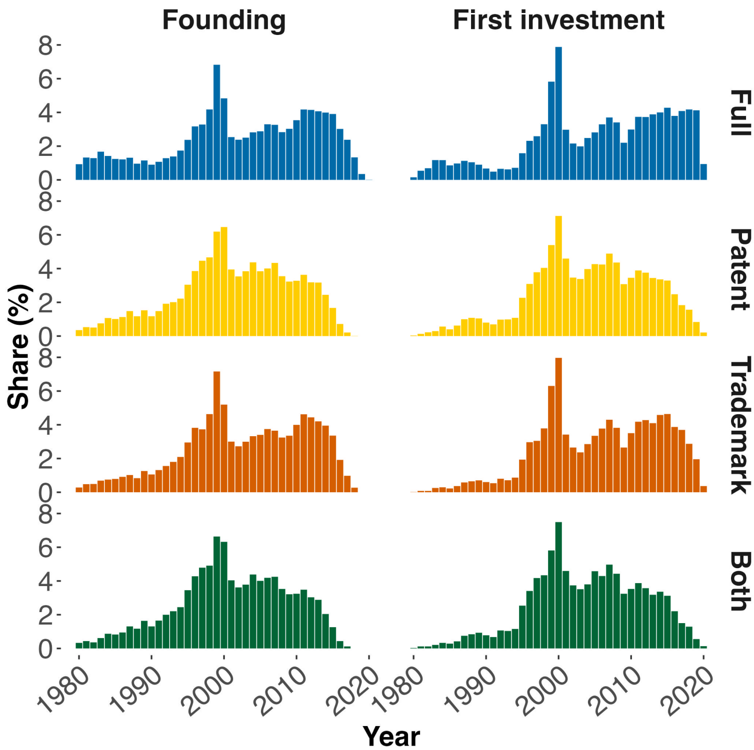

Figure 1.1. **Age Distribution Startup Samples** Distribution of the sample startup firms' founding year and year of first (VC) investment across the different samples/subsamples; the full sample of firms includes all startup firms in the original sample from Venturexpert, the trademark sample includes all startups that can be matched to at least one trademark and the patent sample includes the subset of startups that can be matched to at least one patent. The sample with both includes startups that can be matched to at least one trademark and at least one patent.

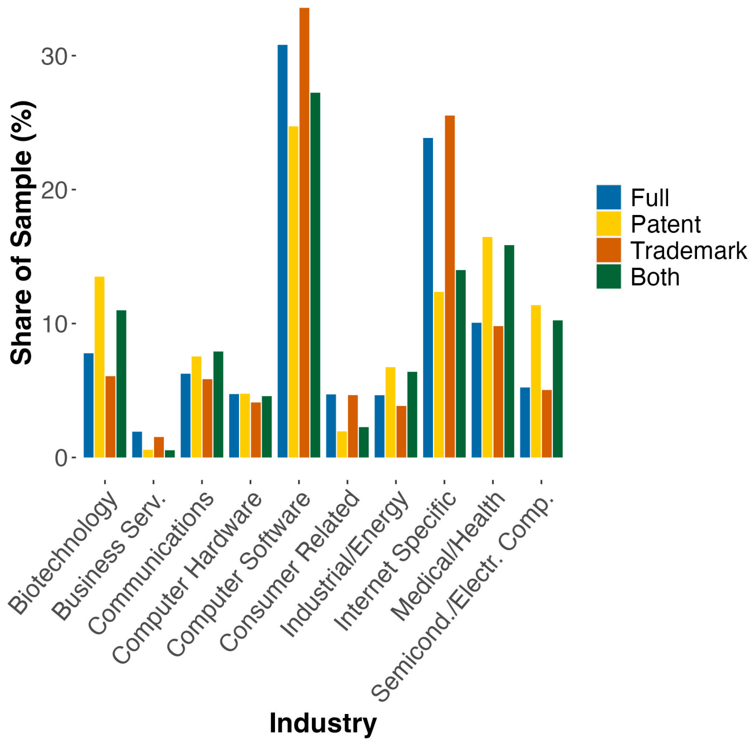

Figure 1.2. **Industry Distribution Startup Sample** This figure shows the industry distribution across the different samples/subsamples; the full sample of firms includes all startup firms in the original sample from Venturexpert, the trademark sample includes all startups that can be matched to at least one trademark and the patent sample includes the subset of startups that can be matched to at least one patent. Sample with both includes startups that can be matched to at least one trademark and at least one patent.

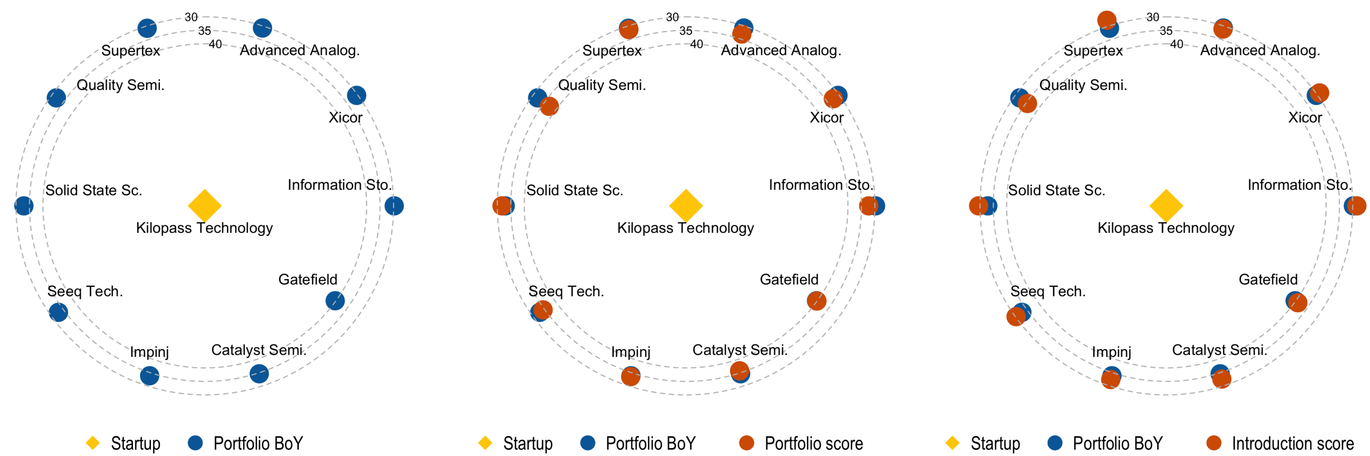

Figure 1.3. **Illustration of network evolution** These figures illustrate one startup-year observation, specifically Kilopass Technology Inc. in 2003 from the patent sample. Kilopass is displayed in yellow in the center and surrounded by its ten closest potential acquirers, the blue and red circles. The potential acquirers are closer to the center when the score is higher. Figure (a) illustrates the portfolio score at the beginning of the year; the score used to determine the relevant set of potential acquirers. Figure (b) shows the introduction score, and figure (c) the portfolio score, comparing the startup portfolio at the end of the year to the potential acquirer portfolios at the beginning of the year. All scores are within the 27.75-40.22 range, and the grey circles highlight the relative positions of 30, 35, and 40 points.

1.8. Tables

Table 1.1. **Descriptive Statistics Startup Samples** This table shows the overlap between different samples split on whether the startup firm has trademarks or patents and the differences in exit outcomes across the samples. *Success* is the sum of *IPO* and *Acquired*, and *Failed* include firms that are defunct, bankrupt, or in some way ceased to exist, as well as those where more than ten years have passed since any observed changes to the firm. Most firms founded more recently remain *Unresolved*.

	Full	**Trademark**	**Patent**	**Both**
Firms	33, 435	17, 722	8, 510	6, 661
>1 Patent year (%)	17.96	27.67	70.56	73.62
>1 Trademark yr (%)	30.93	58.35	54.14	69.16
Success (%)	35.70	40.41	45.84	48.60
IPO (%)	9.44	10.05	15.19	16.50
Acquired (%)	26.27	30.36	30.65	32.10
Failed (%)	27.81	23.21	23.57	21.12
Unresolved (%)	34.69	34.05	28.40	27.82

Table 1.2. **Descriptive Statistics Startup Life-Cycle** This table describes differences across the startups' life cycles across the sample of firms with patents, trademarks, or both. Panel A includes all startup firms with at least one trademark, Panel B all startups with at least one patent, and Panel C includes startups with at least one patent *and* at least one trademark.

Panel A: Patent	**N**	**Mean**	**Q25**	**Median**	**Q75**
Number of financing rounds	8,510	5.07	2	4	7
Age at first Patent	8,510	2.73	0	2	4
Age at first investment	8,510	3.17	1	2	4
Number of Patents	8,510	11.36	2	4	11
Number of Patent years	8,510	3.65	1	3	5
Panel B: Trademark					
Number of financing rounds	17,722	4.18	2	3	6
Age at first TM	17,722	2.94	1	2	4
Age at first investment	17,722	1.88	0	1	3
Number of Trademarks	17,722	5.14	1	3	6
Number of Trademark years	17,722	2.55	1	2	3
Panel C: Patent & Trademark					
Number of financing rounds	6,661	5.35	2	5	7
Age at first Trademark	6,661	2.81	0	2	4
Age at first Patent	6,661	2.23	0	1	3
Age at first investment	6,661	3.20	1	2	4
Number of Trademarks	6,661	6.52	2	4	8
Number of Trademark years	6,661	3.08	1	2	4
Number of Patents	6,661	12.80	2	5	13
Number of Patent years	6,661	3.93	1	3	5

Table 1.3. **Summary statistics innovation scores** This table displays summary statistics of the trademark (panel A) and patent sample's (panel B) innovation scores. In the first four rows of each panel, the observation unit is a startup-potential acquirer pair in a year where the startup introduces a new trademark or patent. In the subsequent rows, the observational unit is a startup year, taking the difference between the highest and smallest observations. The *introduction score* is the similarity score of the startup's newly introduced trademarks or patents compared to the potential acquirer's portfolio at the beginning of the year. The *beginning of year score* compares the startup's and potential acquirer's portfolios at the beginning of the year, while the *end of year score* compares the portfolios at the end of the year. The *portfolio score* compares the startup's portfolio at the end of the year (after the newly introduced trademark has been added) to the potential acquirer's portfolio at the beginning of the year.

	N	**Mean**	**SD**	**Min**	**Q25**	**Q50**	**Q75**	**Max**
Panel A: Patent								
		Startup-potential acquirer-year						
Introduction score	347,690	22.94	8.51	0.72	17.09	21.94	27.52	100
Beginning of year score	347,690	35.46	15.34	7.87	26.67	32.29	39.51	100
Portfolio score	347,690	35.85	14.12	3.93	27.55	33.35	40.33	100
End of year score	347,690	36.13	15.36	2.16	27.45	33.32	40.34	100
		Max-min within startup-year						
Introduction score	34,706	9.99	7.05	0.89	5.58	7.93	11.91	78.09
Portfolio score	34,706	24.07	25.8	0.43	3.48	6.65	51.29	81.46
Beginning of year score	34,706	26.3	30.35	0.27	2.52	4.42	60	91.14
End of year score	34,706	27.71	29.81	0.43	3.86	7.23	59.96	97.14
Panel B: Trademark								
		Startup-potential acquirer-year						
Introduction score	394,778	24.6	13.94	0.56	14.7	22.71	31.78	100
Beginning of year score	394,778	36.48	14.55	1.24	28.7	34.05	40.09	100
Portfolio score	394,778	33.79	13.74	1.6	26.31	31.98	37.8	100
End of year score	394,778	33.52	14.86	0	25.68	31.55	37.5	100
		Max-min within startup-year						
Introduction score	37,419	21.89	12.96	0	12.83	18.7	27.53	98.32
Beginning of year score	37,419	27.22	26.41	0	6.76	12.16	58.55	93.59
Portfolio score	37,419	26.34	23.66	0	8.13	13.91	50.65	90.72
End of year score	37,419	31.81	27.11	0	10.01	17.84	62.44	100

Table 1.4. **Evolution of the innovation network** This table displays summary statistics of the change in the trademark and patent networks and acquisition and IPO activity surrounding the potential acquirers. The observation unit is a startup-potential acquirer pair in a year where the startup introduces a new trademark or patent and a startup year observation in the rows displaying max-min. The row *Top 10 portfolio score* displays how many of the top ten closest potential acquirers at the beginning of the year are among the top ten in terms of the portfolio score. The portfolio score compares the startup portfolio at the end of the year, after any new trademark or patent additions, to the potential acquirer portfolio at the beginning of the year. The *top 10 end of year score* and *top 10 introduction score* display the share that is among the top ten using the end-of-years portfolio and introduction scores. The *3-year acquisition activity* and *3-year IPO activity* is the lagged three-year average of the number of startup acquisitions and IPOs closely related to the potential acquirer. *Max-min* activity score is the difference between the highest and the lowest 3-year activity score within the startup-year observation group.

	N	Mean	SD	Min	Q25	Q50	Q75	Max
Panel A: Patent								
Top 10 portfolio score	347,690	0.74	0.44	0	0	1	1	1
Top 10 end of year score	347,690	0.69	0.46	0	0	1	1	1
Top 10 introduction score	347,690	0.21	0.41	0	0	0	0	1
3 year acquisition activity	347,690	0.19	0.37	0	0	0	0.33	3
Max-min acquisition activity	34,706	0.67	0.62	0	0.33	0.33	1	3
3 year IPO activity	347,690	0.25	0.44	0	0	0	0.33	4.67
Max-min IPO activity	34,706	0.81	0.7	0	0.33	0.67	1	4.67
Panel B: Trademark								
Top 10 portfolio score	394,778	0.7	0.46	0	0	1	1	1
Top 10 end of year score	394,778	0.64	0.48	0	0	1	1	1
Top 10 introduction score	394,778	0.26	0.44	0	0	0	1	1
3 year acquisition activity	394,778	0.12	0.27	0	0	0	0	3
Max-min acquisition activity	37,419	0.5	0.47	0	0	0.33	0.67	3
3 year IPO activity	394,778	0.17	0.41	0	0	0	0.33	6
Max-min IPO activity	37,419	0.67	0.83	0	0.33	0.33	0.67	6

Table 1.5. This table displays the results from the estimation of the model in equation 1.2. In columns 1 and 2, the dependent variable is the introduction score, and in columns 3 through 6, the dependent variable is the portfolio score. Panel A presents the estimation within the trademark sample, and Panel B the results from the patent sample. The samples include years in which new trademarks or patents are added to the startup's portfolio and startup-potential acquirer pairs such that the potential acquirer was among the startup's top ten closest potential acquirers at the beginning of the year. *3-year Acq.* and *3-year IPO* are the lagged three-year average of acquisitions and IPOs among startups closely related to the potential acquirer. The *BoY score* is the similarity score between the startup's and the potential acquirer's portfolios at the beginning of the year. Columns 1, 3, and 5 include startup fixed effects and year fixed effects, while columns 2, 4, and 6 include interacted startup-year fixed effects. No other controls are included, and standard errors are clustered at the potential acquirer-year level.

Panel A: Patent						
	Introduction score		Portfolio score			
3-year Acq.	0.177**	0.173***	0.093	−0.553***	0.136***	0.161***
	(0.078)	(0.061)	(0.123)	(0.147)	(0.032)	(0.026)
3-year IPO	0.225***	−0.236***	−0.510***	−1.657***	0.486***	0.286***
	(0.067)	(0.041)	(0.109)	(0.159)	(0.046)	(0.041)
BoY score					0.851***	0.849***
					(0.008)	(0.009)
Startup & year FE	Yes	No	Yes	No	Yes	No
Startup-year FE	No	Yes	No	Yes	No	Yes
Observations	347,690	347,690	347,690	347,690	347,690	347,690
Adjusted R^2	0.485	0.812	0.412	0.408	0.965	0.972
Panel B: Trademark						
	Introduction score		Portfolio score			
3-year Acq.	1.322***	1.102***	0.037	−0.250	0.093	0.080
	(0.111)	(0.107)	(0.188)	(0.161)	(0.121)	(0.065)
3-year IPO	0.632***	0.424***	−0.253***	−0.730***	0.256***	0.205***
	(0.166)	(0.126)	(0.077)	(0.142)	(0.082)	(0.046)
BoY score					0.848***	0.889***
					(0.005)	(0.004)
Startup & year FE	Yes	No	Yes	No	Yes	No
Startup-year FE	No	Yes	No	Yes	No	Yes
Observations	394,778	394,778	394,778	394,778	394,778	394,778
Adjusted R^2	0.440	0.681	0.347	0.395	0.874	0.951

Note: *p<0.1; **p<0.05; ***p<0.01

Table 1.6. This table displays the results from the estimation of the model in equation 1.3 using the patent data sample. The dependent variable in panel A is the introduction score, and in panels B and C, the portfolio score is the dependent variable. Each cohort consists of firms with patent applications before and after the cohort-specific implementation year of the Prudent Person Rules, both in the "treated" and control groups. *PPR* is a dummy equal to one if the startup is located in a state that implemented the PPR, and *Post* is a dummy equal to one if the observation is after the implementation year. The *BoY score* is the similarity score between the startup's and the potential acquirer's portfolios at the beginning of the year. All columns include separate startup and year fixed effects, while columns 3 and 4 also include interacted potential acquirer-year fixed effects. In odd-numbered columns, the inclusion criterion into the control group is based on a five-year window around the cohort PPR event year. In even-numbered colums, the criterium is seven years. No other controls are included, and standard errors are clustered at the state-year level.

Panel A: Patent introduction				
	Introduction score			
Post·PPR	-0.601^{***}	-0.509^{**}	-0.287	-0.297
	(0.224)	(0.230)	(0.278)	(0.304)
Startup & year FE	Yes	Yes	Yes	Yes
Acquirer-year FE	No	No	Yes	Yes
Observations	468,301	401,553	468,301	401,553
Adjusted R^2	0.558	0.568	0.610	0.615
Panel B: Patent portfolio				
	Portfolio score			
Post·PPR	-0.229^{*}	-0.197	-0.005	-0.194
	(0.128)	(0.132)	(0.209)	(0.226)
Startup & year FE	Yes	Yes	Yes	Yes
Acquirer-year FE	No	No	Yes	Yes
Observations	468,301	401,553	468,301	401,553
Adjusted R^2	0.363	0.374	0.515	0.522
Panel C: Patent change in portfolio				
	Portfolio score			
Post·PPR	-0.035	-0.047	0.011	-0.029
	(0.061)	(0.063)	(0.070)	(0.073)
BoY Score	0.861^{***}	0.860^{***}	0.877^{***}	0.877^{***}
	(0.004)	(0.005)	(0.004)	(0.005)
Startup & year FE	Yes	Yes	Yes	Yes
Acquirer-year FE	No	No	Yes	Yes
Observations	468,301	401,553	468,301	401,553
Adjusted R^2	0.972	0.972	0.984	0.984
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table 1.7. This table displays the results from the estimation of the model in equation 1.3 using the trademark data sample. The dependent variable in panel A is the introduction score, and in panels B and C, the portfolio score is the dependent variable. Each cohort consists of firms with trademark introductions before and after the cohort-specific implementation year of the Prudent Person Rules, both in the "treated" and control groups. *PPR* is a dummy equal to one if the startup is located in a state that implemented the PPR, and *Post* is a dummy equal to one if the observation is after the implementation year. The *BoY score* is the similarity score between the startup's and the potential acquirer's portfolios at the beginning of the year. All columns include separate startup and year fixed effects, while columns 3 and 4 also include interacted potential acquirer-year fixed effects. In odd-numbered columns, the inclusion criterion into the control group is based on a five-year window around the cohort PPR event year. In even-numbered colums, the criterium is seven years. No other controls are included, and standard errors are clustered at the state-year level.

Panel A: Trademark introduction				
	Introduction score			
Post·PPR	-0.902^{***}	-1.042^{***}	-1.126^{**}	-1.208^{**}
	(0.348)	(0.368)	(0.537)	(0.534)
Startup & year FE	Yes	Yes	Yes	Yes
Acquirer-year FE	No	No	Yes	Yes
Observations	521,669	411,201	521,669	411,201
Adjusted R^2	0.418	0.405	0.523	0.521
Panel B: Trademark portfolio				
	Portfolio score			
Post·PPR	-0.359	-0.418^{*}	-0.182	-0.468
	(0.222)	(0.224)	(0.338)	(0.303)
Startup & year FE	Yes	Yes	Yes	Yes
Acquirer-year FE	No	No	Yes	Yes
Observations	521,669	411,201	521,669	411,201
Adjusted R^2	0.284	0.281	0.488	0.476
Panel C: Trademark change in portfolio				
	Portfolio score			
Post·PPR	-0.030	-0.093	-0.125	-0.316
	(0.192)	(0.198)	(0.343)	(0.269)
BoY Score	0.880^{***}	0.881^{***}	0.871^{***}	0.875^{***}
	(0.002)	(0.002)	(0.004)	(0.005)
Startup & year FE	Yes	Yes	Yes	Yes
Acquirer-year FE	No	No	Yes	Yes
Observations	521,669	411,201	521,669	411,201
Adjusted R^2	0.907	0.906	0.927	0.928
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table 1.8. This table displays the results from the estimation of the model in equation 1.4 using the patent data sample. The dependent variable in columns 1 and 2 is the introduction score, and in columns 3 through 6, the portfolio score is the dependent variable. Each cohort consists of firms with patent applications before and after the cohort-specific implementation year of the Prudent Person Rules, both in the "treated" and control groups. *PPR* is a dummy equal to one if the startup is located in a state that implemented the PPR, and *Post* is a dummy equal to one if the observation is after the implementation year. *3-year Acq.* and *3-year IPO* are the lagged three-year average of acquisitions and IPOs among startups closely related to the potential acquirer. The *BoY score* is the similarity score between the startup's and the potential acquirer's portfolios at the beginning of the year. All columns include interacted startup-year fixed effects and interacted potential acquirer-year fixed effects. In odd-numbered columns, the inclusion criterion into the control group is based on a five-year window around the cohort PPR event year. In even-numbered colums, the criterium is seven years. No other controls are included, and standard errors are clustered at the state-year level.

Patent						
	Introduction score		Portfolio score			
PPR·3-year Acq.	−0.030	−0.044	−0.046	−0.049	0.220	0.122
	(0.169)	(0.162)	(0.610)	(0.613)	(0.138)	(0.139)
PPR·3-year IPO	−0.005	−0.022	0.239	0.315	−0.068	−0.059
	(0.091)	(0.092)	(0.276)	(0.288)	(0.100)	(0.099)
PPR·Post·3-year Acq.	-0.391^{*}	-0.393^{*}	-1.496^{**}	-1.444^{**}	−0.237	−0.131
	(0.208)	(0.202)	(0.722)	(0.724)	(0.148)	(0.151)
PPR·Post·3-year IPO	−0.017	−0.010	0.129	−0.082	0.095	0.095
	(0.121)	(0.126)	(0.412)	(0.429)	(0.107)	(0.108)
BoY score					0.888^{***}	0.888^{***}
					(0.003)	(0.004)
Startup-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Acquirer-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort window	5	7	5	7	5	7
Observations	468,301	401,553	468,301	401,553	468,301	401,553
Adjusted R^2	0.909	0.914	0.496	0.504	0.988	0.988

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 1.9. This table displays the results from the estimation of the model in equation 1.4 using the trademark data sample. The dependent variable in columns 1 and 2 is the introduction score, and in columns 3 through 6, the portfolio score is the dependent variable. Each cohort consists of firms with trademark introductions before and after the cohort-specific implementation year of the Prudent Person Rules, both in the "treated" and control groups. *PPR* is a dummy equal to one if the startup is located in a state that implemented the PPR, and *Post* is a dummy equal to one if the observation is after the implementation year. *3-year Acq.* and *3-year IPO* are the lagged three-year average of acquisitions and IPOs among startups closely related to the potential acquirer. The *BoY score* is the similarity score between the startup's and the potential acquirer's portfolios at the beginning of the year. All columns include interacted startup-year fixed effects and interacted potential acquirer-year fixed effects. In odd-numbered columns, the inclusion criterion into the control group is based on a five-year window around the cohort PPR event year. In even-numbered colums, the criterium is seven years. No other controls are included, and standard errors are clustered at the state-year level.

Trademark						
	Introduction score		Portfolio score			
PPR·3-year Acq.	−0.063	−0.249	−0.633	−0.581	−0.226	−0.295
	(0.616)	(0.651)	(0.504)	(0.525)	(0.216)	(0.233)
PPR·3-year IPO	0.414**	0.456***	0.417***	0.473***	0.019	0.057
	(0.162)	(0.170)	(0.155)	(0.166)	(0.061)	(0.067)
PPR·Post·3-year Acq.	0.017	0.580	0.936	1.284*	0.320	0.492*
	(0.728)	(0.774)	(0.641)	(0.669)	(0.240)	(0.259)
PPR·Post·3-year IPO	−0.374	−0.539**	−0.489**	−0.465	0.023	0.028
	(0.235)	(0.262)	(0.246)	(0.284)	(0.081)	(0.090)
BoY score					0.908***	0.910***
					(0.002)	(0.002)
Startup-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Acquirer-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort window	5	7	5	7	5	7
Observations	521,669	411,201	521,669	411,201	521,669	411,201
Adjusted R^2	0.755	0.753	0.490	0.474	0.974	0.974

Note: *p<0.1; **p<0.05; ***p<0.01

1.A1 Appendix: Additional tables

This appendix includes supplementary tables to table 1.5. All results presented in this section display different estimation results of the model in equation 1.2, but varying the inclusion of the explanatory variables and the fixed effects. Table 1.10 presents results using the patent sample data, while table 1.11 is estimated using the trademark sample data.

Table 1.10. This table displays the results from the estimation of the model in equation 1.2 using the patent sample to complement the results in table 1.5. The sample includes years in which new patents are added to the startup's portfolio and startup-potential acquirer pairs such that the potential acquirer was among the startup's top ten closest potential acquirers at the beginning of the year. *3-year Acq.* and *3-year IPO* are the lagged three-year average of acquisitions and IPOs among startups closely related to the potential acquirer. The *BoY score* is the similarity score between the startup's and the potential acquirer's portfolios at the beginning of the year. Columns 1 through 3 include startup fixed effects and year fixed effects, while columns 4 through 6 include interacted startup-year fixed effects. No other controls are included, and standard errors are clustered at the potential acquirer-year level.

Patent						
	Introduction score					
3-year Acq.	0.259***		0.177**	0.087		0.173***
	(0.078)		(0.078)	(0.055)		(0.061)
3-year IPO		0.269***	0.225***		−0.188***	−0.236***
		(0.063)	(0.067)		(0.037)	(0.041)
Observations	347,690	347,690	347,690	347,690	347,690	347,690
Adjusted R^2	0.485	0.485	0.485	0.812	0.812	0.812
	Portfolio score					
3-year Acq.	−0.094		0.093	−1.162***		−0.553***
	(0.107)		(0.123)	(0.170)		(0.147)
3-year IPO		−0.487***	−0.510***		−1.810***	−1.657***
		(0.103)	(0.109)		(0.167)	(0.159)
Observations	347,690	347,690	347,690	347,690	347,690	347,690
Adjusted R^2	0.411	0.412	0.412	0.406	0.408	0.408
	Portfolio score					
3-year Acq.	0.313***		0.136***	0.265***		0.161***
	(0.040)		(0.032)	(0.026)		(0.026)
3-year IPO		0.520***	0.486***		0.331***	0.286***
		(0.046)	(0.046)		(0.038)	(0.041)
BoY Score	0.850***	0.851***	0.851***	0.848***	0.849***	0.849***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
Observations	347,690	347,690	347,690	347,690	347,690	347,690
Adjusted R^2	0.485	0.485	0.485	0.812	0.812	0.812
Startup & year FE	Yes	Yes	Yes	No	No	No
Startup-year FE	No	No	No	Yes	Yes	Yes

Note: *p<0.1; **p<0.05; ***p<0.01

Table 1.11. This table displays the results from the estimation of the model in equation 1.2 using the trademark sample to complement the results in table 1.5. The sample includes years in which new goods and services are added to the startup's portfolio and startup-potential acquirer pairs such that the potential acquirer was among the startup's top ten closest potential acquirers at the beginning of the year. *3-year Acq.* and *3-year IPO* are the lagged three-year average of acquisitions and IPOs among startups closely related to the potential acquirer. The *BoY score* is the similarity score between the startup's and the potential acquirer's portfolios at the beginning of the year. Columns 1 through 3 include startup fixed effects and year fixed effects, while columns 4 through 6 include interacted startup-year fixed effects. No other controls are included, and standard errors are clustered at the potential acquirer-year level.

Trademark						
	Introduction score					
3-year Acq.	1.537***		1.322***	1.246***		1.102***
	(0.119)		(0.111)	(0.121)		(0.107)
3-year IPO		0.829***	0.632***		0.592***	0.424***
		(0.169)	(0.166)		(0.132)	(0.126)
Observations	394,778	394,778	394,778	394,778	394,778	394,778
Adjusted R^2	0.439	0.439	0.440	0.681	0.681	0.681
	Portfolio score					
3-year Acq.	−0.050		0.037	−0.498***		−0.250
	(0.206)		(0.188)	(0.189)		(0.161)
3-year IPO		−0.247***	−0.253***		−0.768***	−0.730***
		(0.087)	(0.077)		(0.142)	(0.142)
Observations	394,778	394,778	394,778	394,778	394,778	394,778
Adjusted R^2	0.347	0.347	0.347	0.395	0.395	0.395
	Portfolio score					
3-year Acq.	0.180		0.093	0.150***		0.080
	(0.119)		(0.121)	(0.058)		(0.065)
3-year IPO		0.270***	0.256***		0.217***	0.205***
		(0.091)	(0.082)		(0.048)	(0.046)
BoY Score	0.848***	0.848***	0.848***	0.889***	0.889***	0.889***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Observations	394,778	394,778	394,778	394,778	394,778	394,778
Adjusted R^2	0.874	0.874	0.874	0.951	0.951	0.951
Startup & year FE	Yes	Yes	Yes	No	No	No
Startup-year FE	No	No	No	Yes	Yes	Yes
Note:						*p<0.1; **p<0.05; ***p<0.01

1.A2 Appendix: Cohort construction

Appendix table 1.12 shows the timing of implementation across all states used for the construction of the cohort data. However, not all states are ultimately included in the cohort samples, as more constraints are imposed. For a state to be included, there must exists a VC-financed firm with new patents or goods and services in the five years prior to the cohort-event year, *and* in the five years following the cohort-event year. Such firms must exists in both the state that implemented the regulation, and in other states that have not implemented the regulation in the five/seven years prior to the cohort-event year, nor in the five/seven years after. Tables 1.13 and 1.14 shows which states are ultimately represented in the subgroups of each cohort in the patent and trademark sample. The two tables implement the less strict five-year cohort window. When a longer window is imposed (e.g., seven years), the set of states eligible for inclusion in the control group decreases. One firm-observation can be included in multiple cohorts. For example, firm A located in Arizona with patent applications in 1990 and 1995 can be included in the control group of both the 1992 and 1993 cohorts. For this reason, the firm-fixed effects are interacted with cohort indicators, effectively creating firm-cohort fixed effects.

Table 1.12. This table displays the timing of the implementation of the Prudent Person Rule (PPR) across different states.

Year	**States**
1992	Illinois
1993	Florida
1995	California, Colorado, New Mexico, New York, Oklahoma, Washington
1996	Minnesota, Rhode Island, West Virginia
1997	Connecticut, Hawaii, Idaho, New Jersey
1998	Alaska, Massachusetts, Michigan
1999	Indiana, Iowa, Pennsylvania, Virginia
2000	Kansas
2001	Arkansas
2002	Tennessee
2003	Nebraska, Nevada, Texas, Wyoming
2004	District of Columbia, Maine, Missouri, New Hampshire, Utah, Virgin Islands, Wisconsin
2005	North Carolina, Oregon, South Carolina
2006	Alabama, Mississippi, Ohio
2007	North Dakota
2008	Arizona
2009	Vermont
2013	Montana

Table 1.13. This table presents the states represented in the subgroups of each cohort in the patent sample. The cohort window applied is five years, which is the less strict implementation.

Cohort	**Treated**	**Control**
1992	Illinois	Arizona, Georgia, Indiana, Louisiana, Maine, Maryland, Massachusetts, Michigan, Montana, North Carolina, Ohio, Oregon, Pennsylvania, Texas, Virginia, Wisconsin
1993	Florida	Arizona, Georgia, Indiana, Maryland, Montana, Nevada, North Carolina, Ohio, Oregon, Pennsylvania, Texas, Utah, Virginia, Wisconsin
1995	California, Colorado, New Mexico, New York, Washington	Arizona, Delaware, Georgia, Louisiana, Maine, Maryland, Montana, New Hampshire, North Carolina, North Dakota, Ohio, Oregon, Tennessee, Texas, Utah, Wisconsin
1996	Minnesota, Rhode Island	Arizona, Delaware, Georgia, Maryland, Montana, North Carolina, Ohio, Oregon, Tennessee, Texas, Utah, Wisconsin
1997	Connecticut, Idaho, New Jersey	Alabama, Arizona, Delaware, District of Columbia, Georgia, Louisiana, Maine, Maryland, Missouri, Montana, New Hampshire, North Carolina, Ohio, Oregon, Texas, Utah, Wisconsin
1998	Massachusetts, Michigan	Alabama, Arizona, Delaware, District of Columbia, Georgia, Illinois, Louisiana, Maine, Maryland, Missouri, Montana, New Hampshire, North Carolina, Ohio, Oregon, Utah, Wisconsin
1999	Indiana, Iowa, Pennsylvania, Virginia	Alabama, Arizona, Delaware, Florida, Georgia, Illinois, Maryland, Montana, North Carolina, Ohio, Oregon
2002	Tennessee	Arizona, California, Colorado, Delaware, Florida, Georgia, Illinois, Kentucky, Maryland, Minnesota, New York, Washington
2003	Nebraska, Nevada, Texas	California, Colorado, Connecticut, Delaware, Florida, Georgia, Illinois, Kentucky, Louisiana, Maryland, Minnesota, Montana, New Jersey, New Mexico, New York, Oklahoma, Vermont, Washington
2004	District of Columbia, Maine, Missouri, New Hampshire, Utah, Wisconsin	California, Colorado, Connecticut, Delaware, Florida, Georgia, Illinois, Louisiana, Maryland, Massachusetts, Michigan, Minnesota, Montana, New Jersey, New Mexico, New York, Oklahoma, Washington
2005	North Carolina, Oregon	California, Colorado, Connecticut, Delaware, Florida, Georgia, Hawaii, Illinois, Indiana, Iowa, Kentucky, Louisiana, Maryland, Massachusetts, Michigan, Minnesota, Montana, New Jersey, New Mexico, New York, Oklahoma, Pennsylvania, Rhode Island, Virginia, Washington
2006	Alabama, Mississippi, Ohio	California, Colorado, Connecticut, Delaware, Florida, Georgia, Hawaii, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Maryland, Massachusetts, Michigan, Minnesota, Montana, New Jersey, New Mexico, New York, Oklahoma, Pennsylvania, Rhode Island, Virginia, Washington, West Virginia
2008	Arizona	California, Colorado, Connecticut, Florida, Georgia, Hawaii, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Maryland, Massachusetts, Michigan, Minnesota, New Jersey, New Mexico, New York, Oklahoma, Pennsylvania, Rhode Island, Tennessee, Virginia, Washington, West Virginia
2009	Vermont	California, Colorado, Connecticut, Florida, Georgia, Idaho, Illinois, Indiana, Louisiana, Maryland, Massachusetts, Michigan, Minnesota, New Jersey, New York, Pennsylvania, Rhode Island, Texas, Virginia, Washington
2013	Montana	Alabama, Arkansas, California, Colorado, Connecticut, Florida, Georgia, Idaho, Illinois, Indiana, Louisiana, Maryland, Massachusetts, Michigan, Minnesota, Nevada, New Hampshire, New Jersey, New York, North Carolina, Ohio, Oregon, Pennsylvania, Rhode Island, Texas, Virginia, Washington, Wisconsin

Table 1.14. This table presents the states represented in the subgroups of each cohort in the trademark sample. The cohort window applied is five years, which is the less strict implementation.

Cohort	Treated	Control
1992	Illinois	Arizona, Delaware, Georgia, Indiana, Kansas, Kentucky, Maine, Maryland, Massachusetts, Michigan, Missouri, Nebraska, New Hampshire, North Carolina, Ohio, Oregon, Pennsylvania, Tennessee, Texas, Utah, Vermont, Virginia, Wisconsin
1993	Florida	Alabama, Arizona, Delaware, Georgia, Indiana, Kentucky, Maine, Maryland, Missouri, Nebraska, New Hampshire, North Carolina, Ohio, Oregon, Pennsylvania, Tennessee, Texas, Vermont, Virginia, Wisconsin
1995	California, Colorado, New York, Washington	Alabama, Arizona, Delaware, Georgia, Kentucky, Maine, Maryland, Missouri, Nebraska, Nevada, New Hampshire, North Carolina, Ohio, Oregon, Tennessee, Texas, Utah, Vermont, Wisconsin
1996	Minnesota	Alabama, Arizona, Delaware, Georgia, Kentucky, Maine, Maryland, Missouri, Nebraska, Nevada, New Hampshire, North Carolina, Ohio, Oregon, Tennessee, Texas, Utah, Vermont, Wisconsin
1997	Connecticut, Idaho, New Jersey	Alabama, Arizona, Delaware, Georgia, Kentucky, Maine, Maryland, Missouri, Nebraska, Nevada, New Hampshire, North Carolina, Ohio, Oregon, Texas, Utah, Vermont, Wisconsin
1998	Massachusetts, Michigan	Alabama, Arizona, Delaware, District of Columbia, Georgia, Illinois, Kentucky, Maine, Maryland, Missouri, New Hampshire, North Carolina, Ohio, Oregon, Utah, Vermont, Wisconsin
1999	Indiana, Iowa, Pennsylvania, Virginia	Alabama, Arizona, Delaware, Florida, Georgia, Illinois, Kentucky, Louisiana, Maryland, North Carolina, Ohio, Oregon, South Carolina, Vermont
2000	Kansas	Alabama, Arizona, Delaware, Florida, Georgia, Illinois, Kentucky, Maryland, Ohio, Vermont
2002	Tennessee	Arizona, California, Colorado, Delaware, Florida, Georgia, Illinois, Kentucky, Louisiana, Maryland, Minnesota, Montana, New Mexico, New York, Oklahoma, Rhode Island, Vermont, Washington
2003	Nebraska, Nevada, Texas	California, Colorado, Connecticut, Delaware, Florida, Georgia, Illinois, Kentucky, Louisiana, Maryland, Minnesota, Montana, New Jersey, New Mexico, New York, Oklahoma, Rhode Island, Vermont, Washington
2004	District of Columbia, Maine, Missouri, New Hampshire, Utah, Wisconsin	California, Colorado, Connecticut, Delaware, Florida, Georgia, Hawaii, Illinois, Kentucky, Louisiana, Maryland, Massachusetts, Michigan, Minnesota, New Jersey, New Mexico, New York, Oklahoma, Rhode Island, Washington
2005	North Carolina, Oregon, South Carolina	California, Colorado, Connecticut, Delaware, Florida, Georgia, Hawaii, Illinois, Indiana, Iowa, Kentucky, Louisiana, Maryland, Massachusetts, Michigan, Minnesota, New Jersey, New Mexico, New York, Oklahoma, Pennsylvania, Rhode Island, Virginia, Washington
2006	Alabama, Ohio	California, Colorado, Connecticut, Delaware, Florida, Georgia, Hawaii, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Maryland, Massachusetts, Michigan, Minnesota, New Jersey, New York, Oklahoma, Pennsylvania, Rhode Island, Virginia, Washington
2008	Arizona	Arkansas, California, Colorado, Connecticut, Delaware, Florida, Georgia, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Maryland, Massachusetts, Michigan, Minnesota, New Jersey, New Mexico, New York, Oklahoma, Pennsylvania, Rhode Island, Tennessee, Virginia, Washington
2009	Vermont	Arkansas, California, Colorado, Connecticut, Delaware, Florida, Georgia, Idaho, Illinois, Indiana, Kentucky, Louisiana, Maryland, Massachusetts, Michigan, Minnesota, Nevada, New Jersey, New York, Oklahoma, Pennsylvania, Rhode Island, Tennessee, Texas, Virginia, Washington

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Chapter 2

Capital market competition and startup catering incentives

Abstract

This paper outlines a tractable empirical framework to illustrate the role of capital market supply in shaping startups' innovation trajectories. Startups cater to potential acquirers to increase the expected value in the event of an acquisition. The incentive to engage in catering activities increases as capital becomes more scarce. The model illustrates how changes in capital scarcity can cause startup innovations to become more similar to incumbent firms' assets. The only friction in the model operates through the relative capital supply—the cost of delay represents search costs, and the costs associated with finding an investor or investments map directly to the relative capital supply.

This chapter is complementary to the first chapter of this thesis. This chapter were formerly part of an earlier version of the article titled "The Acquisition Option and Startup Innovations." This earlier version now constitute the basis for the two first chapters of this thesis.

2.1. Introduction

Exceptionally high levels of risk and immense uncertainty are distinguishing features of many startup investments. In addition, information asymmetries and agency frictions characterize the entrepreneur-investor relationship. Venture capital (VC) is an established source of startup financing specialized in addressing the conditions constraining other intermediaries from entering this market, and previous literature has documented VC's importance in the commercialization of novel innovations (e.g., Kortum and Lerner, 2000; Samila and Sorenson, 2011). However, the venture capital market is cyclical (e.g., Gompers and Lerner, 2004; Kaplan and Schoar, 2005).

Investment cycles are a key determinant of both the quantity of innovation and the nature of innovations. Brown et al. (2009) empirically document this in the larger economy, arguing that the R&D boom in the mid-90s to the mid-2000s was primarily finance-driven, and Chava et al. (2013) and Cornaggia et al. (2015) document an increase in small firm innovation output following an increase in banking competition. Nanda and Rhodes-Kropf (2013) show that startups founded in "hot VC markets" are associated with a higher risk of failure but also with higher valuations and higher quantity and quality of patent output. Moreover, they argue that hot financial markets lower the cost of experimentation for investors, enabling VCs to fund more experimental ventures. They provide the theoretical intuition for this finding in Nanda and Rhodes-Kropf (2017); financing risk is lower when capital is abundant, disproportionately impacting startups with the greatest real option value—the startups with the most radical innovation strategies.

Changes in the demand and supply of startup financing have thus received much attention in both the empirical and theoretical literature. These fluctuations have been shown to have a first-order impact on startup activity and innovation output. This paper aims to add to this literature by focusing on another key feature of the VC business model—the importance of the exit—and how exit markets interact with competition in VC markets to shape the startups' optimal innovation path. This paper introduces a simple theoretical framework modeling how startups' incentives to innovate in a less independent direction are affected by exit market expectations. The analysis focuses on the startup's decision to adjust its innovation strategy to accommodate catering incentives by redirecting effort toward innovation activities complementary to potential acquirers. By catering, the value of the startup as an acquired entity increases. An increase in the acquisition option benefits the current owners of the startup in three ways: i) in the event of an acquisition, the owners fully enjoy the increase in the value of the startup as an acquired entity; ii) the bargaining position of the firm owners vis-à-vis external investors improve and the current owners expect to retain a larger share of the surplus following future external financing rounds; and iii) if multiple external financing rounds are needed, the firm will benefit from an increase in the expected value of the firm.

Incumbents have a disincentive to innovate in a direction that cannibalizes their market share and make their assets obsolete (e.g., Arrow, 1962), creating a key economic role for new firm entry in driving technological advancements and growth (e.g., Schumpeter, 1942). When a startup anticipates an acquisition, its innovation incentives should align with the potential acquirer to maximize its expected exit value. The direction of innovations should change to become more complementary to the incumbents' assets. The startup firm incorporates the potential acquirers' disincentive to innovate if the relative importance of an exit by acquisition increases. Conversely, the startups' innovation strategy should be less directed toward existing assets in the market if the relative expected value of staying independent and possibly going public increases. However, new firms, both firms anticipating an exit through acquisition and firms that remain independent, have incentives to cater, but the trade-off depends on market characteristics. The types of innovations that eventually reach the market become, on aggregate, more similar to incumbents' assets when firms strategically cater.

The catering motive influences the innovation strategy of startup firms, and the relative supply of VC determines to what extent the catering motives influence the innovation strategy of startups. Firms innovate more in the direction of more attractive acquisition markets. However, the incentive to cater to prospective acquirers is weaker when the capital supply is high. When capital supply, or equivalently competition in the VC markets, is higher, firms can raise capital more readily and at more favorable terms, increasing the relative value of staying independent. The innovating firm faces a trade-off between maximizing the value as an independent firm or as an acquired entity. The extent to which startup firms cater to potential acquirers depends on VC market competition.

The theoretical framework formalizes this economic mechanism, building on a model of search commonly used in the labor literature and applied to the startup and VC market by Inderst and Müller (2004) and Michelacci and Suarez (2004).[1] This type of model is applied to a setting with the explicit purpose of illustrating how acquisition markets and VC markets jointly shape the startup firms' innovation incentives by introducing two possible exit paths and a decision on the direction of innovation by the startup firms' owners. The only friction in the model is imperfect competition in (VC) capital markets. The objective is to capture the influence of capital market characteristics on startups' *incentives to cater*.

One insight from the model is that complementary innovations benefit the current owners of the startup in the event of acquisition and through an improved bargaining position when raising additional external capital. A decrease (increase) in capital supply increases (decreases) the incentive to cater to potential acquirers through two channels. First, an exit through an acquisition becomes relatively more (less) attractive as the expected

[1]See, e.g., Pissarides (2000) for applications of search models in the labor literature.

value of staying independent decreases (increases). Second, the startup's owners' incentive to improve their bargaining position increases (decreases).

The model suggests that startups would engage less in catering activities following an exogenous increase in VC inflows. This prediction applies to changes in the innovation strategy within firms. When adjustment costs are higher, firms are more likely to respond stronger to exogenous shifts in capital market competition. Similarly, more mature firms or firms more likely to successfully realize the firm's value as an independent entity would also respond stronger to such an exogenous change, all else equal. Warg (2022) provide evidence supporting this empirical prediction.

Using the staggered implementation of the Prudent Person Rule across US states, which led to an increase in inflows to VC funds from local state pension funds, Warg (2022) shows that startup innovations become less similar to incumbent firms' assets. Particularly, firms commercialized innovations become more distinct from potential acquirers' products. However, startups decrease their technological overlap with assets associated with more attractive acquisition markets, suggesting that the catering objective becomes less important as a determinant of startups' innovation trajectories. Wang (2018) provides evidence that startups cater more to incumbent firms in more attractive acquisition markets, specifically when the potential acquirers' market is larger and more fragmented. The predictions in this paper suggest that when firms are less financially constrained—when capital is abundant—this catering motive becomes less influential. Moraga-González et al. (2021) develop a model to study how startups strategically cater to incumbents to increase expected acquisition rents and the implications on social welfare. The model in this paper is silent about any welfare implications, and the implications on aggregate innovation output as entrepreneurial entry and VC inflows adjust. Instead, this paper documents the role of financial markets in shaping these incentives and highlights a mechanism through which lack of, or abundance of, VC capital can shape the trajectory of startup innovations. Empirically, catering objectives can be challenging to distinguish from other characteristics of firms' innovation output. For example, previous literature often equates high similarity, and technological overlap, as more marginal or incremental innovation output.

A key assumption of the model is that startups can take action to enhance the strategic value of the startup in the event of an acquisition. Previous literature suggests mergers are primarily motivated by complementarities; asset complementarities determine the incidence and value of acquisition (e.g., Rhodes-Kropf and Robinson, 2008) and the property rights theory suggests these synergies are most effectively realized when assets are under shared control (e.g., Grossman and Hart, 1986; Hart and Moore, 1990). The property rights theory can also motivate the adjustment costs; however, it is sufficient to assume that by directing effort to acquisition-enhancing activities, less effort is dedicated to maximizing the firm's value as a stand-alone entity.

This paper also makes two predictions related to changes in the cost of experimentation. A decrease in the cost of experimentation is often associated with increased entrepreneurial entry; given lower set-up costs, more entrepreneurs can reach the initial milestones required before searching for external capital. Within the model framework, this corresponds to a higher new firm inflow and, consequently, more demand for VC capital and decreased VC competition. Less VC competition corresponds to an increase in the existing firms' incentives to cater to potential acquirers.

However, a decrease in the cost of experimentation can also be interpreted as firms, on average, being more mature conditional on receiving an initial investment. Within the framework outlined in this paper, such a change corresponds to a higher probability of succeeding as an independent entity conditional on receiving the investment. Such a change in the cost of experimentation would lead to weaker incentives to cater to potential acquirers. These contradictory findings highlight that, on the one hand, a decrease in the cost of experimentation could put more emphasis on the catering incentive—leading startups to produce more similar innovations. On the other hand, it suggests that startups are less inclined to cater to potential acquirers if a decrease in the cost of experimentation is associated with less capital required to reach maturity. Ultimately, it is an empirical question of which effect dominates.

The remainder of the paper are organized as follows: section 2.2 introduces the model frameworks and the key ingredients. Section 2.3 outlines the equilibrium concept and the key predictions, while section 2.4 discusses the empirical predictions, focusing on changes in capital market competition and changes to the cost of experimentation. Section 2.5 concludes.

2.2. Model set-up

The model builds on a search market framework commonly known as the Diamond-Mortensen-Pissarides model (e.g., Pissarides, 2000) with startups searching for an investor. An innovation choice, how much innovation efforts to direct toward complementary innovations, is embedded into the model with two plausible exit markets; an exit through an acquisition or an exit as an independent company (e.g., IPO). Startup firms and investors, potential acquirers' arrivals and behavior, like the firms' probability of success, is exogenously given. As such, all exit parameters are exogenously determined. Time is continuous, and the discount rate is $r > 0$. The discount rate is common across all investors, including investors searching for investments, those already invested, and any other current startup owners (e.g., founders). Search frictions are thus represented by the cost of delay. The objective is to investigate how competition in VC markets and the characteristics of the two exit markets affect the startups' incentives to engage in complementary innovation activities.

The startup requires (at least) one additional round of financing, an investment of size I, before the current owners can exit the company in an IPO and receive a payoff R_{IPO}. Alternatively, an acquirer arrives and makes an offer $R_A(c)$. The payoff in the event of acquisition is an increasing function of the level of complementarity $c \geq 0$. I assume that R_A is concave and increasing in c, such that $\partial R_A / \partial c > 0$ and $\partial^2 R_A / \partial c^2 < 0$. To ensure that both exit paths are viable, I assume that $\lim_{c \to 0} R_A(c) = \underline{R_A}$ such that $0 \leq \underline{R_A} < \frac{r+\mu}{\mu} R_{IPO}$, and that $\lim_{c \to \infty} R_A(c) = \overline{R_A} < \infty$.[2] Thus, both exit directions are plausible for the startup; however, while an acquirer can arrive at any time during the startup's life, an IPO requires at least one more external financing round.

The startup's current owners (including the founder and prior investors) are making an innovation decision today, anticipating the two exit routes' relative probability and expected value. The decision they make is independent of their current level of innovation output. It is a forward-looking decision and represents how much of the efforts exerted going forward will be focused on catering to the preferences of future potential acquirers. The startup already has a business model, and the arrival rates and exit parameters reflect the startup's inherent characteristics.[3] An increase in complementary innovation efforts increases the expected payoff in an acquisition but lowers the expected payoff in an IPO. I assume the adjustment costs are linear in the magnitude of the adjustment such that the costs incurred are given by κc.

[2] This is to ensure that an investment is valuable to the owners for some investor arrival rate (λ), otherwise raising external capital would be a negative NPV project even if $\lambda \to 0$. The firm will only engage in complementary innovations if this condition does not hold.

[3] Currently, this model assumes that startups are homogenous in this regard. The model could be extended to allow for a distribution of different characteristics. This extension is, however, outside the scope of this paper.

The idea that the startup can take action to improve its value in the event of acquisition is motivated by the extensive literature on mergers and acquisitions. One strand of this literature suggests mergers are primarily motivated by complementarities; asset complementarities determine the incidence and value of acquisition (e.g., Rhodes-Kropf and Robinson, 2008) and the property rights theory suggests these synergies are most effectively realized when assets are under shared control (e.g., Grossman and Hart, 1986; Hart and Moore, 1990). Complementarities arising from innovation activities as determinants of acquisitions have been documented by, e.g., Hoberg and Phillips (2010) and Bena and Li (2014). A different view emphasizes the incumbent firms' incentives to escape competition and increase market power by acquiring new entrants (e.g., Baker and Bresnahan, 1985; Cunningham et al., 2021). The choice variable c represents whatever actions the startup might take that would increase the value of the firm's assets to a potential acquirer, but that would be costly if the firm remains independent. It could involve introducing a new feature to an existing asset that would primarily be valuable when used in conjunction with assets that already are in place among potential acquirers. The startup does not have the resources to develop or acquire such assets and consequently allocates less effort to other, more relevant activities at the startup's current stage.

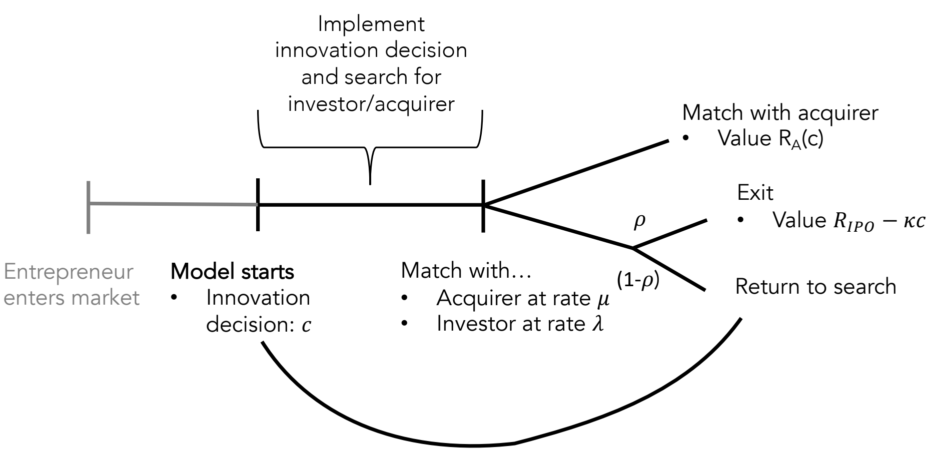

Figure 2.1. Timeline

Figure 2.1 illustrates the sequence of events. During the search stage, there is always some probability that an acquirer or an investor will arrive. An acquirer arrives with a Poisson arrival rate of μ and makes a take-it-or-leave-it-offer to the current owners of $R_A(c)$. The arrival rate is exogenously determined, and not affected by the startup's owners' decision to adjust their innovation strategy.[4] The deal arrival rate is akin to a probability measure. A deal will arrive with a probability $\mu \cdot \Delta$ over the next Δ units of time.

The mass of startups currently searching for an investor is given by M_S, and the mass of investors searching for an investment is given by M_V. I define the capital market tightness measure as $\theta = \frac{M_V}{M_S}$, with a higher value of θ representing a market where capital supply is high relative to capital demand. I model the rate at which a startup and an investor match as $m(M_V, M_S)$, where $m(.)$ is assumed homogeneous of degree one, increasing in both arguments, concave and continuously differentiable. For an investor, the Poisson deal arrival rate is given by $M(\theta) \equiv m(M_V, M_S)/M_V = m(1, \frac{1}{\theta})$ where the equivalence follows from the homogeneity of the matching function. The investors' deal arrival rate thus decreases in the capital market tightness measure θ, indicating that the higher the relative supply of capital (M_V) to the demand for capital (M_S), the more difficult it is for an investor to find an investment. Similarly, the Poisson arrival rate from the perspective of the startup is given by $\lambda = \theta M(\theta) \equiv m(M_V, M_S)/M_S = m(\theta, 1)$ which is strictly increasing in the capital market tightness measure (θ). To ensure an interior equilibrium, I assume that:

$$\begin{aligned} \lim_{\theta \to 0} M(\theta) &= \lim_{\theta \to \infty} \theta M(\theta) = \infty \\ \lim_{\theta \to \infty} M(\theta) &= \lim_{\theta \to 0} \theta M(\theta) = 0 \end{aligned} \tag{2.1}$$

Conditional on matching with an investor, the firm's current owners ("the insiders") will bargain with the external investors ("the outsiders") over how to split the surplus generated by the investment. I assume a generalized Nash bargaining solution with the insiders' and outsiders' bargaining power given by β and $(1-\beta)$, respectively. The parameter $\beta \in (0, 1)$ is exogenously given. After the investment, the firm's owners (including the new investor) find out whether they can exit through an IPO or whether an additional round of financing is required. With a probability ρ, an IPO exit is possible, and with a probability $(1-\rho)$, the startup will need to return to the search market. In practice, the probability ρ is likely to be a function of the startup's life cycle, including its fixed characteristics and time-varying factors internal and external to the firm. For simplicity, I model it as a lottery with an exogenously determined probability distribution. A higher ρ implies the firm is nearer a plausible exit. If the startup finds it will require an additional round of financing, they return to the search stage and will be able to adjust their innovation strategy again.

One feature of this framework is that when the startup receives an investment that results in the startup returning to the search market, the previously external investors

[4] An alternative specification of the model, where μ is increasing in the level of complementarity instead of R_A, yields very similar results. An increase in c would then increase the expected value of an acquisition, as the probability of an acquisition would increase. In the current set-up, the expected value increases in c as the payoff conditional on an acquisition increase.

now become "insiders" and can enjoy the benefits of the acquisition option. Moreover, I abstract from any contracting issues that might arise from conflicts of interest between the startup's founders, earlier investors, and later investors. For simplicity, I assume that the interests of all current startup owners are aligned—to maximize the expected value of the startup—and that the primary trade-off of interest is given by current owners' interests vis-à-vis future external investors' interests. However, an important feature of the model is that the ability to extract surplus when bargaining depends on whether (VC) capital or good investment opportunities are in relatively short supply. A common assumption in the entrepreneurial finance literature is that capital markets are competitive, and the entrepreneur extracts all the surplus. I relax this assumption and allow the (VC) investors' and founders' relative share of the surplus to vary with the capital market tightness measure and study the implications on firms' innovation choice. A similar search market set-up where relative supply affects firm outcomes has been studied by, e.g., Inderst and Müller (2004) and Michelacci and Suarez (2004). Inderst and Müller (2004) theoretically study the role of the capital market tightness measure on pricing, contracting, and value creation, while Michelacci and Suarez (2004) focus on the timing of the exit (through an IPO). Neither considers the implications of this on innovation strategy nor the exit mode.

2.3. Equilibrium

2.3.1. Expected Value in Search Stage

The expected value of the current owners' stake in the startup at the start of the model is given by the discounted value of future payoffs ($Ins^O(c)$) as defined in equation 2.2a. With a probability $\theta M(\theta)\Delta$ an investor arrives over the next Δ units of time, and conditional on matching the expected value of the current owners' stake in the startup after the investment is given by $Ins_I(c)$. Similarly, an acquirer arrives with a probability $\mu\Delta$ and offers $R_A(c)$. By rearranging and taking the limit as $\Delta \longrightarrow 0$, I obtain the expression for the expected value of the startup in equation 2.2b. This is the expected value of the startup of being in the search stage. The expected value is increasing in the arrival rate of an investor θ as well as an acquirer μ, but also in the expected deal values $Ins_I(c)$ and $R_A(c)$.

$$\begin{aligned} Ins^O(c) &= \theta M(\theta)\Delta e^{-r\Delta} \cdot Ins_I(c) \\ &\quad + \mu\Delta e^{-r\Delta} \cdot R_A(c) + \big(1 - (\theta M(\theta) + \mu)\Delta\big)e^{-r\Delta} \cdot Ins^O \end{aligned} \tag{2.2a}$$

$$Ins^O(c) = \frac{\theta M(\theta) \cdot Ins_I(c) + \mu \cdot R_A(c)}{r + \theta M(\theta) + \mu} \tag{2.2b}$$

Similarly, the investors' value of being in the search stage, conditional on expecting to invest I, is given in equation 2.3b where $Out_I(c)$ is the expected value of the new investor's stake in the company post-investment. The searching investors' value of a free unit of capital is clearly increasing in the expected deal utility $Out_I(c)$ but decreasing in the capital market tightness measure as $M(\theta)$ is decreasing in θ.

$$Out^O(c) + I = M(\theta)\Delta e^{-r\Delta} \cdot Out_I(c) + \big(1 - M(\theta))\Delta\big)e^{-r\Delta} \cdot \big(Out^O(c) + I\big) \tag{2.3a}$$

$$Out^O(c) + I = \frac{M(\theta) \cdot Out_I(c)}{r + M(\theta)} \tag{2.3b}$$

2.3.2. Bargaining

The respective expected values conditional on an investment, the deal values, are determined by the bargaining outcome, specifically the solution to the Nash problem given in equation 2.4. If the bargaining breaks down, the investors and current owners realize their outside options.[5] The current owners (the insiders) retain a share $(1 - \alpha)$, and the outsiders obtain a share α.[6] At the time of the bargaining, the investors take the outside options as given. The surplus generated by the investment is given by the expected value

[5]If bargaining breaks down, the expected deal values are zero in equilibrium. The current owners' outside option is given by the expected value of being acquired, while the investors' outside option is zero in equilibrium.

[6]In this paper I never present a formal solution for α, this requires some additional algebra but does not add anything to the analysis.

conditional on the investment net of the respective value of continuing the search. The respective expected deal values can be expressed in terms of the generated surplus as in equations 2.5. Each party's deal value increases in their own outside option (the value in search) but decreases in the other party's outside option.

$$\max_{\alpha}\left(Out_I - (Out^O + I)\right)^{(1-\beta)}\left(Ins_I - Ins^O\right)^{\beta} \quad \text{s.t. } \alpha \in (0,1) \tag{2.4}$$

$$Ins_I(c) = \beta S(c) + Ins^O(c) \tag{2.5a}$$

$$Out_I(c) = (1-\beta)S(c) + Out^O(c) + I \tag{2.5b}$$

$$S(c) = \rho(R_{IPO} - \kappa c - Ins^O(c)) - (Out^O(c) + I) \tag{2.5c}$$

2.3.3. The Innovation Decision

When the startup is in the search state, the owners have the opportunity to adjust their innovation strategy. The current owners of the startup firm choose the level of complementary innovation that maximizes the firm's expected value in the search stage (Ins^O). I assume that the startup is small relative to the total mass of searching startups M_S and therefore does not consider their impact on the equilibrium. Specifically, the firm does not consider the implications their innovation decisions have on the equilibrium value of the investors' outside option Out^O. This is highlighted in equation 2.6 by removing the dependence on c in Out^O.

$$\max_{c>0} Ins^O = \max_{c>0} \frac{\theta M(\theta)\beta\left[\rho(R_{IPO} - \kappa c) - (Out^O + I)\right]}{r + \beta\rho\theta M(\theta) + \mu} + \frac{\mu R_A(c)}{r + \beta\rho\theta M(\theta) + \mu} \tag{2.6}$$

The expression in equation 2.6 is obtained by substituting equations 2.5a and 2.5c into equation 2.2b and solving for the expected value of the startup. The current owners benefit from a higher level of complementarity c in three ways. If an acquirer arrives with a deal, the owners enjoy the full benefit of the higher acquisition offer $R_A(c)$ but do not have to bear the costs. Related but somewhat different, the owners also enjoy (part of) the benefit from the increase in the expected value of the startup firm conditional on an investment and returning to the search market. Lastly, when matching with an investor, the owners increase the value of their outside option and thus retain a larger share of the generated surplus but do not have to bear the full costs incurred in the event of an IPO.

$$\frac{\partial R_A(c^*)}{\partial c} = \kappa\beta\rho\frac{\theta M(\theta)}{\mu} \tag{2.7}$$

The optimal level of complementary innovation (c^*) satisfies the first-order condition in equation 2.7. The left-hand side decreases in the level of complementarity, while the right-hand side is determined by exogenously given variables and is strictly positive. If the right-hand side is too large, e.g., if the costs κ are too high, the capital market tightness measure is very large, or the arrival rate of an acquirer is low, then the optimal level of complementarity goes to zero or is equal to zero.[7] However, if the right-hand side is very small, then the optimal level of complementarity goes to infinity. Under the assumption that all parameters are well-defined, the program in equation 2.6 has a unique solution.

Proposition 1 (Optimal level of complementarity) *The optimal level of complementarity c^* satisfies*

$$\frac{\partial R_A(c^*)}{\partial c} = \begin{cases} \kappa\beta\rho\frac{\theta M(\theta)}{\mu} & \text{if } \kappa\beta\rho\frac{\theta M(\theta)}{\mu} < \frac{\partial R_A(0)}{\partial c} \\ \frac{\partial R_A(0)}{\partial c} & \text{otherwise} \end{cases}$$

This implies that complementarity increases in the arrival rate of an acquirer μ and decreases in the capital market tightness measure, as well as in the probability of an IPO conditional on receiving an investment ρ, the bargaining power of the entrepreneur β and the costs incurred in the event of an exit by IPO. As such:

- *An increase in relative capital supply will decrease the startups' incentives to engage in complementary innovation activities;*
- *If the expected time to exit in an IPO is long, the startup's optimal innovation strategy is more sensitive to changes in the relative expected value of the two exit modes; and*
- *If the probability of an acquisition is very low, the startup is unlikely to engage in complementary innovation activities but is more sensitive to changes in relative capital supply.*

Proposition 1 states that the marginal benefit from complementarity must equal the marginal cost of complementarity. This trade-off depends on model fundamentals such as the expected time to exit in an IPO, the probability of finding an acquirer, and the costs of complementary innovations. More importantly, however, the relative importance of such factors depends on the availability of capital, specifically the competition in the VC market.

2.3.4. Equilibrium

I consider a stationary equilibrium, in line with the search market literature. This requires that the inflows of new entrepreneurs and investors equal the outflows. If m_S and m_V are

[7] I have not made any assumptions concerning $\frac{\partial R_A(0)}{\partial c}$, except that it is positive. It is possible that $\frac{\partial R_A(0)}{\partial c} < \kappa\beta\rho\frac{\theta M(\theta)}{\mu}$, in which case $c^* = 0$ as c cannot be negative (by assumption).

the inflows of new startups and investors, respectively, then the conditions in equation 2.8 must hold in equilibrium.

$$\begin{aligned} \dot{M}_S &= m_S - M_S(\mu + \rho\theta M(\theta)) = 0 \\ \dot{M}_V &= m_V - M_V M(\theta) = 0 \end{aligned} \tag{2.8}$$

I obtain the equilibrium level of capital market tightness by solving for the masses M_V and M_S in equation 2.8, dividing the expressions with each other and solving for $\theta M(\theta)$ (equation 2.9). This has a unique solution as long as $m_S > \rho m_V$. The stationarity condition determines the equilibrium capital market tightness measure for exogenously given inflows, given that there is a unique mapping from θ to $\theta M(\theta)$.

$$\theta M(\theta) = \mu \frac{m_V}{m_S - \rho m_V} \tag{2.9}$$

Definition 1 (Equilibrium) *In equilibrium the following conditions must hold:*

- *The bargaining outcome (α) solves the program in equation 2.4;*
- *The expected value of the startup and VC capital in the search stage satisfy equation 2.3;*
- *The startups' owners choose the complementary innovation level c to maximize equation 2.6; and*
- *The inflows and outflows satisfy the stationarity condition in equation 2.8.*

I obtained the second expression in equation 2.6 by combining the solution to the bargaining problem (equation 2.5) and the expected value equations in equation 2.3. The solution to this problem is given in equation 2.7. By substituting the summarized stationarity condition equation 2.9 into the optimal innovation choice condition, I obtain the equilibrium condition in proposition 2.

Proposition 2 (Equilibrium) *Given the inflows m_S and m_V such that $m_S > \rho m_V$, an equilibrium exists and is unique. The equilibrium is fully characterized by:*

$$\frac{\partial R_A(c^*)}{\partial c} = \begin{cases} \kappa\beta\rho\frac{m_V}{m_S-\rho m_V} & \textit{if} \quad \kappa\beta\rho\frac{m_V}{m_S-\rho m_V} < \frac{\partial R_A(0)}{\partial c} \\ \frac{\partial R_A(0)}{\partial c} & \textit{otherwise} \end{cases}$$

The equilibrium condition implies that:

- *The optimal level of complementarity is non-negative but can be zero when the costs are too high, or the inflow of new capital is high; that*

- *The optimal level of complementarity is* always *(weakly) decreasing in the inflow of new capital for all reasonable levels of m_V relative to m_S; and that*
- *The optimal level of complementarity is independent of the rate at which acquirers arrive.*

The optimal innovation choice in equilibrium is a function of the relative inflows of new entrepreneurs and new investors, assumed to be exogenously given in this model. An exogenous increase in the inflow of capital results, in equilibrium, in a decrease in the startup firms' catering incentives, as shown in proposition 2. The inflows pin down the innovation choice, which is independent of the arrival rate of a potential acquirer. As the potential acquirer arrives and acquires a startup, the startup exits the market, resulting in an outflow. These flows uniquely determine the capital market tightness measure.

2.4. Empirical predictions

2.4.1. Capital market tightness

The equilibrium condition outlined in proposition 2 suggests that the optimal level of complementarity decreases in the capital market tightness measures, implying that the type of innovation projects startups engage in fluctuates with the capital market cycles. Specifically, the proposition suggests that startups engage in more complementary innovation activities when there is less competition in VC markets. The result indicates that we should observe an empirical correlation between capital market overlap and complementarity measures such as technological overlap and other similarity measures. The incentive to cater to potential acquirers increases with capital market tightness, and any changes to the VC environment should impact the nature of startups' innovations. Moreover, to the extent that such actions are associated with costs depressing the value of staying independent, IPOs in such environments should have a lower value.

A large and growing body of literature has documented a causal effect of financing conditions on innovation output. The paper that is most closely related to this paper is Nanda and Rhodes-Kropf (2013), who argue that experimental and risky startups, startups with a high real options value, require "hot" markets to receive funding. In a different paper, Nanda and Rhodes-Kropf (2017) provide empirical evidence that startups funded in hot markets are riskier but have a higher pay-off conditional on success. This paper instead highlights a different channel through which the state of capital markets shapes startups' optimal innovation path. Increased capital supply reduces the startups' incentives to engage in complementary innovation activities. To the extent that more complementary innovations are associated with less radical innovations and lower IPO values, this channel could confound the results of the earlier literature. Previous literature has documented a positive relationship between acquisition incidence and success, and technological overlap and product market similarity (e.g., Bena and Li, 2014; Hoberg and Phillips, 2010). At the same time, higher backward similarity has been associated with more incremental, less radical innovations, while forward similarity suggests breakthrough innovations (e.g., Kelly et al., 2021).

Following an exogenous shock increasing (decreasing) VC inflows, without any, or before entrepreneurial entry has adjusted, startup firms' innovations should, on average, become less (more) similar to incumbent firms' assets. In particular, startups' innovation trajectories should become more independent of *potential acquirers'* innovations. This effect should be more substantial when the costs associated with adjusting the innovation strategy are high. Thus, if the costs, conditional on remaining independent, associated with engaging in more complementary innovations are high, the startups will respond *more* to changes in the financing environment.

For example, suppose startups cater to potential acquirers by engaging in similar commercialization activities. In that case, such activities should be associated with increased future competition if the firm stays independent and correspond to high costs within the model framework. On the other hand, a catering activity associated with developing a new technology that seamlessly integrates with many potential future commercialization strategies would be less costly if the startup remains independent. The startup could then exploit the technology itself for a different commercialization strategy than the commercialization strategy associated with

If the startup is later in its life cycle, or if the probability of success conditional on receiving one more investment is high, startups will respond more to changes in capital market competition. More mature firms, which have reached more "milestones", such as being post-revenue, have launched a product, or are profitable, should respond stronger to changes in the financing environment. Similarly, startups of a less experimental nature, with fundamentally less uncertain and risky innovation strategies and business models, should respond stronger to increased capital availability than riskier ventures.

2.4.2. The cost of experimentation

Previous research has studied how changes in initial experimentation costs affect startups and their innovation outcomes. For example, Ewens et al. (2018) showed that a decrease in the cost of starting a new business changed the nature of innovations that received funding, favoring projects where uncertainty can be revealed quickly and at low cost and disfavoring more complex initiatives. Within this model, it is possible to think of two sources of a reduction in the cost of experimentation. The first source concerns the cost of entrepreneurial entry, such as a decrease in the cost of setting up a new firm. There could be multiple sources stimulating such a change. Examples include lowered equity capital requirements for new firms, technological innovations facilitating entrepreneurial activities or lowering the acquisition costs of assets needed at the very early stage, improved unemployment benefits for entrepreneurs if the new venture fails, or increased supply of very early seed capital. Within the model framework, this would translate into an increase in the inflow of new firms, m_S. An increase in the flow of new entrepreneurs operates through the capital market tightness measure and mirrors the development of an increase in capital inflows. A higher rate of startup entry would hence cause an increase in the optimal catering level. The change in innovation incentives would mirror the story outlined in 2.4.1.

An increase in the probability of success measure ρ is an alternative representation of a decrease in the cost of experimentation. An increase in ρ suggests that startups are more likely to succeed conditional on receiving an additional investment—a startup can do *more* with less capital. An increase in ρ is associated with a decrease in the optimal catering choice, i.e., startups cater less when they can do more with one additional round of capital. With low experimentation costs, e.g., when firms are more likely to succeed conditional on receiving a first investment I, the incentives to cater to potential acquirers are lower. However, low experimentation costs also imply a more robust response to changes in relative capital supply. Section 2.4.1 discusses similar implications, more mature firms respond more strongly to changes in the capital market tightness parameter. More mature firms are further along in the "experimental journey" and, conditional on the information already revealed in previous rounds, should require fewer or smaller investments to reach a resolution.

2.5. Conclusion

This paper provides a tractable empirical framework illustrating how exit markets condition and exit objectives interact with capital market conditions to shape startups' innovation trajectories. The model framework builds on a search framework commonly applied in the theoretical labor market literature, applied to the context of startups (investments) and VCs (investors). The relative capital supply determines the expected search time, and the cost of delay represents search costs. When capital is abundant, startups face fewer search frictions, while investors (VCs) experience longer search times, and vice versa when capital is scarce.

If a searching startup matches with an investor, all investors can realize their investment with a probability ρ; otherwise, they return to the search market for a second round. Alternatively, a startup in the search stage can match with an acquirer, and investors can exit their investment. If the search cost of finding an investor is high, e.g., when capital is relatively scarce, an acquisition becomes relatively more likely. In that case, the startup is more likely to engage in innovation activities that enhance the expected value of an acquisition. The startups' incentives to engage in catering activities increase.

The paper highlights that fluctuations in the relative supply of capital can give rise to changing innovation trajectories, specifically to increase or decrease startup catering efforts. The predictions apply to changes in a firm's innovation trajectories as capital market conditions change, conditional on the startup project having a positive net present value. The predictions do not extend to the innovation profiles of the marginal new firm entrant.

Previous literature has documented that technological overlap, asset similarities, and intersecting product markets are associated with increased acquisition probability and successful, valuable acquisitions, and high synergy realizations. At the same time, more similarities in innovation output are often interpreted as less radical, more incremental, and explorative innovations. The entrepreneurial finance and innovation literature has documented a causal relationship between the state of VC capital markets and the type of innovation projects that receive financing. This literature has documented that more explorative innovations are more likely to be funded at times when capital is relatively more abundant. This paper illustrates another channel, the prospects of an exit by acquisition, that could incentivize startups to produce more "similar" innovations without necessarily being associated with a decrease in the experimental nature of the startups' innovation activities.

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Chapter 3

Who becomes a business angel?

Abstract

The availability of external finance for early-stage enterprises is vital for entrepreneurship and innovation. Using data from Swedish administrative registries, we identify business angels, that is, individuals repeatedly financing startups, and characterize who among the general population eventually becomes a business angel. Angels are overwhelmingly drawn from the top 1% of the wealth distribution and are just as likely as other rich people to originate from wealthy families. However, angels have distinguishing characteristics compared to the rich in general. Angels are generally highly educated and have often chosen business-relevant degrees. Similarly, many angels have leadership experience from startups, public companies, or transactional (IPO, M&A, LBO) experience. Angels also have much higher general ability than even other very wealthy peers and relevant comparison groups. Their asset allocation is very biased towards the riskiest assets, suggesting unusually low levels of risk aversion and strong non-pecuniary investment motivations. Our analysis provides important insights for the design of policies encouraging the financing of early-stage ventures.

Joint work with Laurent Bach, Ramin Baghai, and Per Strömberg. Bach (bach@essec.edu): ESSEC Business School Paris; Baghai (ramin.baghai@hhs.se): Stockholm School of Economics; Strömberg (per.stromberg@hhs.se): Stockholm School of Economics; Warg (kwa.fi@cbs.dk): Copenhagen Business School and DFI. We thank seminar participants at the Toulouse School of Economics and the Toulouse Business School for helpful comments and suggestions. We are grateful to the Swedish Agency for Growth Policy Analysis (Tillväxtanalys) for making available data. Funding from the Mistra Center for Sustainable Markets, the NASDAQ Nordic Foundation, and Vinnova is gratefully acknowledged.

3.1. Introduction

Entrepreneurship is crucial for economic growth, job creation, and innovation. The availability of financing for startup firms is thus important for an economy's success. Given common features of early-stage investments such as asymmetric information and moral hazard stemming from a lack of track record, unproven management, and high uncertainty, financial frictions are likely more severe for startups than other firms.[1] So-called business angels–wealthy individuals investing in startups on their own accounts–have become increasingly important as a source of equity finance at the seed and early stages of company formation. It is estimated that the volume of early-stage financing by business angels exceeds financing by venture capital (VC) firms in the US and elsewhere (Lerner et al. 2018; OECD 2016). Besides supplying equity finance, many angel investors are believed to provide non-financial value to the entrepreneurial firms they invest in, similar to VC firms (e.g., monitoring, developing, supporting management, and providing contacts with suppliers and customers).

Owing to the importance of business angels, governments throughout the world have put in place policies to develop a local population of business angels (Lerner, 2009). Such policies are premised on the idea that a local supply of investors exists, who may become angels, provided the right regulations and tax incentives are in place. However, these policies may have adverse distributional effects if substantial public resources are channeled to already well-off individuals with no specific investing ability (Denes et al., 2020). In addition, to the extent such policies encourage less well-off individuals to invest in unlisted firms, this may push households into excessively risky savings portfolios (Moskowitz and Vissing-Jørgensen, 2002). In this paper, we provide an in-depth description of the personal characteristics of business angels. In particular, we ask whether business angels differ from other informal investors, wealthy individuals, and relevant professional groups and whether their skills and professional experience stand out in meaningful ways.

Studying business angels poses unique empirical challenges due to the informal nature of angel financing. Business angels invest their own money rather than acting as financial intermediaries like VC firms, which makes them more difficult to track. Furthermore, while examples exist of prominent angel investors, many business angels may value discretion and prefer to "fly below the radar" of public interest. Moreover, common sources of information on angel investing, such as angel platforms (e.g., *Angellist*), are often incomplete and may be biased towards specific industries or successful investments. We base our analyses on primary business registration data from Sweden to avoid selection biases and to systematically identify angel investors. Sweden is one of the few countries

[1]Common sources of initial business financing are the personal savings of the entrepreneur, financing from friends and family, and, to some extent, bank loans (Robb and Robinson, 2014).

with detailed population-wide administrative data and a highly developed, high-growth startup scene (similar to the US and UK despite its smaller financial market).[2]

Because business angels are informal investors, we must operationalize what should encompass this group of individuals in our analysis. The definition of business angels has been debated in the entrepreneurship literature (Avdeitchikova et al. 2008). We consider business angels to be individuals who make multiple investments of their own money directly into unlisted firms to which they have no employment relationship or family connection. Based on this definition and using administrative data on the universe of equity issuances in Sweden, we identify more than 700 business angels directly from the equity investments they make into startups, either directly as individuals or indirectly via legal vehicles they use for their angel investments. We verify that our procedure captures well-known business angels (whom we identify using external data sources, including news searches and lists of important early-stage investors provided by the Swedish Venture Capital Association). In addition to these "visible" angels, using this procedure, we are able to identify a much larger number of other business angels whose activity is more discrete.

We then connect the identity of business angels via their social security numbers with various sources of personal data, including the wealth and income registry, the education registry, and the military enlistment registry. These registries allow us to compare the personal background of angel investors with other informal investors, the rest of the Swedish population, and the sub-population of wealthy individuals and relevant professional groups.

Our findings are as follows. First, angel investors are overwhelmingly drawn from the population of wealthy individuals. The median angel in our sample belongs to the top 1% of the wealth distribution, and nearly 90% of angels belong to the top 10% in the year prior to their first observed investment. Many angels are exceptionally wealthy, as nearly a quarter are drawn from the top 0.1%. The concentration is even higher when weighing angel investments by the amount invested. In terms of labor income, angels earn higher incomes than other individuals in the top 1% by wealth. For example, the median angel is in the top 7% of the labor income distribution in the Swedish population, while the median non-angel wealthy individual is just below the top quartile. Overall, however, wealthy people–both angels and others–are not at the very top of the labor income distribution. Is the wealth of angels self-made? This may be the case for some angels; however, it is not generally true: similar to other rich individuals, angels are similarly likely to come from wealthy parental backgrounds but more likely to be highly educated. In fact, individuals' socioeconomic class is highly predictive of their propensity to become

[2]See e.g. "How Sweden Became the Silicon Valley of Europe", Reuters August 11, 2021, https://www.reuters.com/business/finance/how-sweden-became-silicon-valley-europe-2021-08-11/.

business angels: even compared to other rich individuals, the parents of business angels have higher incomes and are better educated.

While the observations on angels' wealth may not all be surprising—sufficient financial resources are required for long-term, illiquid, lumpy investments in risky assets—they illustrate that policies fostering angel investing will be regressive by design. Furthermore, these distributional observations also make clear that to characterize the factors determining who becomes an angel; one must pre-select high-net-worth individuals to draw meaningful inferences. Therefore, in the subsequent analyses, we compare the characteristics of business angels to those of non-angel individuals who belong to the top 1% of the wealth distribution and are working-age (between 20 and 65 years old). In addition to comparing angels to other wealthy individuals, we also identify three groups of professionals with relevant backgrounds—individuals with management and finance experience and a group of VC professionals to compare angels to in the subsequent analyses.

Second, there is evidence that angel investors are individuals with high general ability, measured using military enlistment tests (available for males only).[3] The military test scores are standardized so that about 11% of the conscript population receives one of the two top scores. In comparison, about a quarter of wealthy individuals receive one of the top two IQ scores, while more than 40% of angel investors score in the top two highest score buckets. Similarly, about 20% of wealthy individuals receive one of the top two non-cognitive skill scores, while this is the case for 27% of angel investors. Furthermore, about 20% of wealthy individuals receive one of the top two leadership ability scores, while 30% of angels do. The only other group with comparable performance on military tests is VC professionals. Military test scores are only available for a subset of the population, effectively only males. Therefore, we also consider the scholastic aptitude using high school grades of business angels and impute cognitive scores following Böhm et al. (2022). Consistent with the observations based on military enlistment tests, we find that business angels exhibit exceptionally high cognitive skills relative to all other comparison groups also using these alternative measures.

Third, we document that the personal portfolio allocation of angel investors is significantly more tilted towards risky assets compared to other wealthy individuals: More than 50% of angels' gross wealth is invested in equities versus less than 10% (top gross wealth) and 18% (top accumulate capital income) in the rest of the top 1% population, suggesting that angels exhibit a markedly lower level of risk aversion than other wealthy individuals. Importantly, this bias persists when separately focusing on private equity investments and public equities. While one may expect a higher share of private equity holdings to be a direct consequence of angel investing, we observe a significantly higher share of wealth already invested by angels in private equity prior to their first angel investment in our sample. Therefore, angels are likely to be entrepreneurs invested in their own

[3] 82% of the business angels in our sample are men.

companies. The results suggest they have a particularly low risk aversion and strong non-pecuniary investment motive. However, because angels' share in the target is small, such non-pecuniary benefits cannot come from control benefits, as would be the case for entrepreneurial investments.

Fourth, we assess the angels' life experiences prior to the time of their first angel investment in our sample. We find that angels are 50% more likely to hold a university diploma and more than twice as likely to hold a doctorate than individuals in the top 1% of the wealth distribution. Interestingly, angels also pursue specific university studies: about half of the angels have a degree in the social sciences, and about one third have a business degree compared to less than a quarter of all wealthy individuals. Relative to wealthy individuals, angels more commonly have a STEM degree. As such, in terms of education choice, business angels are a hybrid of VC professionals where STEM subjects, and in particular business degrees, are common educational choices. Further, we find that angels' work history often involves leadership positions. Angels are 60–75% more likely to have been in the top hierarchy at their previous place of employment relative to other rich individuals and six times more likely to have been in a top managerial position at a public company. Relative to other groups, including VC professionals, founders, and other informal investors, angels appear especially prone to take on leadership roles. Perhaps surprisingly, 26% of the angel investors have prior work experience in the financial industry (compared to only 10% of all wealthy individuals). These results imply that specific work experience and skills affect the likelihood of becoming an angel. Prior leadership experience and financial know-how may be particularly important and may matter more than technical experience in order to select between various opaque, early-stage ventures and to provide useful advice to invested entrepreneurs. Moreover, financial and business backgrounds might help angels tap into the right networks needed to access deals.

Fifth, we examine the extent to which angels are actively involved in the governance of target firms. We find that angels take a board seat in about one-fifth of the firms in which they invest, or less than half when considering all angels investing contemporaneously. The low board representation suggests that angels differ in their degree of active involvement in companies and raises some issues with previous studies that use board memberships to identify angel investors (Andersson and Lodefalk, 2020).

Last, we compare the characteristics of the investments depending on the angels' backgrounds. Generally, angels make larger investments than other informal individual investors and exhibit signs of a higher degree of sophistication. However, the investment characteristics of angels with a doctoral background are strikingly distinctive. Doctoral angels appear to match with firms based on skills related to the firm's business, while other angels excel in terms of business acumen and financial skills. Doctoral angels contribute significantly less capital than other angels and are less prevalent in the economy but appear to serve a distinct role, possibly taking a more advisory role. These angels take board positions 50% more frequently than the average angel. Our previous results suggest angels are able investors; as a group, they exhibit high cognitive abilities and the ability to manage risk. However, other skills directly relevant to the angels' target group of firms might be a key factor for becoming an angel.

Contribution to the literature. A large literature studies the consequences and features of early-stage entrepreneurial finance. Most of this literature has focused on VC investments and has emphasized how VC investors contribute to start-up performance and growth (see, for example, Hellmann and Puri (2000), Hellmann and Puri (2002), Kaplan and Strömberg (2003), Kaplan and Strömberg (2004), Sorensen (2007), Chemmanur et al. (2011), Puri and Zarutskie (2012), Bernstein et al. (2016)). Kerr et al. (2011) show that ventures funded by angel groups experience superior outcomes compared to rejected ventures. Lerner et al. (2018) study 13 angel groups across 21 countries and find that angel investors positively impact firms' growth, performance, survival, and follow-on fundraising. Hellmann, Schure, et al. (2021) investigate how angel financing interacts with VC financing. Using early-stage financing data related to a government program in Canada, they find that angels and VCs finance different types of firms (consistent with Hellmann and Thiele 2015). Kisseleva et al. (2020) use administrative records from Norway to measure the returns to investing in angel-backed companies. Their evidence suggests that firms grow faster subsequent to angel involvement. A similar result is found in Andersson and Lodefalk (2020), who apply an algorithm to Swedish registry data to identify 156 angel-financed firms.[4] To date, no previous study systematically investigates the factors determining who becomes an angel investor—understanding which individuals become business angels, and when, is an important issue for both research and policy.

Our paper also delivers critical insights for evaluating VC and entrepreneurship-related public policies (Hellmann and Thiele, 2019; Lerner, 2009). Our results suggest that public policy supporting early-stage entrepreneurial ventures cannot start from the premise that there is a deep supply of potential angel investors. Such policies are likely to be more effective if they aim to increase the quality of the pool of potential angel investors or if they subsidize angel investors conditional on strict standards of ability and experience. In addition, given that angels come from the top of the wealth distribution, policies that aim to subsidize angel investments are likely to be regressive and therefore politically challenging to implement.

[4] While also using Swedish registry data like we do, Andersson and Lodefalk (2020) do not have data on actual investments and instead apply an algorithm to identify presumed angels. When applying their algorithm to Swedish corporations in existence in 2010, their algorithm identifies 156 firms involving 134 individuals classified as angels. Since the algorithm relies on board membership and other criteria to indirectly identify angel involvement, their sampling method only captures a subset of all angels and will also include some misclassified firms.

Finally, we also provide new evidence on the asset allocation of wealthy households. Existing evidence has so far focused on the risk and return characteristics of investments by the rich (Bach et al., 2020). We are among the first to consider the degree to which wealthy investors engage with the companies they invest in, in a context that is value-relevant both from a private and a social point of view.

3.2. Data and variable definitions

3.2.1. Data on equity issues

Our primary data source to identify business angels are mandatory filings on equity and equity-linked issuances (warrants and convertibles) by Swedish limited liability companies. Firms are required to report any changes to their share capital to the Swedish Companies Registration Office (Bolagsverket), which we obtain as pdfs. Each filing contains a standard filing form with information on the decision date for the share issue, the number and type of shares issued, the amount of capital raised, and whether the capital was paid in cash, in kind, or by the cancellation of outstanding debt. The standardized form also has a section for the total number of shares outstanding after the issue. In addition to the standard filing form, the issuer must append relevant documents, such as shareholder voting records and share subscription agreements, which list the investors and some contractual terms. This information was extracted manually as the appendices are not machine-readable and do not follow a standard format.

We received a total sample of 55,941 equity issue filings, including all equity issues reported to the Swedish Companies Registration Office from 2004 through the beginning of 2014. We coded the entire equity issue history of all non-trivial firms and a random sample of all firms. Section 3.3 provides further details on the sampling procedure. In addition to the equity issue filings, we coded all warrant and convertible issues for all firms in the non-trivial and random samples. Other coded filings include changes to the terms of the outstanding shares, convertibles, and warrant securities, such as increases or decreases in share capital, converting convertibles, exercising warrants, and cancellations of convertibles or warrants.

3.2.2. Measuring wealth and the value of balance sheet components

To construct the balance sheet of individuals' wealth, we largely follow Bach et al. (2020). The wealth data we use are mainly drawn from the Swedish Income and Wealth Registry, which is compiled by Statistics Sweden (SCB) from tax returns and third-party information. For every Swedish resident, the data include the debt and disaggregated worldwide financial and real estate holdings at year-end from 1999 to 2007, including bank account balances, stock and mutual fund investments, and real estate holdings. The data also include total debt outstanding by each individual at year-end and the interest paid during the year. Data on private equity holdings are obtained from income tax forms (so called "K10 forms") combined with accounting data from Serrano (further described in 3.2.4). For every unlisted limited liability company, these forms provide the number of shares held by each Swedish resident actively participating in the firm. Unlike Bach et al. (2020) we use the book equity of private equity holdings.

We distinguish the following balance sheet components in the paper. A household's debt is the sum of mortgages and all other liabilities to financial institutions. Gross financial wealth consists of bank account balances, mutual funds, stocks, bonds, derivatives, and capital insurance. Gross financial wealth is further divided into cash (bank accounts and Swedish money market funds) and risky financial wealth (all other securities). Real estate wealth consists of residential properties (i.e., primary and secondary residences) and commercial properties (i.e., rental, industrial, and agricultural properties). We define total gross wealth as the sum of financial wealth, pension wealth, real estate wealth, and private equity. Net wealth (or net worth) is the difference between total gross wealth and household debt. For additional details, please see Bach et al. (2020).

3.2.3. Data sources for personal characteristics of angels

The main source of data on socio-economic outcomes is the Longitudinal Database on Education, Income and Occupation (LISA) from SCB. LISA contains a large set of socio-economic variables, such as age, gender, employment, uncensored wages, and social security benefits for the whole Swedish population aged 16 years or older. This dataset allows us to track individuals over time and to study career paths. Our measure of wages is the declared annual labor income, which includes all taxable labor income after deducting benefits.

The information from LISA can be linked to other registry data via social security numbers. We use military records to measure cognitive, non-cognitive, and leadership skills. The military data cover the years 1968-2016 and are obtained from The National Archives ('Riksarkivet') and The Swedish Defence Recruitment Agency ('Rekryteringsmyndigheten'). Since 1968, all Swedish males aged 18 or over were required to participate in enlistment tests for up to two days.[5] The enlistment test consisted of four parts, assessing cognitive ability, non-cognitive ability, physical ability, and health status. Whether someone had to do military service was determined by their health status, and the capacity in which they served was determined by the joint outcome of all the tests. The cognitive ability test consisted of four parts: synonyms, inductions, spatial reasoning, and technical comprehension; the combined score from the four parts was converted to a cognitive ability score from one to nine on the Stanine scale.[6] Non-cognitive ability was assessed through a structured interview with a psychologist, who graded test-takers on psychological abilities (the score was also mapped into the Stanine scale). Individuals with the following character traits obtain high non-cognitive test scores: willingness to assume

[5]In 2007, the military started pre-screening potential conscripts via an internet survey, and fewer men were required to participate in the enlistment tests, affecting cohorts born in 1988 or later. In 2010 mandatory military service was abandoned, to be reinstated in 2017. Only seven of the identified angels were born in 1988 or later.

[6]The Stanine scale is a method of scaling test scores resulting in approximately normally distributed data with a mean of 5, standard deviation of 2, and a range from 1 to 9.

responsibility, independence, outgoing character, persistence, emotional stability, initiative, and ability to work in groups (for further details, see, e.g., Lindqvist and Vestman (2011)). In addition, leadership ability was assessed by a psychologist for all test-takers who received at least an average score on the cognitive ability test.

A limitation of the military enlistment data is that the test scores are effectively only available for males.[7] We, therefore, supplement the enlistment scores with other measures of ability provided by SCB. We obtain further information on education (such as grades, track, school, and university) from the high school ('Gymnasieskolan') and university ('Universitet/högskolan') registers. We use information from the high school register on the final grade, graduation year, and the track the person was enrolled in from 1973 onward.

Finally, we add information from the family register ('Flergenerationsregistret'), which contains complete family ties of the whole Swedish population.

3.2.4. Firm characteristics

Most of the firm-level data are based on financial statements drawn from the Serrano database. The data cover both privately and publicly held firms. We obtain from the PAtLink database information on the patents filed by Swedish companies during the period 1990-2018 together with the amount of citations they receive up to year 2018.

[7] Less than 1% of the military test-takers are volunteering females.

3.3. What is a business angel?

3.3.1. Identifying business angels and angel investment vehicles

Our goal in this section is to define and identify business angels in the data in a way that does not rely on convenience samples, lists of prominent angels, or angel clubs. While there is no universally accepted definition of what precisely angel investing entails, there are some common features that these investors are likely to share. According to Lerner (2000), a business angel is a "wealthy individual who invests in entrepreneurial firms. Although angels perform many of the same functions as venture capitalists, they invest their own capital rather than that of institutional or other individual investors. (p.515)" In a similar vein, Mason and Harrison (2008) define a business angel as a "high net worth individual, acting alone or in a formal or informal syndicate, who invests his or her own money directly in an unquoted business in which there is no family connection and who, after making the investment, generally takes an active involvement in the business, for example, as an advisor or member of the board of directors. (p. 309)" Based on these definitions, a reasonable starting point to identify angels from their investments may be to require that such investors make multiple investments in unlisted, pre-IPO companies. Further, some of their investments should be in companies they or their family members are not employed in ("unrelated investments"). Hence, our main definition of an angel is an individual who has invested in at least two unrelated unlisted companies during our sample period.

To begin, we consider the universe of firms that reported an equity issuance to Bolagsverket (The Swedish Companies Registration Office) between 2004 and 2014.[8] We then limit the sample to early-stage companies; specifically, we consider only equity issuances by firms that are not yet listed and remain independent at the time of the emission. We further require that the firms have accounting data available in at least one of the two years prior to or after the equity issue (from the Serrano database).[9] Given constraints on data processing (the issuance filings were manually and individually coded as they include hand-written information and non-standard documentation), we primarily focus on non-trivial firms. We record the entire 2004 through 2014 filings history for all firms that at some point raised at least 5 million Swedish kronor (roughly $500,000) in at least one equity issue (we consider all equity issues of firms that meet this requirement). Because this sample arguably selects on some (moderate) measure of success, we also code the available 2004 through 2014 equity issuance history for a random five percent sample of all firms that is meeting the above criteria and raising equity of any amount.

[8]The 2004-2013 filing history is near complete, and a significant portion, though incomplete, of the 2014 filing history is coded. A negligible number of filings from 2003 are also available and coded.

[9]Out of more than 30 000 firms, only 180 firms do not have any accounting data in the five-year window around the equity issue.

The front sheet is generally standardized across all filings and machine-readable. Panel A in table 3.1 shows summary statistics of the universe of equity issuances and how the sample shrinks as further restrictions are imposed on the sample, using an automatically coded data set of the front sheet.[10] The most considerable attrition occurs following the exclusion of subsidiaries, i.e., within-group transactions. There are striking differences between the sample of firms that at some point raised more than 5 million (1, 811 firms) SEK and the random selection of firms (998 firms), both in terms of the number of capital raising rounds, the aggregated amount raised, and the average and median round size. The automated process has some limitations; most notably, the algorithm misclassifies warrant and convertible events as equity issues and occasionally inflates the amount raised due to inconsistent numbering conventions across filings. As such, there are substantial differences in the summary statistics using the manually coded data, presented in panel B of table 3.1. Due to these discrepancies, we have ensured that all firms meet the inclusion criteria in the sample also based on the manually coded data. Outliers appear more frequently in the machine-read data, as evidenced by the larger mean and median round size discrepancy. These discrepancies are, to some extent, driven by the problem of the algorithm in handling inconsistent numbering conventions.

The coded sample includes not only equity issues, but also convertible and warrant issues, as well the conversion and exercise events or other changes to these securities. For all equity, convertible, and warrant issues, we record the investors' names and social security numbers, the number of securities purchased, and the price paid, among other issue-level details.[11] The sample containing non-trivial firms covers 1,811 firms with 8,924 fundraising events. 6,816 of these events include an equity issue, raising a total amount of about 176 billion Swedish kronor. Convertible issues constitute a smaller share of all capital-raising events, with only 558 events and a total amount of about 7 billion Swedish kronor. Warrant issues occur more frequently (1,403 events).

We classify investors into nine overall categories. Five different groups of individuals—Angels, Founders/Employees, Family, Informal investors, and Visible angels/Family offices—and four groups of distinct entities—VC/PE, Government, other Financial corporations, and non-financial corporations. For about 33% of all capital raised in equity and convertibles issues, we are unable to identify the social security number of the individual or the company registration number of the company, and unable to classify the investor into one of the above groups based on the name alone.[12] However, for the remaining capital, we have the investors' social security numbers or company registration

[10] We thank Tillväxtanalys for providing this data set.

[11] In addition, we code the investor- and issue-level information when convertibles are converted or canceled and warrants are exercised or canceled. Lastly, in a subset of filings, we can observe the owners prior to the investment; these data are incomplete, but we record the ownership to the extent it exists.

[12] These investors likely contain a mix of investors from all groups, some foreign individuals and entities, and foreign subsidiaries owned by Swedish corporations and individuals.

numbers, or were able to match it to an external data source.[13] If an individual owns an investment vehicle, we consider it as the individual investing their own money. This share of capital is included in the individual investor categories.[14] These individual investors, who are investing their own capital, are all potential angels.

All individuals that at some point are employed in the firm are categorized as founders or employees, and their family members are included in the family category.[15] There is a small overlap between individuals in this group, and the other three groups, depending on the firm the individual invests in, but the three remaining groups are mutually exclusive. More than 50% of all capital by individual investors are provided by individuals without an employee or family connection with the firm, and we separate these individuals into repeat investors who invest in two different "unrelated firms" and informal investors, who only make one such investment. We classify individuals that make multiple investments into unrelated firms (repeat investors) as business angels, and the remaining individuals as informal investors, or potentially business angels "in the making".

How do we verify if this procedure indeed identifies business angels? There are business angels that are more "visible". We draft a list of such better-known angel investors based on member lists from the Swedish Private Equity and Venture Capital Association (SVCA), lists constructed through news searches, and investments in databases such as Preqin, Privco, Pitchbook, and Nordic9. This type of search picks up the most visible angel investors. While our ambition is to capture a larger set of angel investors through our procedure that flags repeat investors in "unrelated" companies, we would expect a significant overlap between the list of the most visible angel investors (we will henceforth designate these investors as "visible angels") and those identified through our procedure. To implement this cross-validation, we match the visible angels to the database on equity issuances. Table 3.2 tabulates how individual investors invest and flags whether individual investors are visible angels.

First, investments made by individuals who only invest in one unrelated firm are frequent but distinct from repeat investors. The investments made by this group are heterogeneous, sometimes very similar to investors in related investments and sometimes

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[13] With the corporate identifier or social security number, we can match the investor to the person or firm registries.

[14] We identify the individual owners by matching the investment vehicles from the Bolagsverket data to income tax reforms (henceforth, "K10 data"). The K10 data provides the number of shares held in these vehicles by any Swedish resident actively participating in the firm. During our sample period, there were significant tax benefits from investing through a vehicle compared to investing directly as an individual. In some instances, we could also match the vehicles to external data sources such as commercial private equity databases, the SVCA member lists, etc., informing us about the investor type.

[15] More specifically, we consider whether the investors' partner, children, parents, or siblings are employed within the broader company group (that is, in the company itself, its parent company, or any majority-owned subsidiary). We obtain employment histories from LISA and family ties from the Swedish family register ("Flergenerationsregistret"), further described in section 3.2.3. We consider all employment data available for each individual, including the entire history and non-primary employers.

similar to repeat investors and angels. This group is likely a mixed bag of angels that cannot be identified because they had not made enough investments by 2014 or due to data limitations, contributions from founders or extended family or friends of the founders, as well as other forms of informal financing. Very few of these individuals are found in our sample of visible angels.

Second, we observe that investors in related firms (Founders/Employees) are typically not visible angels (2%), and the share of family investors that are visible angels (9%) is significantly smaller than in the angel sample. About 35% of the individual investors that make two or more "unrelated" investments in our dataset are indeed visible angels and more than half of the firms invested in by repeat investors also raise capital from the visible angel group.[16] Moreover, angels (repeat investors) more frequently invests through vehicles, indicating a higer level of sophistication as there are significant tax benefits from investing through a vehicle. Lastly, capital contributions by informal investors are important in aggregate, about 5.8 billion kronor over our sample period while angels contribute about 3 billion kronor. However, the population of informal investors is more than 8 times the size and the relative contribution by the individual is much larger in the group of angels. This is also reflected in the larger investment size.

These observations validate our definition of business angels: by focusing on investors that undertake two or more investments in unrelated firms, we are likely to capture a large fraction of both "visible" as well as "hidden" angel investors. Defining angel investors as those that invest in at least two unrelated companies yields a set of 720 business angels. In the subsequent analysis, we will employ a classification of investors into nine categories. All individuals investing in related companies are either classified as "Founder/Employee" or "Family". All individuals with more than two unrelated investments are in the "Angel" category. The remaining individuals are classified as "Family office/Visible angel" if matched to the visible angel and family offices lists and "Informal investor" otherwise. Not all investors in the "Family office/Visible angel" group are identified with a social security or company registration number. The remaining identified investors are all corporations or organizations. We classify these investors into four overall categories—VC/PE, Government, Financial corporations, and non-financial corporations, by matching to the Serrano database, external databases such as CapitalIQ, Preqin, Privco, Pitchbook, and Nordic9 and the SVCA member lists, as well as through manual searches.

3.3.2. Where do angels fit in the entrepreneurial ecosystem?

Table 3.2 shows that informal investors and related individuals contribute a larger share than angels as a share of total capital. Yet, the total investments aggregated at the individual level are larger for angels than other informal investors suggesting that individual angels contribute more capital to entrepreneurial firms. This section addresses how angels differ

[16]Only about a third of the capital from visible angels can be attributed to an identified individual.

in their investments from other groups of investors, with the objective of documenting angels' role in financing startup firms and where angels fit into the entrepreneurial ecosystem.

Table 3.3 adds some nuance to the relative importance of different investor groups across investment stages, as proxied by the round size. First, angels are most prevalent in investment rounds of medium size and are more similar to visible angels and family offices.[17] In contrast, informal investors, founders, and founders' families are most prevalent in the earlier (smaller) stages. VC/PE enter in later and larger rounds.

These dynamic participation patterns by different investor groups are further illustrated in table 3.4, detailing the frequency at which these investors invest in the same firm, both contemporaneously and at different points in time. Angels are somewhat more likely to contemporaneously co-invest with VC/PE investors than informal investors. This finding is particularly evident when looking at all rounds, not just not at the time of the first investment, suggesting that angels are able to "stay in the game" longer than informal investors. About 40% of both angels' and informal investors' investments subsequently raise VC/PE funding, but fewer firms receiving angel financing have previously received VC financing (about 17%) than informal investor firms (about 20%), again suggesting that angels are capable of remaining invested and commit additional capital for longer and in later firm stages. Lastly, while 40% of all firms that receive financing from angels or informal investors ultimately receive VC or PE financing, only 46% of VC/PE financed firms have received previous angel financing, but 65% received funding from informal investors. These results suggest informal investors are more likely to enter at earlier stages and take a step back as institutional capital enter, dynamically complementing VC/PE capital. A large segment of the angel-financed market remains independent of VC and PE financing. Yet, at the same time, angels provide an important deal flow to VC/PE and stay committed to the firm as the institutional investors enter. The first set of results is consistent with the role of angels and VCs as dynamic substitutes proposed by Hellmann, Schure, et al. (2021), where firms either receive angel financing or VC financing. Angels finance a different subset of firms, fostering entrepreneurship in a distinct market segment. However, our evidence suggests that while angels serve the purpose of providing an alternative source of funding, a subset of the angel group also serves as a complement to VC financing, where angels function as a launch pad to receive further VC financing. Conversely, informal investors appear to be key capital providers to firms that eventually receive VC funding. However, informal investors appear to be stepping stones toward institutional capital, as these investors are relatively less likely to pursue further investments as VC firms enter.

Lastly, we look at firm and deal characteristics across the different investments by the various investor groups. Along these dimensions, angels appear like a hybrid of informal

[17] It is worth noting that family offices contribute a relatively large share of capital in the rounds raising more than 50 million kronor, primarily driven by a few very large investments. The frequency of such investments is much lower in the top round-size bucket.

investors and VC/PE. Table 3.5 shows that angels are slightly more likely to invest in more distantly located firms than informal investors but similarly prone to do so as VCs. Angel firms are similar in age to VC firms but slightly older than firms when informal investors enter but less likely to be profitable than both VC and informal investor firms. The results in table 3.6 suggest that angel-financed firms are significantly smaller than VC-financed firms at the time of investor entry, and the industry distribution is similar across the two investor groups. Angels are somewhat more inclined to invest in finance and real estate firms. The industry distribution of firms that receive funding from informal investors is more dispersed, and the tech and health sectors have a lower representation. However, the firms are similar in size to angel firms at the time of investment.

Tables 3.7 and 3.8 reports deal characteristics and shows that angels make significantly smaller deals than VCs and take a smaller round share. VCs are more sophisticated in using different securities and frequently structure deals using preferred equity, convertible loans, and warrants. However, angel deals are larger, and their investment sizes and stakes are larger than informal investors. Similarly, angels more frequently participate in rounds involving preferred equity and convertible loans, suggesting a slightly higher level of sophistication.[18] Surprisingly, both angels and informal investors are unlikely to hold board seats. Only about 20% take a board seat following an investment. Informal investors are more likely to hold a board position as a group, but the relationship is reversed at the individual level. This result is likely mechanical. First, informal investors are more prevalent and larger as a group. Second, newly appointed board members are likely encouraged to invest in the firm, and board members investing in the firms they are on the board of would be classified as informal investors.

[18] Angels also invest directly in convertibles. 21.7% of angels have invested directly in convertible securities. Only 8.2% of informal investors have ever participated in a convertible issue.

3.4. How wealthy are business angels?

Because they invest significant sums in startups, business angels are expected to be fairly wealthy individuals. In this section, we report details on business angels' wealth, including the average allocation of angels' gross wealth to financial assets, pension wealth, real estate, and private equity. In doing so, we compare business angels to other wealthy individuals. To characterize how wealthy business angels are, we measure wealth in two complementary ways to reduce sample selection problems and measurement errors. While gross wealth is a meaningful measure, these data are drawn from the wealth register and cover the period from 1999 to 2007 (corresponding to the years before the Swedish wealth tax was abolished). Therefore, we also use individuals' capital income, which is available for all sample years, as an indirect proxy for wealth. Specifically, we use the accumulated capital income over the preceding ten years. We also compare the angels to a subset of high-wage earners—individuals in the top decile of the labor income distribution.

Panel A of table 3.9 shows that angels are wealthy individuals, tabulating the mean and median wealth levels of all individuals in the respective subsamples in the year before the first observed investment, or entry into the respective subsamples. The average angel's gross wealth is about 56 million kronor. This mean reflects significant outliers with a substantially lower median of 9.74 million kronor (about 1.4 million US dollars).[19] The median angel's gross wealth is similar in size to the median individual in the top gross wealth percentile. Nearly all angels are found in the top quartile of the wealth distribution and more than 57% in the top percentile. Most strikingly, almost a quarter of all angels are found in the 0.1% of the wealth distribution. Angels are primarily drawn from the top of the wealth distribution, and angels are significantly more wealthy than informal investors, founders, employees, and their families.

These patterns are very similar when considering alternative measures of wealth available for the full sample period. Panel B of table 3.9 displays similar statistics using ten-year accumulated capital income as a proxy for wealth. Angels are primarily drawn from the top of the wealth distribution when also considering this alternative wealth measure and significantly wealthier than other individuals investing capital into startup firms. Panel A and B of appendix table 3.13 display more detailed summary statistics of wealth levels. Lastly, while angels are overwhelmingly drawn from the top of the wealth distribution, they represent a tiny fraction of all wealthy individuals suggesting that wealth is not a sufficient condition for becoming an angel.

In panel C of table 3.9, we also consider the labor income of business angels. The table shows that, in the year prior to the first angel investment in our sample, the average angel has a gross annual income of 808 thousand Swedish kronor, and the median angel has a yearly labor income of 473 thousand kronor. It is evident from the table that angels earn high incomes, but also that the incomes do not place them at the very top of the

[19]The average exchange rate during our sample was 7 Swedish kronor per US dollar.

distribution, especially when compared to their ranking based on wealth. For example, while the median angel was in the top percentile of the wealth distribution, the median angel is only in the top decile of the income distribution. The table also compares angels to non-angel wealthy individuals (those that belong to the top 1% of gross wealth or based on capital income). The median angel earns roughly 393,000 kronor, more than twice the labor income earned by the median non-angel rich person (about 70% more using capital income as a proxy for wealth). In short, angels earn higher labor incomes than other wealthy individuals. However, neither angels nor other wealthy people are at the very top of the labor income distribution. These results suggest that angels are typically not like Frank Frugal, the fictitious character depicted by Mankiw, 2019 who manages a major corporation at the same time he successfully invests in startups.

3.5. The preferences and abilities of business

In this section, we investigate whether angels may differ from other rich or successful individuals in terms of personal characteristics which are set very early on (if not at birth) and hardly affected by public policy: their ability (as opposed to skills and network connections accumulated via higher education and work experience) and their preferences in terms of risk and non-pecuniary benefits of their investments.

3.5.1. Do angels exhibit higher ability ahead of their adult career?

A key question in understanding the supply of any group of "elite" individuals is whether these are drawn from a very specific part of the distribution of "talent." This question has already been asked in other contexts, such as politicians (Dal Bó et al., 2017) and CEOs (Adams et al., 2018), and here we try to provide an answer in the case of business angels. We shed light on their general ability as captured by standardized test scores obtained from military records. These measures have been widely used in the Finance and Economics literature as proxies for ability and talent; Lindqvist and Vestman (2011), for example, show that they relate to labor market outcomes in a meaningful way.

We compare individuals along these dimensions to the sample of informal investors, as well as investing founders, employees, and their families, and the subsets of rich individuals. In addition, we construct relevant comparison groups of managers/leaders, banking professionals, and VC professionals. Böhm et al. (2022) documents that finance professionals have, on average, high cognitive scores. The ratio of the fraction of individuals in the top cognitive score bucket among finance workers compared to the population is 2.5x.[20] Our group of banking professionals capture about 47% of the entire group of finance workers. The average large company CEO belongs to the top 5% of the population combining cognitive, non-cognitive, and leadership skills, but primarily excels in non-cognitive ability tests as documented by Adams et al. (2018). Our sample of leaders is inspired by this finding and consists of all individuals that hold top hierarchy positions at their place of employment. Lastly, we identify a group of VC professionals among the employees at VC firms. We limit the sample to individuals who hold a top hierarchy position or a position that requires some higher qualification.[21]

Panel A and B of table 3.10 report demographic characteristics within each subsample. There are only about 18% women within the angel group, which is a lower share than all other subsamples. Foreign-born individuals have less representation in the samples of angels and wealthy individuals compared to the other subsample. Angels' average age is comparable to informal investors' as well as wealthy individuals and leaders, but angels

[20] In comparison, we document a ratio of 5x in the angel group.

[21] We use SSYK codes to identify occupations in the two top qualification levels.

are slightly older than founders and banking and VC professionals. Regarding family backgrounds, the investor subsamples, including angels, stand out in terms of parents' education level. Not surprisingly, most individuals in all groups come from relatively wealthy, high-income families.

Panel C of table 3.10 reports, respectively, the share of individuals within each sample with a cognitive, non-cognitive, and leadership score among the two highest, corresponding to the top 11% of the population. The results show that business angels are exceptionally high-ability individuals compared to the population at large and other wealthy individuals. The angels also stand out compared to the other investor groups, the sample of leaders, and banking professionals. The only other group with nearly as high test scores is VC professionals.

Military test scores are effectively only available for the male population born before 1988. To overcome this challenge, we additionally investigate the high school grade distribution. The final measure of general ability that we consider is high school grades. These grades measure scholastic performance in the year of graduation and are available for both males and females. Following Böhm et al. (2022), we also construct imputed cognitive scores using high school grades and educational attainment to assess the cognitive abilities of the entire population.

The findings using the military test scores persist using these alternative measures. As evidenced in Panel D of table 3.10, the share of angels in the 10% of the high school grade distribution or top 11% of imputed cognitive scores is slightly lower than the share of individuals in the comparable cognitive score bucket. However, relative to the other subsamples, angels score significantly higher on average, and the distance to VC professionals increases using these alternative measures.

3.5.2. What angels' asset allocation reveals on their preferences

A large literature in household finance (Guiso and Sodini, 2013) uses the observed asset allocations of individuals to infer their risk preferences. In what follows, we apply this methodology to the case of business angels. How do they allocate their wealth between different asset classes? How much of their wealth is invested in equities, fixed income assets, cash, pension assets, real estate, and private equity? How does the allocation of angels differ from other wealthy individuals?

Panel E of table 3.10 reports the within-group mean and median of individuals' risky shares. The important takeaway from Panel E is that the personal asset allocation of angel investors is significantly more tilted toward risky assets when compared to the other subsamples: about 55% of angels' gross wealth is invested in risky financial assets and about 50% in equities. The risky share measure across the other subsamples ranges from 6.88% (banking professionals) to 48.12% (family).

Angels may be expected to invest more in private equity; however, this tilt towards private equity does not appear to be due to the angel investments themselves, as it exists even before the angels have made their first angel investment in our sample. It most likely represents a stake in a company the angel controls either on her own or together with family members and/or co-founders. Importantly, this equity bias exists also when excluding private equity holdings. The equity excluding PE share is the ratio of all public equity holdings to gross wealth net of private equity. Angels have among the highest shares across all groups, even when excluding their (risky) private equity holdings.

In sum, these results suggest that angels exhibit a significantly riskier and more underdiversified asset allocation profile than other wealthy individuals. This may reflect a markedly lower level of risk aversion. However, given the amount of money they leave on the table due to poor diversification, it is also likely that, similar to entrepreneurs (Moskowitz and Vissing-Jørgensen, 2002), angels derive substantial non-pecuniary benefits from their investments in startups. The nature of such benefits must however be very different from those enjoyed by entrepreneurs since angels make minority investments and hence do not exert control over their targets.

3.6. The life experiences of business angels

In this section, we characterize the population of business angels in much more detail, focusing on their prior life experiences at work and in the higher education system. Life experiences may matter to understand the supply of angels for two reasons. First, life experiences proxy for a joint set of skills and network connections which may be critical to the decision to become an angel. Second, the life experiences of angels are, to some degree, the result of the environment they are exposed to before becoming an angel. This may help document an intergenerational linkage between the current cohort of angels and prior states of the local startup ecosystem angels evolve in (Hellmann and Thiele, 2015). Such a linkage would suggest the existence of multiple equilibria in the context of innovation ecosystems, which provide a motivation for active public policies in this domain (Hellmann and Thiele, 2019).

Before we dig further into the past of angels, it is worth mentioning a few salient demographics. 82% of the angels in our sample are male, and they are, on average, 55 years old in the year of their first angel investment. They generally come from well-off families, nearly all angels have one parent in the top decile of the income distribution, and more than 70% have parents in the top wealth decile. Yet, what we document in the rest of this section is only in small part the result of such age and gender selection as we systematically compare our angel population with other wealthy individuals, who are also largely selected on age and gender.

The educational experience of angels Panel A of table 3.11 presents information on the educational attainment of business angels compared to the same subsamples as in 3.4. The table reports that about 8% of the angels hold a doctoral degree, and 65% of them have extended their education after completing high school. In comparison, about 3% of wealthy individuals that are not angels have a doctorate, and around 46% of them have pursued higher education (the specific numbers depend on the wealth definition considered). VC professionals and founders/employees exhibit a nearly as high share of individuals with a doctoral education as business angels, and VC professionals exhibit a similar share, even slightly higher, of individuals that attended higher education.

Panel B of table 3.11 displays the field of education for individuals that have obtained a post-graduate education. Interestingly, more than half of the business angels that have pursued a higher education have a degree in the social sciences, law, or business, compared to about 34% of the other wealthy individuals. Angels are more likely to have a business or STEM education than other rich people (26% versus 20-23%), while they are less likely to obtain a degree in the health sciences (11% versus 15%).

The work experience of angels Panel C of table 3.11 tabulates the work experience. It aggregates the full employment history at the individual level since 1990 leading up to the year of first investment or entry into the subsample. We find that nearly 18% of the angels have some work experience in a startup which is comparable to most other subsamples (excluding banking professionals). About 2% of the angels have been C-suite executives in a startup which is higher than for the rich in general and informal investors. Mechanically the founder/employee and Leader samples are expected to have a high share of leaders and startup experience. Angels stand out in terms of general leadership experience and being in the top leadership of a public company relative to all other samples. Business angels also have significantly more experience working in firms that undergo ownership transitions: 3.9% have been employed during an IPO (compared to 1.1% of all wealthy individuals), 6% during an M&A (compared to 1% of the rich), and 2.3% during an LBO (compared to 1% of the rich). Together with our findings on the educational background of angels, these results suggest that prior leadership experience and financial know-how may be important and may matter more than technical experience.

In sum, it is conceivable that the differences in business angels' and other wealthy individuals' investment decisions are due to the differences in the environments that business angels have evolved in across the years. Those environments might have given angels the opportunity to develop useful network connections and specific skills for detecting and monitoring young business ventures. However, the results in 3.5 suggest that business angels also share specific innate characteristics. In the next section we further investigate whether differences in innate characteristics and life experiences have implications for the characteristic of the business angels' investment.

3.7. Angel heterogeneity and investment characteristics

Angels are a heterogeneous group of individuals. As a group, some characteristics such as high cognitive ability, own wealth and family wealth, high educational attainments work experience in finance or leadership positions are particularly prevalent. In this section, we further study whether investors who share some of these characteristics have a significantly different investment behavior than other angels.

Table 3.12 presents the results from this analysis, where Panel A focuses on firm characteristics, panel B displays board engagement, and various proxies for sophistication. Panel C presents statistics on the co-investment behavior of the individuals, while panel D studies the differences in investment size.

There are some groups of individuals with striking differences relative to other groups, and the group of investors with the most striking differences from other investors are angels with doctoral education. The investments by this subset of individuals are outliers regarding firm characteristics, sophistication, co-investment behavior, and investment size. Individuals with a doctoral education tend to invest in the health sector and are twice as likely to invest in firms in this industry compared to other angels. On the other hand, these investors are half as likely to invest in tech sector firms. The firms they invest in are less mature than other angel firms, much smaller, and less likely to be post-revenue and profitable. These results indicate that these individuals' skill sets are relevant when evaluating, supporting, or sourcing the firms they invest in, as most doctoral education angels have biology, medicine, or health-related educational backgrounds. They frequently sit on the board of the firms they invest in, suggesting that they support these firms and contribute with valuable experience, knowledge, and skill relevant to the firms' businesses.

Regarding sophistication measures, doctoral angels are generally less likely to invest through a vehicle, participate in multiple subsequent rounds, and invest in convertibles. We interpret these results as doctoral angels having less business acumen than other angels but a distinct and possibly valuable skill set when investing in a particular subset of firms. Moreover, while these individuals are equally likely to always co-invest with other angels, they rarely formalize this co-investment strategy by setting up a join-vehicle. Lastly, doctoral angels generally invest smaller amounts than other angels and take a smaller round share. Combined, all these results highlight the distinctiveness of this group of investors. While looking only at the results related to these investors' business acumen, relative prevalence, and capital contribution, one might conclude that these are uninformed investors with little importance. However, given the possible matching between the firms and the particular skill set of these individuals, their contribution lies elsewhere, possibly in guiding and mentoring budding entrepreneurs.

Women angels are unlikely to hold board positions and are significantly more likely to co-invest with family members. These observations suggest that, despite women's low representation in the angel group, they might be overrepresented in our sample if some other family member invests capital into startup firms on their behalf. Lastly, and not surprisingly, wealthy angels make significantly larger investments than other angels. The median investment by rich angels is about twice as large as the median investment among all angels. The individuals also tend to take a larger round share.

3.8. Conclusion

Entrepreneurship is an important driver of growth and prosperity, and ensuring the availability of a deep pool of risk capital to fund early-stage ventures is thus an essential policy goal in many countries. Business angels are a key source of funding for start-ups. Our study is the first to comprehensively answer the question of who angel investors are. We document that business angels are necessarily drawn from the uppermost tail of the wealth distribution. Most angels also come from privileged backgrounds with rich, high-income, and highly educated parents. However, business angels differ from other wealthy individuals in key ways: they have lower risk aversion (their wealth portfolios are tilted towards equities, both private and public), higher general ability (e.g., cognitive, non-cognitive, and leadership skills), and they are more educated. Business angels also have more business experience than other wealthy people: they are more likely to have studied for business degrees at university, and many have a background in financial services.

Our analysis should help inform the design of policies encouraging the development and financing of early-stage ventures. Policies aimed at developing a local supply of business angels may have adverse distributional effects if substantial public resources are channeled to well-off individuals with no specific abilities, particularly if such individuals are primarily drawn from the highest percentiles of the wealth and income distribution. Our analysis shows, however, that business angels are more able, educated, and risk-tolerant than other wealthy people. This finding has important policy implications, suggesting that public policy supporting early-stage entrepreneurial ventures cannot start from the premise that there is a deep supply of potential angel investors. Such policies are likely to be more effective if they are aimed at increasing the quality of the pool of potential angel investors or if they subsidize angel investors conditional on strict standards of ability and experience. A corollary of our analysis is that sound income and wealth tax policies must balance distributional objectives with the distorting effects of high tax rates, such as the possibility of deadweight losses in the form of a decrease in the availability of funding for early-stage ventures.

3.9. Tables

Table 3.1. This table describes the sample selection procedure. Panel A shows summary statistics for the machine-processed data used to identify which firms to include in the sample and how the data reduces with the imposed selection criteria. The imposed restrictions are i) only private firms, ii) only firms with available accounting data, iii) only independent firms (no equity issues by subsidiaries), and iv) only firms with consistent filings. The last restriction excludes firms with foreign currency issues and where the change in share capital is inconsistent with the amount raised. The coded firms include all issues by all firms that at some point raised more than five million SEK in a round (Large sample) and all issues by a random sample of 5% of all firms (Random sample). Panel B displays the same statistics using the coded data.

	N		Bn SEK	Mn SEK	
	Rounds	Firms	Amount	Round size Mean	Round size Median
Panel A: Summary statistics from machine processed data					
All issues	53, 828	32, 039	1, 587.93	28.67	0.60
Excluding Listed	47, 202	31, 052	1, 228	25.39	0.45
Excluding No Book	42, 663	27, 272	1, 206.29	27.56	0.50
Excluding Subsidiaries	31, 595	19, 029	344.94	10.63	0.40
Excluding inconsistent issues	31, 382	18, 922	341.49	10.60	0.40
Large sample	6, 782	1, 810	271.85	37.70	5
Random sample	1, 659	998	6.28	3.67	0.40
Random sample excl. large	1, 436	949	1.80	1.23	0.30
Panel B: Summary statistics from coded sample					
Equity issues					
Large sample	6, 816	1, 811	176.39	25.88	5
Random sample	1, 662	998	9.47	5.70	0.40
Random sample excl. large	1, 433	949	4.96	3.46	0.30
Convertible issues					
Coded Large	558	292	6.90	12.36	3.72
Coded Random	54	31	0.61	11.24	3
Random sample excl. large	20	15	0.07	3.30	1.50
Warrant issues					
Large sample	1, 430	509			
Random sample	143	55			
Random sample excl. large	71	32			

Table 3.2. This table presents an overview of individual investors identified by their social security numbers. *Founder/Employee* are all individuals ever employed in the firms in which they invest, and *Family* includes all of their relatives (parents, children, and partners). *Informal investor* and *Angel* include all other unrelated individuals. Angels, unlike informal investors, invest in at least two unrelated firms. The groups in the last three columns are mutually exclusive but might overlap with the group of founders/employees while investing in different firms. Some individuals are "Visible angels", identified through news searches, member lists from SVCA, and other external sources.

Number	All individuals	Founders/ Employees	Family	Informal investor	Angels
Individuals	9,041	2,283	293	5929	720
Firms	1,445	853	189	917	529
Rounds	3,745	1,721	447	2,396	1,432
Share of (%)					
Individuals in subsample	100.00	25.25	3.24	65.58	7.96
Individuals is visible angel	4.91	2.06	8.87	2.82	35.42
Firms with visible angel	24.08	4.92	11.64	10.14	52.17
Rounds with visible angel	26.65	6.57	18.12	10.27	50.91
Total across all individuals (Bn SEK)					
Equity	17,845.13	8,226.57	707.33	5,856.47	3,054.76
Convertible	479.87	56.92	8.77	212.44	201.73
Share of individuals (%)					
Invests through vehicle	0.52	0.27	0.64	0.53	0.72
Ever invests through vehicle	0.57	0.32	0.70	0.56	0.82
Size (Th SEK)					
Mean investment	987.34	2,156.60	1,086.65	591.63	856.52
Median investment	93.96	99.98	131.87	79.42	109.00
Mean round size	17,340.40	17,696.01	13,580.80	18,782.50	13,752.19
Median round size	4,900.00	4,000.27	4,968.02	4,954.37	4,992.30

Table 3.3. This table presents an overview of the representation of different investor groups in all rounds and rounds of varying sizes. The table includes all equity and convertible issues to investors in either of the investor groups. The table presents the total number of investment rounds in which any member of the investor group participated, as well as the aggregate capital share attributed to the investor group. The capital shares constitute the share of the aggregate capital raised by the sample firms from identified investors only.

	All		**≤ 1 Mn SEK**		**1–10 Mn SEK**		**10–50 Mn SEK**		**≥ 50 Mn SEK**	
	N	Capital (%)	N	Capital (%)	N	Capital (%)	N	Capital (%)	N	Capital (%)
Angel	1432	2.58	213	7	869	7.48	293	4.35	57	1.46
Founder/Employee	1721	6.56	549	19.32	801	7.54	289	6.26	82	6.45
Family	447	0.57	73	2.42	260	1.12	90	0.92	24	0.39
Family office/Visible angel w/o ID	1335	8.26	145	6.54	831	10.37	299	6.37	60	8.5
Informal investor	2297	4.52	530	21.96	1299	12.61	390	5.73	78	3.08
VC/PE	2161	36.34	231	14.73	1073	28.48	656	39.96	201	36.51
Government	535	11.12	54	2.96	310	5.6	134	6.89	37	12.99
Financial corporations	669	10.09	61	3.7	323	4.61	187	5.06	98	12.14
Non-financial corporations	2792	19.96	482	21.37	1465	22.2	653	24.46	192	18.48

Table 3.4. This table displays at what rate different investor groups overlap regarding the firms they invest in and the within-firm timing of such investments. Panel A presents at what rate Angels, informal investors, and VC/PEs invest in the same round as other investor groups. Panel B displays the same statistics, restricting the underlying sample of observations to the first time the investors made an observed investment in the firm. Panel C and D introduce a dynamic perspective, detailing how common it is that other investors invest in a firm after the first investment by an Angel, informal investor, or VC/PE (Panel C) or before the first investment (Panel D).

	N	Angel	Founder/ Employee	Family	Family off. Vis. angel	Informal investor	VC/PE	Government	Financial corp.	Non-fin. corp.	Unidentified
Panel A: Contemporary, all rounds											
Angel	1478	100	35.25	13.26	41.2	63.19	26.25	12.18	14.68	52.98	71.99
Informal investor	2499	37.37	36.09	12.44	28.45	100	22.25	7	12.04	46.7	66.79
VC/PE	2294	16.91	19.14	5.06	18.66	24.24	100	9.55	7.37	29.21	58.28
Panel B: Contemporary, first round											
Angel	530	100	24.91	13.4	30.38	43.77	12.83	6.98	14.53	36.42	40.94
Informal investor	924	32.47	31.82	12.23	19.16	100	11.69	5.19	10.5	37.55	42.21
VC/PE	649	16.02	19.41	6.63	15.56	22.34	100	10.17	9.4	30.35	46.84
Panel C: Forward, first round											
Angel	426	69.95	51.64	19.25	49.3	66.9	39.2	14.08	21.83	72.07	86.38
Informal investor	640	43.75	50.78	17.81	37.97	74.69	40.31	11.41	18.91	70	85.78
VC/PE	548	28.28	40.88	10.77	29.01	41.61	77.92	15.51	13.69	52.92	76.82
Panel D: Backward, first round											
Angel	317		26.5	14.2	18.93	22.4	17.35	6.31	16.09	27.76	21.45
Informal investor	408	33.09	31.13	15.69	25	NA	19.85	8.82	19.36	38.97	31.13
VC/PE	232	46.12	62.93	20.26	35.78	64.66		15.52	22.41	75.43	68.1

Table 3.5. This table presents an overview of firm characteristics when an investor from the respective groups first invested in the firm. Age represents years since registration of the oldest entity within the company group (including all subsidiaries). The share of investor and target firm pairs located in the same region—municipality or county—is reported for investor groups where all investors are identified by social security or company registration numbers. The last two columns report the share of firms with positive revenue or operating profit at the time of first investment.

		Age		**Same location**		**Maturity**	
	N	Mean	Median	Munici-pality	County	Positive revenue	Positive profit
Angel	530	5.14	3	38.19	66.74	79	21.2
Founder/Employee	889	5.44	2	57.36	82.48	84.95	37.61
Family	194	6.73	4	39.18	68.42	91.44	30.48
Family off./Vis. angel	446	4.59	3			81.16	19.77
Informal investor	924	4.9	2	45.36	72.5	76.96	26.59
VC/PE	649	4.06	2	51.7	67.61	80.58	25.73
Government	196	5.85	3			80.65	20.43
Financial corp.	290	5.12	3.5	44.94	61.39	82.55	26.91
Non-financial corp.	1186	5.12	2	54.76	72.67	79.68	30.71

Table 3.6. This table presents an overview of the firm's size characteristics when an investor from the respective groups first invested (Panel A), and the industry distribution (Panel B). Sales, operating profit, total assets, leverage, and the number of employees are all book values aggregated to the group level. Leverage is the ratio of total debt (short-term and long-term) to the book value of total assets. A firm's industry is based on the SNI code but converted into eleven overall sectors.

Panel A: Size at first round (Mn SEK)

	N	**Sales**		**Op.profit**		**Tot. assets**		**Leverage**		**Has debt**	**Employees**		
		Mean	Median	Mean	Median	Mean	Median	Mean	Median		Mean	Median	≥ 5
Angel	530	53.38	1.6	-1.37	-1.27	145.61	13.69	0.47	0.41	98.8	25.44	5	46.8
Founder/Employee	889	120.97	6.85	3.56	-0.22	259	14.99	0.52	0.5	98.18	57.13	8	56.81
Family	194	94.65	9.93	3.56	-1.77	208.62	23.25	0.52	0.5	99.47	39.92	10	67.91
Fam. off./Vis. angel	446	60.81	2.2	-1.01	-1.96	212.17	12.17	0.44	0.38	98.37	40.18	6	51.63
Informal investor	924	87.81	1.87	0.23	-0.58	148.6	11.43	0.49	0.45	98.41	52.61	4	42.89
VC/PE	649	167.47	4.71	-2.61	-1.34	514.02	24.22	0.53	0.41	98.38	115.18	10	60.52
Government	196	174.58	1.67	9.16	-1.35	2144.35	16.57	0.45	0.42	100	61.21	5	46.24
Financial corp.	290	114.38	4.91	10.56	-1.56	799.22	33.13	0.43	0.4	99.64	49.94	7	52.73
Non-fin. corp.	1186	115.5	4.22	0.62	-0.62	326.04	20.68	0.47	0.43	97.87	51.93	6	50

Panel B: Industry	N	IT & Electronics	Health & Education	Corporate services	Finance & Real Estate	Industrial goods	Shopping goods	Other	Unknown
Angel	530	18.11	18.11	17.17	12.45	10	7.36	13.58	3.21
Founder/Employee	889	12.82	12.15	22.83	10.01	10.69	14.06	15.3	2.14
Family	194	17.01	13.4	23.71	8.76	8.76	9.79	18.04	0.52
Fam. off./Vis. angel	446	17.49	19.73	19.73	10.31	10.09	8.3	11.88	2.47
Informal investor	924	13.64	14.39	20.45	13.31	9.2	10.06	15.48	3.46
VC/PE	649	20.18	20.34	19.72	6.78	10.63	8.17	10.17	4.01
Government	196	15.31	24.49	15.31	11.73	8.16	5.61	17.86	1.53
Financial corp.	290	13.1	15.17	17.59	18.97	8.28	6.21	16.55	4.14
Non-fin. corp.	1186	13.24	12.9	21.33	13.24	8.6	9.95	17.28	3.46

Table 3.7. This table presents an overview of the deal characteristics in rounds where a member of the investor group participated. "Investors in round" refers to the number of investors belonging to the investor group who participated in the round. The amount invested and round share are presented as an aggregate across all investors in the investment round ("Total across") and at the level of the investor ("Per investor").

Deal characteristics: Size of investment											
	N			**Amount invested in round (Th SEK)**				**Share of round (%)**			
	Rounds	Investors in round		Total across investors		Per individual investors		Total across investors		Per individual investors	
		Mean	*Median*	*Mean*	*Median*	*Mean*	*Median*	*Mean*	*Median*	*Mean*	*Median*
Angel	1478	2.56	1	2203.31	462.98	976.83	130.63	24.96	14.35	11.07	3.5
Founder/Employee	1987	2.27	1	4168.84	183.89	2055.89	84.08	38.39	21.22	18.78	4.53
Family	472	1.39	1	1517.17	222.03	1196.77	144	16.48	7	12.59	3.92
Fam. off./Vis. angel	1392	1.5	1	7499.78	930.3	5189.85	475.56	33.04	24.05	22.29	11.02
Informal investor	2499	3.84	2	2287.08	360	713.73	89.26	32.67	20.81	10.14	2.2
VC/PE	2294	1.87	1	20016.94	3550.25	11399.54	2000.03	66.55	74.81	35.87	27.43
Government	547	1.18	1	25694.19	1999.94	22494.29	1500.02	49.4	44.48	42.73	33.33
Financial corp.	699	1.58	1	18229.09	1256.11	12125.82	900	40.89	29.04	27.16	12.5
Non-financial corp.	3070	1.69	1	8215.08	900	4972.26	411.47	43.84	33.35	27.09	11.69
Unidentified	6411	3.95	2	9665.22	463.49	3481.36	100	53.47	50.18	16.77	2.93

Table 3.8. This table presents an overview of the deal characteristics in rounds where a member of the investor group participated. "Only common" is the share of all investment rounds where the firm only raised common equity. Alternatively, the firm issued some preferred equity securities, convertible loans, or warrants. "Board seats" refers to the number of board seats ("N") or share of all board seats ("Share") held by the investor group immediately following the issue. The last columns present the percentage of rounds where the individual investor, or any individual in the investor group, holds a board seat immediately after the investment round. Board seats are only presented in investor groups where all investors are identified by social security number.

Deal characteristics: Securities and board seats

	N	Share of rounds (%)				Board seats investor type				Share of rounds on board	
	Rounds	Only common	Some preferred	Some convertible	Some warrant	N mean	N median	Share Mean	Share Median	Investor type	Individual investor
Angel	1478	74.36	12.04	6.5	7.98	0.73	1	8.98	0	46.55	22.47
Founder/Employee	1987	69.3	10.97	3.52	17.36	1.23	1	18.58	16.67	75.29	46.04
Family	472	74.79	10.81	6.78	8.69	0.56	1	7.34	0	43.64	32.72
Fam. off./Vis. angel	1392	70.55	12.14	9.05	10.34						
Informal investor	2499	74.63	9	5.76	11.88	0.94	1	12.29	11.11	55.14	19.53
VC/PE	2294	52.35	26.9	11.86	13.16						
Government	547	69.29	13.16	11.88	7.5						
Financial corp.	699	72.25	12.3	8.15	8.58						
Non-financial corp.	3070	72.44	10.13	6.22	12.44						
Unidentified	6411	64.22	17.41	5.19	15.35						

Table 3.9. This table presents an overview of the wealth and income of the individual investors in the sample, as well as three relevant comparison groups—individuals in the top percentile of the wealth distribution, measured using either gross wealth or 10-year accumulated capital income, and individuals in the top percentile of the labor income distribution. Wealth and income are measured the year before the individual makes their first observed investment or enters the top percentile/decile distribution in the wealth/income samples. The table also reports group means and medians and the percentage share of individuals in the sample who are in the top quartile, decile, percentile, or permille. Gross wealth is only available in years before 2007, while accumulated capital income and labor income are available over all relevant years.

	N	Mean Mn SEK	Median Mn SEK	% top Quartile	% top Decile	% top Percentile	% top Permillile
Panel A: Gross wealth in year preceding first investment (2002-2007)							
Angel	426	56.19	9.74	94.6	86.62	57.04	23.71
Founder/Employee	1217	5.18	1.81	66.47	41.17	12.74	2.71
Family	143	13.37	4	79.02	66.43	30.77	13.29
Informal investor	2493	10.18	3.07	80.47	62.09	23.59	6.22
Top percentile							
Gross wealth	89653	17.8	9.59	100	100	100	10.56
Acc. cap. inc	85214	12.97	5.23	96.44	88.89	43.99	8.51
Top decile							
Labor income	803635	2.13	1.27	62.62	33.21	4.02	0.51
Panel B: Accumulated 10-year capital income preceding first investment							
Angel	633	1.69	0.18	82.62	75.67	52.13	27.8
Founder/Employee	2506	0.15	0	45.05	32	13.17	3.67
Family	252	0.46	0.02	65.08	53.97	28.17	9.92
Informal investor	5031	0.43	0.02	65.49	55.2	25.78	8.25
Top percentile							
Gross wealth	89653	0.39	0.09	83.82	78.06	41.81	8.59
Acc. cap. inc	119917	0.66	0.29	100	100	100	10
Top decile							
Labor income	1078475	0.02	-0.01	39.92	24.64	4.52	0.64
Panel C: Labor income in year preceding first investment							
Angel	633	808.04	473.5	69.67	57.66	23.7	7.42
Founder/Employee	2506	568.03	452.1	73.62	55.19	14.09	2.11
Family	252	558.6	356.4	56.75	40.48	13.1	3.97
Informal investor	5031	564.76	385.8	62.25	44.52	13.36	3.66
Top percentile							
Gross wealth	89653	362.06	205.15	48.13	36	12.23	3.67
Acc. cap. inc	119917	406.5	280.9	52.98	40.68	12.47	3.28
Top decile							
Labor income	1078475	617.91	533.3	100	100	13.2	1.78

Table 3.10. This table presents the innate characteristics of the individual investors in our sample, Angels, Founders/employees, Family, and Informal investors, and three relevant comparison samples—leaders, banking professionals, and VC professionals. Leaders include all individuals in the population in a top hierarchy position, banking professionals are employees at financial corporations in the three most common occupation code classifications, and VCs are employees at VC firms in qualified occupations. Panel A presents demographic statistics, and Panel B displays statistics illustrating the individuals' family backgrounds. Panel C shows the share of individuals who scored in the top two highest score buckets (approximately the top 11% of the population) on military enlistment tests for cognitive, non-cognitive, and leadership skills. Leadership test results are only available for individuals who scored in the top 40% on both cognitive and non-cognitive tests, and military enlistment data is effectively only available for the male population. Therefore, Panel D displays similar statistics using imputed cognitive scores and high school grades available for both genders. Panel E displays metrics representing risk attitudes inferred from individuals' wealth allocation. Wealth data is only available in years before 2007 and is measured in the year of first investment or entry into the sample.

	Angel	Founder/ Employee	Family	Informal investor	Acc.Cap.Inc Top 1%	Gross wealth Top 1%	Leaders	Banking professional	VC professional
Panel A: Demographics									
N	662	2537	271	5246	104168	67820	247857	66011	775
Male	82.02	85.30	64.94	80.98	72.38	73.70	69.47	40.66	61.81
Age (mean)	55.89	48.57	54.13	55.04	58.25	59.85	54.02	46.71	49.94
Age (median)	55.5	47.0	55.0	55.0	60.0	61.0	54.0	46.0	50.0
Above age 65	27.95	8.24	23.99	22.87	28.69	34.75	19.04	10.81	9.94
Foreign born	3.32	8.75	2.95	4.73	4.23	3.63	8.68	6.44	7.24
Born outside EU15	1.81	5.16	1.48	2.19	1.93	1.62	4.84	4.26	5.04
Panel B: Family background									
N	720	2591	302	5752	107417	69724	255558	67768	793
Oldest sibling	41.56	42.99	44.96	42.99	37.05	37.61	39.02	38.60	39.37
Youngest sibling	34.10	34.50	28.99	33.46	37.54	37.01	34.33	38.97	36.03
Parent with higher education	56.30	50.10	55.61	45.72	35.69	33.22	29.16	38.33	50.16
Parent top 10% total income 2002 (%)	92.03	93.01	97.01	90.88	89.21	88.41	90.26	94.35	90.31
Parent top 10% gross wealth 2002 (%)	72.46	82.63	85.07	78.96	72.90	70.67	78.37	84.08	83.54

3.10 *continued*

	Angel	Founder/ Employee	Family	Informal investor	Acc.Cap.Inc Top 1%	Gross wealth Top 1%	Leaders	Banking professional	VC professional
Panel C: Innate talent (males only)									
N	264	1414	82	2176	30368	17416	78706	17454	305
Top cognitive	42.80	33.97	36.59	28.97	26.16	24.15	17.48	12.81	39.67
Top noncognitive	27.20	19.96	24.36	22.23	20.11	20.23	17.00	13.32	29.01
Top leadership	30.86	21.29	25.00	22.20	20.28	20.72	16.29	12.29	32.00
Panel D: Innate talent (both genders)									
N	376	1820	156	2993	45278	25899	128480	47758	567
Top grade decile	35.37	22.75	28.21	21.75	19.90	19.97	11.45	12.97	26.28
Top imputed cognitive	36.97	33.08	33.33	27.80	23.85	22.65	12.80	10.43	29.98
Panel E: Implied risk aversion									
N	352	891	119	1834	67076	69724	154233	47119	230
Risky share (Mean)	53.12	17.69	48.12	39.26	33.43	26.57	22.42	22.24	20.26
Risky share (Median)	55.18	13.95	48.41	34.73	27.30	12.26	7.97	6.88	8.57
Equity share (Mean)	50.11	13.76	42.95	35.11	26.52	23.44	17.98	16.83	16.23
Equity share (Median)	51.77	10.29	38.66	29.21	17.73	8.76	4.80	4.19	5.27
PE share (Mean)	34.78	1.10	26.45	21.04	5.87	10.43	5.18	0.08	1.46
PE share (Median)	25.31	0.00	11.59	4.41	0.00	0.00	0.00	0.00	0.00
Equity excl. PE share (Mean)	21.92	14.16	22.26	17.46	21.54	14.47	13.57	16.77	14.80
Equity excl. PE share (Median)	11.26	3.92	8.91	6.43	11.92	4.06	2.63	4.16	4.00

Table 3.11. This table presents the innate characteristics of the individual investors in our sample, Angels, Founders/employees, Family, and Informal investors, and three relevant comparison samples—leaders, banking professionals, and VC professionals. Leaders include all individuals in the population in a top hierarchy position, banking professionals are employees at financial corporations in the three most common occupation code classifications, and VCs are employees at VC firms in qualified occupations. Panel A presents the level of education attended by the individuals, measured at the time of first investment or entry into the sample, and Panel B displays the chosen major of all individuals who attended higher education. Panel C summarizes individuals' work experience across all places of employment since 1990 leading up to the year of first investment or entry into the sample.

	Angel	Founder/ Employee	Family	Informal investor	Top percentile Acc.Cap.Inc	Top percentile Gross wealth	Leader	Banking professional	VC professional
Panel A: Level of education									
N	622	2504	245	4793	107417	69724	255558	67768	793
Doctoral education (%)	7.61	6.37	4.51	4.56	2.81	3.33	1.05	0.12	6.08
College education (%)	64.89	56.65	62.70	52.16	43.61	43.32	34.77	37.19	67.97
High school education (%)	95.79	95.95	94.67	92.87	88.50	87.47	86.81	94.83	98.99
Panel B: Major (Higher education only)									
N	401	1414	153	2494	46718	30087	88421	25158	537
Business	32.17	22.70	32.03	28.95	22.92	23.02	22.24	58.50	45.62
Law	7.73	1.98	5.88	5.57	6.94	6.94	3.18	9.47	4.84
Other social sciences	11.47	4.03	9.80	6.98	8.14	8.62	8.80	11.92	9.50
STEM	28.93	55.52	24.84	34.04	24.57	21.50	21.40	8.05	26.63
Healthcare	11.22	6.36	11.76	11.63	14.86	14.80	9.31	1.63	7.08
Other or missing	8.48	9.41	15.69	12.83	22.56	25.11	35.07	10.43	6.33

Table 3.11 *continued*

	Angel	Founder/ Employee	Family	Informal investor	Top percentile Acc.Cap.Inc	Top percentile Gross wealth	Leader	Banking professional	VC professional
Panel C: Work experience (since 1990)									
N	701	2580	292	5623	107240	69274	254582	67441	790
$\geq$ 5 years	95.15	96.67	94.18	96.00	98.15	96.53	97.45	90.86	97.34
$\geq$ 10 years	86.16	86.98	83.56	88.08	93.15	88.68	89.69	70.54	89.75
Top hierarchy	44.35	27.47	34.77	33.24	27.55	25.37	43.39	4.36	17.80
Top hierarchy public company	6.38	1.31	2.73	3.03	0.85	1.03	0.44	2.23	2.62
Startup experience	18.16	24.49	19.44	19.41	16.40	19.37	22.54	11.64	16.98
Startup experience top hierarchy	2.16	3.54	2.08	2.51	1.27	1.22	4.17	0.08	2.66
Employeed during IPO	3.85	2.09	1.37	2.81	1.11	1.02	0.91	6.81	4.56
Employeed during MA	6.38	1.31	2.73	3.03	0.85	1.03	0.44	2.23	2.62
Employeed during LBO	2.28	1.43	0.00	1.37	0.70	0.26	0.39	0.22	0.25

Table 3.12. This table displays how different informal investors, angels, and various subsamples of angels differ in their investments. Each subsample includes a subset of angels that meet the corresponding criteria: gender, top percentile using two wealth proxies in the year of first observed investment(gross wealth and 10-year accumulated income), parents' wealth in 2002, top 11% in military assessments of cognitive and non-cognitive skill (available for males only), top decile in high school grade distribution, doctoral or higher education, business education, as well as work experience in finance or from a startup. Panel A shows how firm characteristics vary across the samples, and Panel B displays various proxies of involvement and sophistication. Panel C reports how the individuals co-invest with VC/PE and other angels. Panel D summarizes round amounts and round shares for individuals.

		N		**Share (%)**					
Panel A: Firm characteristics	Individual	Individual ×firm	Individual ×round	Same county	Tech	Health	Positive revenue	Positive profit	≥ 5 employees
Angel	720	1849	3779	56.35	21.85	25.51	75.17	17.89	42.72
Informal investor	5752	5769	9591	60.24	15.23	20.48	75.53	23.71	44.88
Angel subsamples									
Female	135	349	645	49.9	23.45	22.36	75.89	22.32	44.94
Male	574	1473	3079	57.54	21.52	26.3	74.98	16.68	42.26
Top percentile GW	243	659	1480	56.48	18.94	22.73	74.72	17.17	42.61
Top percentile acc. cap. inc.	225	638	1474	54.79	20.04	25.48	75.33	15.56	44.37
Parents top GW percentile	110	288	592	58.01	21.69	20.34	82.18	20.73	50.91
Top cognitive scores	113	303	633	59.47	23.85	21.33	77.32	16.15	42.27
Top noncognitive scores	71	177	387	57.38	25.32	16.54	77.65	18.24	43.53
Top decile high school grade	133	347	706	58.51	24.36	22.95	79.88	16.27	45.27
Doctoral education	46	116	216	50.47	9.72	55.09	62.5	8.93	33.04
College education	404	1048	2170	54.59	19.83	28.69	73.06	18.29	39.26
Business education (college)	130	331	693	59.27	15.17	23.41	76.97	22.4	43.85
Finance experience	190	487	1019	58.08	21.2	29.64	81.7	16.81	47.02
Startup experience	417	1052	2137	60.11	22.2	23.23	76.97	17.72	43.6

Table 3.12 *continued*

	N			Share (%)				
Panel B: Sophistication	Individual	Individual ×firm	Individual ×round	In board at investment	Ever in board	Invests through vehicle	Multiple subsequent rounds	Invest in convertible
Angel	720	1849	3779	19.9	26.18	80	32.29	21.67
Informal investor	5752	5769	9591	17.14	22	52.09	20.02	8.19
Angel subsamples								
Female	135	349	645	4.87	7.16	88.89	26.36	23.7
Male	574	1473	3079	23.83	31.16	78.05	33.67	20.73
Top percentile GW	243	659	1480	24.13	30.96	80.25	32.02	30.86
Top percentile acc. cap. inc.	225	638	1474	26.02	33.39	75.11	33.39	31.11
Parents top GW percentile	110	288	592	10.07	15.28	85.45	30.21	31.82
Top cognitive scores	113	303	633	21.78	31.02	85.84	34.32	21.24
Top noncognitive scores	71	177	387	21.47	31.64	74.65	36.16	21.13
Top decile high school grade	133	347	706	15.27	23.34	77.44	30.55	25.56
Doctoral education	46	116	216	29.31	32.76	60.87	28.45	10.87
College education	404	1048	2170	22.23	28.63	78.96	31.3	22.28
Business education (college)	130	331	693	26.28	32.02	80.77	33.23	25.38
Finance experience	190	487	1019	21.97	30.18	83.68	31.83	27.89
Startup experience	417	1052	2137	20.63	27.57	82.01	32.51	20.86

Table 3.12 *continued*

	N			Share (%)				
Panel C: Co-investment	Individual	Individual ×firm	Individual ×round	Co-invest with VC	Co-invest with VC first round	Always invests with family	Always invests with non-family	Always invests with non-family in vehicle
Angel	720	1849	3779	27.49	12.38	4.31	10.83	8.61
Informal investor	5752	5769	9591	23.19	12.01			
Angel subsamples								
Female	135	349	645	29.15	13.64	10.37	13.33	11.85
Male	574	1473	3079	27.25	12.24	2.79	9.93	7.67
Top percentile GW	243	659	1480	26.89	10.07	2.47	7.41	7
Top percentile acc. cap. inc.	225	638	1474	26.46	10.31	1.78	8	6.67
Parents top GW percentile	110	288	592	31.93	12.5	1.82	12.73	10.91
Top cognitive scores	113	303	633	28.91	13.27	2.65	11.5	10.62
Top noncognitive scores	71	177	387	21.71	6.46	2.82	12.68	9.86
Top decile high school grade	133	347	706	30.74	14.02	6.02	9.02	5.26
Doctoral education	46	116	216	29.63	12.04	4.35	10.87	4.35
College education	404	1048	2170	26.73	11.47	3.96	8.42	5.94
Business education (college)	130	331	693	23.95	9.67	4.62	5.38	4.62
Finance experience	190	487	1019	28.66	11.58	3.68	10.53	8.42
Startup experience	417	1052	2137	28.59	12.87	4.08	10.31	8.63

Table 3.12 *continued*

Panel D: Investment size	**N**			**Share (%)**			
	Individual	Individual ×firm	Individual ×round	Amount mean	Amount median	Amount share mean	Amount share median
Angel	720	1849	3779	861734.76	103392	0.1	0.03
Informal investor	5752	5769	9591	595913.25	66676.3	0.08	0.02
Angel subsamples							
Female	135	349	645	574700.95	55000	0.05	0.01
Male	574	1473	3079	928632.02	120659.52	0.11	0.04
Top percentile GW	243	659	1480	990805.12	203623.86	0.13	0.05
Top percentile acc. cap. inc.	225	638	1474	951613.58	199716.01	0.13	0.05
Parents top GW percentile	110	288	592	563884.44	124799.99	0.08	0.03
Top cognitive scores	113	303	633	648891.89	100014	0.09	0.04
Top noncognitive scores	71	177	387	626394.36	127238.39	0.09	0.05
Top decile high school grade	133	347	706	589419.4	113000	0.09	0.03
Doctoral education	46	116	216	196600.41	45000	0.05	0.01
College education	404	1048	2170	742524.17	99699.83	0.08	0.03
Business education (college)	130	331	693	555800.17	102000	0.1	0.03
Finance experience	190	487	1019	889611.54	182040	0.11	0.04
Startup experience	417	1052	2137	781208.58	100100.81	0.09	0.03

3.A1 Appendix: Additional figures tables

Table 3.13. This table presents an overview of the wealth and income of the individual investors in the sample, as well as three relevant comparison groups—individuals in the top percentile of the wealth distribution, measured using either gross wealth or 10-year accumulated capital income, and individuals in the top percentile of the labor income distribution. Wealth and income are measured the year before the individual makes their first observed investment or enters the top percentile/decile distribution in the wealth/income samples. The table reports gross wealth (panel A) and accumulated capital income (panel B) in millions of Swedish kronor and annual labor income (panel C) in thousands of Swedish kronor.

	Mn SEK									
	N	Mean	SD	Min	Q10	Q25	Q50	Q75	Q90	Max
Panel A: Gross wealth in year preceding first investment (2002-2007)										
Angel	426	56.19	220.95	0	2.04	3.72	9.74	24.7	100.82	2526.41
Founder/Employee	1217	5.18	18.74	-0.56	0.14	0.73	1.81	3.66	8.98	403.74
Family	143	13.37	33.17	0	0.28	1.38	4	10.25	30.54	331.4
Informal investor	2493	10.18	43.54	0	0.57	1.41	3.07	7.11	17.86	1262.39
Top percentile										
Gross wealth	89653	17.8	244.28	4.62	5.74	7.13	9.59	14.12	25.16	74244.45
Acc. cap. inc	85214	12.97	243.73	-82.04	1.55	2.85	5.23	9.87	20.05	74244.45
Top decile										
Labor income	803635	2.13	62.37	-62.41	0.16	0.62	1.27	2.23	3.7	69420.65
Panel B: Accumulated 10-year capital income preceding first investment										
Angel	633	1.69	5.9	-0.63	-0.02	0.01	0.18	1.36	3.9	101.26
Founder/Employee	2506	0.15	0.78	-0.75	-0.04	-0.02	0	0.04	0.28	23.13
Family	252	0.46	1.66	-0.27	-0.03	0	0.02	0.22	1.02	17.12
Informal investor	5031	0.43	1.67	-2.59	-0.03	-0.01	0.02	0.17	0.85	42.17
Top percentile										
Gross wealth	89653	0.39	3.63	-14.68	-0.02	0.02	0.09	0.27	0.79	1082.19
Acc. cap. inc	119917	0.66	5.77	0.11	0.16	0.21	0.29	0.52	1.11	1678.67
Top decile										
Labor income	1078475	0.02	1.7	-25.15	-0.04	-0.03	-0.01	0	0.05	1678.67

Table 3.13 *continued*

	Th SEK									
	N	Mean	SD	Min	Q10	Q25	Q50	Q75	Q90	Max
Panel C: Labor income in year preceding first investment										
Angel	633	808.04	1823.1	0	37.6	249.6	473.5	798.5	1398.34	32150.9
Founder/Employee	2506	568.03	723.14	0	120	304.45	452.1	659.45	983.45	15532.2
Family	252	558.6	1345.68	0	18.5	158.5	356.4	550.88	956.93	19301.7
Informal investor	5031	564.76	1053.5	0	14.1	195.25	385.8	610.4	1003.2	27347.8
Top percentile										
Gross wealth	89653	362.06	817.31	0	0	2	205.15	434.3	757.5	67541.8
Acc. cap. inc	119917	406.5	802.19	0	0	22.8	280.9	530.2	821	120187.1
Top decile										
Labor income	1078475	617.91	399.88	356.8	411.3	463	533.3	657	861.6	120187.1

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