Essays in Private Markets



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This thesis is dedicated to my parents, Sabine and Andreas,
for their endless love, support and encouragement.

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Abstract

This thesis studies questions in the area of private markets, with a focus on entrepreneurial finance and asset management. Chapter 1 provides a general introduction to the topic and outlines how each chapter contributes to the literature.

Chapter 2 builds on the observation that policymakers across the world like to encourage innovation and high impact start-ups to spur growth. Initiatives include tempting US venture capital firms to invest locally, betting on them to bring in capital and expertise. Chapter 2 documents another benefit: US venture capitalists have a distinct investment style that is more tolerant of financial losses when investing abroad compared to non-US venture capital firms. Chapter 2 finds that companies funded by US venture capitalists already have higher cumulative losses at the time of funding, and then incur further cumulative losses. They are more likely to receive subsequent funding, which is necessary to sustain their higher financial losses. Ultimately, they have a higher likelihood of a successful exit, suggesting that incurring financial losses was worthwhile. Chapter 2 also finds that companies backed by US venture capitalists rely more on equity financing rather than debt financing, consistent with equity financing being better suited for loss making firms.

Chapter 3 examines whether and how outside expertise of directors matters for start-up companies. Chapter 3 exploits the fact that some directors sit on multiple boards simultaneously and studies the effects of director attention on a focal company's performance and growth. Identification comes from leveraging distraction events at directors' other companies that plausibly shock their attention. Chapter 3 finds that an increase in a company's fraction of directors who are distracted leads to a decline in return on assets (ROA) and sales growth, especially if distracted directors are more experienced. Effect sizes represent 8% and 11% of the sample median of ROA and sales growth, which is larger than what prior literature has documented for public companies.

Chapter 4 shows that separate account investors outperform category-matched mutual fund investors yearly by 14-24 bps gross and 50-75 bps net. This outperformance is entirely explained by structural and reporting differences between the vehicles and by size differences between investors. Controlling for the average outperformance of separate accounts over their mutual fund twins, separate account investors perform at the same level as mutual fund investors, gross of fees, and slightly below them, net. Separate account investors choose products that, once adjusted, are more expensive than those chosen by mutual fund investors. Their fixed income picks do better whereas their equity picks do worse.

Chapter 5 offers concluding remarks.

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Chapter 1

Introduction

Private markets are important yet relatively understudied. A likely reason for this is the lack of easily available data of research quality. In this thesis I contribute to our understanding of private markets by investigating questions in entrepreneurial finance and asset management by constructing novel and proprietary datasets.

Most businesses are private. Remaining a private company, as opposed to going public, has arguably become easier in recent times. For example, Ewens and Farre-Mensa (2020) documents that the supply of capital to relatively mature private companies in the US has increased as a result of the deregulation of securities laws.

Relatedly, new forms of financing keep emerging. Crowdfunding has become popular starting in the late 2000s. In a crowdfunding campaign a founding team typically seeks capital from many investors, each of whom supplies a relatively small amount of capital. The campaign is usually conducted on an online platform. There are three different types of crowdfunding. In reward-based crowdfunding, private individuals give money to projects that they are enthusiastic about. They receive a token of appreciation for their investments, for example a DVD from a film project or a concert ticket from a music project. The purpose of

reward-based crowdfunding is not to earn a return, but merely to support the entrepreneur financially. Kickstarter is a prominent example of a reward-based crowdfunding platform. In an exploratory study Mollick (2014) provides initial empirical evidence on reward-based crowdfunding using data from Kickstarter. He finds that projects succeed by narrow margins or fail by large amounts when raising capital. Higher signalled project quality and more friends on online social networks are associated with fundraising success. Proposed projects reflect the culture of their geographic area and are unevenly distributed across the US. Many projects are delayed, especially large and overfunded projects. In lending-based crowdfunding, companies raise capital in the form of loans from private individuals or professional investors. Funding Circle and Lending Club are leading lending-based crowdfunding platforms. Equity-crowdfunding is similar to lending-based crowdfunding, with the difference that equity is given instead of debt. Seedrs and Republic, a spin-off of AngelList, are prominent examples of equity-based crowdfunding platforms.

Another new form of financing is cryptocurrencies. The most well-known cryptocurrency is arguably Bitcoin, whose origins go back to a white paper published by Satoshi Nakamoto in 2008 (Nakamoto 2008). Until this date, and despite much speculation, the identity of Satoshi Nakamoto remains unknown. The basic idea of Bitcoin is to decentralise financial transactions by taking out the intermediary, which is usually a bank. Bitcoin aims to replace the traditional system of trust in the middleman with a system of trust in the technology. Bitcoin works in the following way. A decentralised network-based ledger, called blockchain, stores all transactions. Every participant in the network thus stores the complete history of all transactions that have ever taken place. Bitcoin uses cryptography to verify the validity of new transactions before these are added to the ledger; participants in the network ("miners") solve complex problems and whoever gets the solution first receives a certain amount

of bitcoins as a reward. Digital wallets store bitcoins and owners can send bitcoins to others with a wallet or exchange bitcoins into fiat currencies on exchanges like Coinbase. Makarov and Schoar (2020) documents the existence of arbitrage opportunities across different exchanges and how these change over time. The supply of bitcoins is capped at 21 million to ensure scarcity and to limit inflation and manipulation. There are more than 19,000 cryptocurrencies with a combined market capitalisation of USD 1.76 trillion, with Bitcoin being the largest cryptocurrency by market capitalisation representing 42%.[1] Härdle, Harvey, and Reule (2020) outlines some of the mechanics of cryptocurrencies as well as avenues for future research.

There are different concerns surrounding cryptocurrencies and regulators around the world are applying more scrutiny. There is huge heterogeneity in regulatory approaches across different jurisdictions though, ranging from relatively welcoming in the "Crypto Valley" in Switzerland's Zug to an outright ban in China. A reason for concern is the fact that the prices of cryptocurrencies tend to be extremely volatile which can result in significant losses to market participants. This is especially worrisome because anyone can trade in cryptocurrencies. The traditional financial system has checks and balances to ensure that investors, especially retail investors, are protected from such risks as much as possible. The anonymity of cryptocurrencies also makes them an attractive means for the financing of illicit activities. Foley, Karlsen, and Putniņš (2019) estimates that about 25% of Bitcoin users engage in illegal activities. There have also been many instances of fraud and scams, some of which Erica Stanford describes in her recent book "Crypto Wars: Faked Deaths, Missing Billions and Industry Disruption" (Stanford 2021). Another concern relates to the energy usage involved in the mining process. Keeping a copy of the transaction history of a

[1]This information is from CoinMarketCap (`https://coinmarketcap.com/`) as of 30 April 2022.

cryptocurreny with each network participant increases the security of the system (assuming that the network is sufficiently distributed, that is, no single node controls the majority of the network's computing power) but decreases the efficiency of the system. According to the Cambridge Bitcoin Electricity Consumption Index, the daily network power demand has increased by a factor of 1,715 during the last ten years.[2]

The blockchain technology has a spectrum of use cases which is broader than just cryptocurrencies. For example, Filecoin seeks to decentralise file storage by allowing network participants to competitively rent out unused hard drive space. A blockchain records all file storage deals and renters pay using the blockchain's native cryptocurrency, FIL.

An initial coin offering is a process in which a company sells a cryptocurrency to investors. Initial coin offerings are often compared to initial public offerings, though initial coin offerings bear more resemblance to crowdfunding. In keeping with the industry's nascence, some of its terminology does not seem to be fully agreed upon yet. For instance, the terms coin and token describe similar although not identical objects. A common distinction is that a coin is a cryptocurrency that has its own blockchain (e.g., Bitcoin) whereas a token is one that uses another blockchain (e.g., ERC20). Howell, Niessner, and Yermack (2020) provides an empirical investigation of which issuer and ICO characteristics correlate with subsequent successful real outcomes.

More generally, the FinTech sector has grown tremendously in recent years, with machine learning and artificial intelligence being at the centre of attention. Even though some of these algorithms have been in existence for decades, the combination of more available data and cheaper computing power has spurred an increase in their viability. A common distinction between machine learning and artificial intelligence pertains to where the ultimate decision

[2]This information is from the Cambridge Centre for Alternative Finance (`https://ccaf.io/cbeci/index`) as of 30 April 2022.

making power lies, either with a human being (machine learning) or the algorithm (artificial intelligence). The core strength of machine learning and artificial intelligence is prediction. Natural applications of these techniques are therefore, amongst others, in lending and insurance decisions.

The application of machine learning and artificial intelligence comes with complex legal and ethical considerations. What might unintended consequences be, and how should these be addressed? How to ensure fairness, and which definition of fairness should be used? For example, there is a trade-off between maximising prediction accuracy and protecting characteristics of individuals who are the target of the prediction exercise. Using the postal code of a person's home address or a person's political views might help when predicting whether that person will default on a loan, but we might not want to allow for such information to be used in lending decisions. Current laws in many jurisdictions already outline such "protected characteristics". With the increase in data that is available for each person (e.g., a person's footprint on social media), there are more input variables available, which can complicate the issue of protected characteristics further. For instance, there might be new characteristics which are not yet protected by law but which are highly correlated with protected ones. Furthermore, even though automated lending decisions might suffer less from taste-based discrimination because they remove the human decision maker, they might suffer more from statistical discrimination by relying more heavily on data. It is therefore unclear ex-ante whether automated lending reduces or increases overall discrimination. Relatedly, and sticking with the lending decision application, it is not necessarily obvious which metric to use to assess fairness when comparing the outcomes of a particular algorithm across different groups (e.g., sex or ethnicity). Should we ensure that the threshold in lending decisions is the same ("group unawareness") even though this might result in differential fractions of granted loans

across groups? Should we ensure that the fraction of granted loans amongst all applicants ("demographic parity") or only amongst those applicants who could repay ("equal opportunity") is the same across groups even though these might mean that differential thresholds must be used? Each of these metrics are "fair" and involve different trade-offs. Regulatory answers to such questions will be key to maximise the social value of applications of machine learning and artificial intelligence techniques.

Regulators must strive a balance between spurring innovation and protecting market participants, especially consumers. Entrepreneurs might face increased regulatory risk when starting a FinTech company compared to a company that operates in a more traditional sector with an established regulatory framework. This increased regulatory risk might deter some entrepreneurs from acting upon their founding intentions. Regulators in different jurisdictions recognise this and some have created regulatory "sandboxes" in an attempt to encourage the commercialisation of innovation. The UK Financial Conduct Authority pioneered this concept. In the UK, the regulatory "sandbox" is a cohort-based programme to which companies must apply. Once admitted, participating companies can try out their services and products with real consumers in a regulatory-light environment. The programme is open to any company, not just start-ups, and it is not uncommon for large companies to participate (e.g., Barclays). The goal of the "sandbox" is two-fold. On the one hand, it is supposed to be a quality signal for admitted companies, which should make it easier for them to raise external funding by reducing information asymmetry between the admitted company and a potential capital supplier. On the other hand, it is also supposed to be a certification signal for new technologies, which should spur further innovation in that technological space by decreasing regulatory uncertainty.

There are different types of start-ups and there is no commonly agreed upon definition of

what constitutes entrepreneurship. When doing research on "entrepreneurship" it is therefore important to be precise about which phenomenon one is studying. Several scholars have offered different distinctions: substance versus transformational (Schoar 2010); formal versus informal (incorporated versus not) (Levine and Rubinstein 2017); subsistence, self-employed, "traditional" business entrepreneurs, and innovation-driven entrepreneurs (Botelho, Fehder, and Hochberg 2022). Whilst the proposed terminologies might differ, all scholars essentially distinguish between types of entrepreneurs according to their growth aspirations.

Distinguishing between different levels of growth aspirations is important because of the huge asymmetry in entrepreneurial outcomes. The premise for why entrepreneurship research is important is that entrepreneurship contributes to economic growth by increasing, amongst others, productivity and job creation (Haltiwanger, Jarmin, and Miranda 2013; Decker et al. 2014). Most start-ups, however, fail and only few of the survivors achieve phenomenal growth. In fact, most start-ups do not have high growth aspirations at all (Hurst and Pugsley 2011) and non-pecuniary benefits (e.g., being one's own boss) matter (Hamilton 2000). Contrary to common perception, the average high-growth entrepreneur is middle-aged, as oppposed to being young, (Azoulay et al. 2020), and immigrants, at least in the US, contribute to job creation by founding companies, instead of taking jobs away by entering into paid employment (Azoulay et al. 2022). From a regulatory perspective, it would be ideal to be able to credibly measure ex-ante growth aspirations so as to direct different policies to their intended recipients with as much certainty as possible. It is difficult, however, to measure growth aspiration at company birth for the population of start-ups. There is a nascent literature stream that tackles this "nowcasting" exercise, an example is Andrews et al. (2022).

The academic literature often treats start-ups as a single homogeneous unit. Broadly

speaking, there is a trade-off between depth and breadth of data. Detailed data on a few start-ups is available through in-depth interviews and case studies, however, it is not feasible to collect such data for a large number of start-ups. On the other hand, governments have become more open to sharing census data for research purposes. This type of data usually comes from tax or annual reports records and therefore includes only some aspects of start-ups (e.g., information about employment or financial statements). Choosing a particular type of data therefore involves trading off internal and external validity. Large-scale empirical studies usually use the latter type of data and treat start-ups as a single homogeneous unit out of necessity because the data does not allow for a more granular measurement. However, start-ups usually consist of different individuals. There are often multiple founders, and there can also be early employees and advisers.

Chapter 3 takes the point that start-ups are usually not homogeneous units seriously and examines whether and how directors at start-ups contribute to company performance and growth. From a theoretical perspective, it is not obvious which purpose, if one at all, the board of directors serves at a start-up. In contrast to public companies, start-ups are often run by founders who combine ownership of the equity and management of the company. In addition, private companies face fewer regulatory restrictions relating to board composition, oftentimes without a requirement to even form a board. However, boards in start-up companies are commonplace, which begs the question of whether and how important they are for private companies.

There are two main empirical challenges to answering the research question that Chapter 3 addresses, data availability and identification. To overcome the data availability issue, Chapter 3 uses administrative data from Sweden that allows for the tracking of the population of start-up companies from birth over time, including full annual reports and information on

the boards of directors. Just to emphasise, comparable data is not available in the US.

For identification, Chapter 3 exploits the fact that some directors sit on multiple boards simultaneously and measures distraction events at those directors' other companies that plausibly shock their attention. The intuition is that a "shocked" director diverts attention towards the "distracting" company, which leaves the director with less available attention for the focal company. If a director adds value by providing outside expertise, then the director's total contribution should be a function of the attention given to a company.

The main result in Chapter 3 is that if a company's directors become distracted, return on assets and sales growth decline, especially if distracted directors are more experienced. This is inconsistent with a theory according to which the board of directors at start-ups only has a signalling or certification function. The experience results highlight a specific channel through which directors can add value to start-ups and lend empirical support to an argument that practitioners often make, which is that access to expertise is an important barrier to entrepreneurial success.

Whilst Chapter 3 uses data a population level dataset, innovation is typically driven by a small subset of high-growth enterprises, many of which receive risk capital from angel investors or venture capital (VC) funds. Angel investors are wealthy individuals, many of whom are former entrepreneurs, whereas VC funds are professional asset managers who invest capital on behalf of asset owners. Puri and Zarutskie (2012) estimates that about 0.5% of start-ups in the US receive VC financing. Entrepreneurs are willing to pay a premium (by accepting a lower valuation) for financing from more reputable VC funds (Hsu 2004). This evidence suggests that VC funds play a role over and above mere capital providers, a finding that is consistent with other papers in the literature (Hellmann and Puri 2002). Hellmann and Thiele (2015) and Hellmann, Schure, and Vo (2021) study the interactions of angel

investors and VC funds. There is a common belief that angel investors are "hobbyists" who are not too serious about earning money with their investments, however, the evidence in the literature is inconsistent with this claim (Kerr, Lerner, and Schoar 2014). A problem when studying the effects of receiving VC financing on company outcomes empirically is to disentangle selection and treatment effects. Sorensen (2007) estimates a structural model and finds that selection effects are almost twice as important as treatment effects for the likelihood of VC-backed companies going public. This is consistent with a survey of VC investors by Gompers et al. (2020) which documents that 72% of VC investors rate deal flow or selection as most important for value creation in their investments. Taking selection as given, Bernstein, Giroud, and Townsend (2016) finds positive effects of VC monitoring on portfolio company outcomes. The authors use introductions of direct flights between the headquarters of VCs and already invested-in portfolio companies as shocks to monitoring costs.

Risk sharing by way of investing in a limited partnership is not a new phenomenon, early forms can be traced back to the "commenda" used by medieval Italian merchants, but the organisation of the modern VC fund likely has its origins in the US with the founding of the American Research & Development Corporation in 1946 (Lerner and Nanda 2020). In the context of the modern VC industry, VC investors typically invest in syndicates, that is multiple VC funds provide the capital in a particular funding round of a company. A reason for the formation of syndicates, in addition to pure risk sharing, is the benefits associated with information sharing (Hochberg, Ljungqvist, and Lu 2007). A natural question to ask is then, what is the role of different types of VC investors? For example, do domestic and foreign VC funds play different roles, especially considering that the world is becoming more integrated? Most research in the VC literature uses US data, which seems natural because

the US has the most developed VC market. Studying the role of domestic versus foreign VC investors might thus be more appropriate in a country other than the US.

Chapter 2 examines in how far US venture capitalists (USVCs) have an investment style that differs with respect to tolerance for financial losses relative to other VC investors. In addition to the US being the largest market, USVCs have played a significant role in the globalization of the industry. As policymakers across the world like to encourage high impact start-ups to spur growth, many of them have launched initiatives to tempt US venture capital firms to invest locally. One of the core challenges for VC-backed start-ups is that they pursue innovative long-term investment strategies that require prolonged periods of financial losses. This imposes considerable financing risk on the venture as the company relies on future funding rounds to cover its financial losses, and therefore remains dependent on the support of the VC community (Nanda and Rhodes-Kropf 2013; Nanda and Rhodes-Kropf 2017).

To empirically examine loss-tolerance, one needs a credible measure of financial losses in private companies. Such data is difficult to obtain for companies in the US and many other countries. Chapter 2 therefore turns to Sweden as a laboratory to investigate this issue. Ranked by the size of the VC market relative to GDP, Sweden ranks 12th worldwide overall and 7th when looking at early-stage financing so it is a fairly well-developed market. The empirical strategy in Chapter 2 focuses on documenting differences in investment styles, rather than establishing causal selection or treatment effects.

Overall, the empirical findings in Chapter 2 reveal a distinct pattern of companies funded by USVCs. When first receiving an investment from a USVC they have already incurred more losses. They then further descend into the loss-making region and are more likely to end up in the bottom decile of the cumulative net profit distribution. However, these companies remain financially supported and continue to receive subsequent funding, which is what allows them

to sustain their financial losses. Their eventual chances for a successful exit are stronger, suggesting that incurring those financial losses is not to the detriment of these companies.

Chapter 2 thus highlights a novel value proposition that USVCs bring to domestic entrepreneurial ecosystems outside of the US. It also offers a potential explanation for why most unicorns (start-ups that are valued at one billion US dollars or more) tend to be USVC backed, and for why ecosystems outside of the US, in particular in Europe, have so far had trouble generating more unicorns. The evidence in Chapter 2 also rhymes with the long-standing argument that US investors are culturally more risk-tolerant, willing to accept losses in the short-term to achieve higher returns in the long-term, and with that relative to their European counterparts, US stock markets, especially NASDAQ, have admission rules that are much more tolerant of loss-making businesses.

Taking a step back, the asset management industry has experienced an increase in passive management and industry concentration during the last thirty years (Ben-David, Franzoni, and Moussawi 2017). These changes have implications for the real economy. For example, there has been a shift towards "asset manager capitalism" (Braun 2021). In addition, joint ownership of natural competitors can cause higher consumer prices (Azar, Schmalz, and Tecu 2018). Activist asset managers tend to have a bad reputation. The popular press and politicians often depict private equity funds and hedge funds as financial vultures that employ "scorched earth" tactics. The academic literature has shown that the extent of these concerns might not be warranted. For activist hedge funds, the literature has shown the following. A company's stock price increases on average by 7% in response to an investment by an activist hedge fund, with no long-term reversal (Brav, Jiang, Partnoy, et al. 2008). Following the investment, productivity at the plant level increases, primarily through labour productivity, with no decrease in wages and no increase in hours worked (Brav, Jiang, and Kim 2015).

Productivity at sold plants also increases, which is inconsistent with an "asset stripping" story. Following the investment, there are also positive effects on innovation (Brav, Jiang, Ma, et al. 2018). Even though overall R&D expenditure decreases, the quantity and quality of patenting increases. For private equity funds, the literature has documented the following. Operational performance of portfolio companies increases (Bernstein and Sheen 2016). Productivity increases and net job creation decreases slightly (Davis et al. 2014). In how far this is desirable for society, however, depends on the alignment of incentives between different stakeholders. For example, restaurants become cleaner, safer, and better maintained (Bernstein and Sheen 2016), whilst tuition and per-student debt increase at universities (Eaton, Howell, and Yannelis 2020) as a result of investments by private equity funds.

Asset managers offer different investment vehicles from which asset owners can choose when delegating the management of their portfolios. Chapter 4 investigates the gap in reported returns between separate accounts and mutual funds, with a focus on disentangling manager selection and structural differences. The motivation for Chapter 4 is the following. Large institutional investors typically use separate accounts to delegate the management of their portfolios to asset managers. Prior research has shown that investments in separate accounts outperform strategy benchmarks and mutual funds. This finding is consistent with recent theoretical work which suggests that separate account investors are more sophisticated than mutual fund investors and hence better at selecting asset managers. Chapter 4 offers an alternative explanation for the gap in reported returns, namely structural differences between the vehicle types. An example of such a difference is fee reporting practices; mutual fund fees typically have a broader coverage, including custody and set-up costs, which separate account investors pay independently. This results in larger reported fees and lower reported net-of-fees performance for mutual funds compared to separate accounts.

Chapter 4 uses Morningstar as principal source of data on separate accounts and mutual funds. The main advantage of using Morningstar is that it includes a strategy identifier which links investments that have the same asset manager and investment strategy. This allows for the identification of separate account-mutual fund "twins".

Chapter 4 uses these "twins" to quantify the size of structural differences in reported returns between separate accounts and mutual funds. The intuition is that these "twins" have near-identical portfolios, and any gap in their reported returns must therefore stem from structural differences between the two investment vehicle types. Chapter 4 then uses these estimates of structural differences to decompose the return gap between separate accounts and mutual funds into a structural and a selection component.

The main finding in Chapter 4 is that structural differences between separate accounts and mutual funds can fully explain the gap in reported returns. Chapter 4 does not find any evidence of separate account investors being able to pick better asset managers. The results in Chapter 4 highlight the importance of taking structural differences into account when comparing separate accounts and mutual funds.

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Chapter 2

Riding the J-curve: Loss tolerance and US venture capital

ABSTRACT

Policymakers across the world like to encourage innovation and high impact start-ups to spur growth. Initiatives include tempting US venture capital firms to invest locally, betting on them to bring in capital and expertise. We document another benefit: US venture capitalists have a distinct investment style that is more tolerant of financial losses when investing abroad compared to non-US venture capital firms. We find that companies funded by US venture capitalists already have higher cumulative losses at the time of funding, and then incur further cumulative losses. They are more likely to receive subsequent funding, which is necessary to sustain their higher financial losses. Ultimately, they have a higher likelihood of a successful exit, suggesting that incurring financial losses was worthwhile. We also find that companies backed by US venture capitalists rely more on equity financing rather than debt financing, consistent with equity financing being better suited for loss making firms.

2.1 Introduction

Over the last two decades venture capital (VC) has become a global phenomenon. In addition to the US being the largest market, US venture capitalists (USVCs) have played a significant role in the globalization of the industry. As policymakers across the world like to encourage high impact start-ups to spur growth, many of them have launched initiatives to tempt US venture capital firms to invest locally. USVCs are desirable because they are typically more established and tend to have larger funds which allows them to make larger investments and more follow-on investments. They also have strong networks with other VCs in the US, and better access to US markets, including for IPOs, acquisitions, and product markets relevant for their investment companies. Naturally, USVCs also have some disadvantages, especially in terms of local market knowledge.

In this paper, we show that US venture capitalists have a distinct investment style that is more tolerant of financial losses when investing abroad. One of the core challenges for VC-backed start-ups is that they pursue innovative long-term investment strategies that require prolonged periods of financial losses. In the process of building their businesses, these start-ups make considerable investments into R&D and into growing their market share. They follow a so-called "hockey-stick" or "J-curve" logic where the business willingly incurs financial losses for several years, sustaining a high "burn rate", before pursuing the path to profitability. This is a risky financial strategy that involves staged financing where the company receives its required funding across multiple financing rounds. This imposes considerable financing risk on the venture as the company relies on future funding rounds to cover its financial losses, and therefore remains dependent on the support of the VC community (Nanda and Rhodes-Kropf 2013; Nanda and Rhodes-Kropf 2017). The availability of VCs with a tolerance for prolonged financial losses is therefore key for those ambitious start-ups

that want to ride a deep J-curve.

Our paper thus highlights a novel value proposition that USVCs bring to domestic entrepreneurial ecosystems outside of the US. It also offers a potential explanation for why most unicorns (start-ups that are valued at one billion USD or more) tend to be USVC backed, and for why ecosystems outside of the US, in particular in Europe, have so far had trouble generating more unicorns. Our evidence also rhymes with the long-standing argument that US investors are culturally more risk-tolerant, willing to accept losses in the short-term to achieve higher returns in the long-term, and with that relative to their European counterparts, US stock markets, especially NASDAQ, have admission rules that are much more tolerant of loss-making businesses.

To empirically examine loss-tolerance, we need a credible measure of financial losses in private companies. Such data is difficult to obtain for companies in the US and many other countries. We therefore turn to Sweden as a laboratory to investigate this issue. As we note in Section 2.2 that describes the data, every private company in Sweden reports annual financials to the central government authorities, and this data is available for research purposes from the Swedish Companies Registration Office. Ranked by the size of the VC market relative to GDP, Sweden ranks 12th worldwide overall and 7th when looking at early-stage financing so it is a fairly well-developed market.

For the period 1998 to 2019 we match the population of private companies to venture capital investment data obtained from Pitchbook, ThomsonOne, and Preqin. This allows us to create a sample of 1,862 VC-backed companies which we follow from birth to exit or end of the sample period. Our data includes 21,419 company-year observations, and 2,964 VC funding rounds. We find that 14% of companies receive an investment from a USVC, and that 12% of rounds include a USVC. The best way of thinking about our analysis is a

comparison of VC-backed companies that either do or do not also have a US investor: 74% of companies that ever receive funding by USVCs also raise capital from non-USVCs.

In terms of empirical strategy, which we discuss in Section 2.3, we do not try to separate out ex-ante investment selection effects from ex-post treatment effects of USVCs. Instead we focus on characterizing their overall investment style. Concretely, this means analysing the patterns by which companies funded by USVCs differ in terms of their financial performance, empirically showing how they differ in terms of financial losses, subsequent funding patterns, and eventual exit outcomes. Our core focus is thus whether and how USVCs differ in terms of loss-tolerant investment styles.

Our empirical analysis and results are outlined in Section 2.4 and proceeds in five steps. The first step is to examine the preferences of USVCs at the investment selection stage. Our most important finding is that companies with lower cumulative net profits (i.e., greater cumulative losses) are more likely to receive investments from USVCs. This suggests that USVCs already differ at the selection stage, showing greater willingness to finance loss-making businesses. Other notable differences at the selection stage are that USVCs are more focused on information and communication technologies; they are less willing to invest in companies outside the greater Stockholm area; and they invest relatively more into later-stage companies. USVCs also invest in larger rounds.

The second step of the analysis considers the question of subsequent funding rounds. This is an important building block for the analysis of loss-tolerance, since companies incurring on-going financial losses rely on the availability of such follow-on financing. We find that companies funded by USVCs are more likely to receive a subsequent funding round. The amount of subsequent funding is also larger. This confirms the notion that having USVCs improves companies' access to follow-on funding.

The third step examines the core issue of financial losses. Specifically, we consider the evolution of cumulative net profits three and five years after obtaining a VC round. We find a negative and significant association between receiving USVC investment and subsequently having lower cumulative net profits (after controlling for cumulative net profits at the time of the investment). However, we note that the coefficient for USVC shrinks by more than half, and becomes statistically insignificant, if we also control for subsequent funding. This means that having USVC funding is associated with accumulating deeper financial losses, but that statistically this phenomenon is largely accounted for by better access to subsequent funding. This empirical pattern is consistent with companies with USVCs being more willing to incur losses precisely because they can expect that follow-on funding will be available to them. We perform numerous robustness checks on this core finding. For example, we find the same results when considering cumulative cash flows from operations, an alternative measure of financial losses. We also consider "tail events" and find that companies receiving USVC funding are significantly more likely to land in that bottom decile of cumulative net profits, i.e., the decile with the highest financial losses.

The fourth step examines the relationship between USVC, cumulative losses, and the eventual company outcome in terms of successful exits (IPOs or acquisitions). A prior literature establishes exits as a credible performance measure for VC-backed companies (Phalippou and Gottschalg 2009). We find that USVC-backing is positively associated with successful exits. This result continues to hold after controlling for subsequent funding and even subsequent financial losses. The association is stronger for acquisitions than IPOs. We do not, however, find any association with failure. These results are consistent with the notion that investment strategies pursued by USVC-backed ventures, including their higher cumulative losses, ultimately lead to better exit outcomes.

For the fifth step we examine the roles of equity versus debt. The argument so far focuses on equity investments made by VCs. Standard economic reasoning is that equity is better suited for loss-making companies than debt, mainly because of the difficulties of meeting debt repayment schedules. In our context we ask whether the deeper pockets of USVCs allow their companies to rely less on debt financing. Our evidence suggests that companies backed by USVCs rely less on overdraft facilities and bank loans, consistent with the notion that equity is more suitable than debt for loss-making companies.

Overall, our empirical findings reveal a distinct pattern of companies funded by USVCs. When first receiving an investment from a USVC they have already incurred more losses. They then further descend into the loss-making region and are more likely to end up in the bottom decile of the cumulative net profit distribution. However, these companies remain financially supported and continue to receive subsequent funding, which is what allows them to sustain their financial losses. Their eventual chances for a successful exit are stronger, suggesting that incurring those financial losses is not to the detriment of these companies. As Section 2.5 documents, these findings are robust to several possible alternative specifications and analyses.

Our paper is related to four strands of the venture capital literature. First, as we use similar data, our paper relates to work on venture capital investments and portfolio company performance measured using firm financial statement data. The literature has investigated how productivity, costs, sales, employment and payroll evolve under VC ownership (Chemmanur, Krishnan, and Nandy 2011; Puri and Zarutskie 2012; Croce, Martí, and Murtinu 2013; Chemmanur, He, et al. 2018), how investor type (government versus private or corporate versus independent) affects efficiency and profitability (Alperovych, Hübner, and Lobet 2015; Colombo and Murtinu 2017), how financing type affects performance (Giraudo, Giu-

dici, and Grilli 2019), on how non-executive directors affect firm performance (Montag 2021) and on the value relevance of financial statements in the VC market (Hand 2005).

Second, our paper relates to work on the differences between US and non-US venture capital markets. This literature pointed out that the US entrepreneurial ecosystem provides high investor availability, a large market, and an advanced market for acquisitions (Conti and Guzman 2019), that it provides a good institutional environment for venture capital (Lerner and Tåg 2013), and that it deals better with poorly performing companies (Hege, Palomino, and Schwienbacher 2009).

Third, our paper relates to work on venture capital and tolerance for failure/real options that has shown that VC firms that are persistent in investing in underperforming firms are better at supporting innovation (Tian and Wang 2014), that changing costs of experimentation affects venture capital investment strategies (Ewens, Nanda, and Rhodes-Kropf 2018), and investors balance financing risk with real option values when deciding on where and when to invest (Nanda and Rhodes-Kropf 2017).

Fourth, our paper relates to work on differences between foreign and domestic venture capital investors (Devigne, Manigart, Vanacker, et al. 2018). Work in this area shows that foreign investors tend to have no better performance and that geographical and/or cultural distance can hinder their performance (Dai, Jo, and Kassicieh 2012; Li, Vertinsky, and Li 2014; Dai and Nahata 2016; Chemmanur, Hull, and Krishnan 2016; Bernstein, Giroud, and Townsend 2016; Zhang and Zhang 2022). This can be overcome, however, by partnering with local VCs (Nahata, Hazarika, and Tandon 2014). Foreign VCs tend also to be more prudent and invest closer to exits (Zhang and Zhang 2022), tend to be more involved at the strategic level (Pruthi, Wright, and Lockett 2003), have better networks abroad (Humphery-Jenner and Suchard 2013), better governance (Aggarwal et al. 2011), and higher capital expertise

(Chemmanur, Hull, and Krishnan 2016). Research has also found that they can compensate for limited domestic supply of venture capital (Schertler and Tykvová 2012), that they tend to terminate bad performing investments quicker (Devigne, Manigart, and Wright 2016), that they tend to internationalize firms/invest in firms that are internationalizing (Fernhaber, Mcdougall-Covin, and Shepherd 2009; Carneiro, Moreira, and Sheng 2022). Foreign VCs can also help bring the portfolio companies' products to the VC home market by legitimizing them there (Mäkelä and Maula 2005; Mäkelä and Maula 2006), finding exit opportunities there (Bertoni and Groh 2014), or facilitate technology transfer to the home country (Akcigit et al. 2020).

Our contribution to the above four strands of the venture capital literature is to document using novel cash flow data that USVCs have a different investment style that is more loss tolerant when investing abroad compared to non-USVCs. Our paper highlights a novel benefit of encouraging USVCs to invest locally, sheds light on why most unicorn start-ups tend to be USVC backed and offers a potential explanation for why entrepreneurial ecosystems outside of the US have so far generated so few unicorns.

Finally, our paper also relates to the emerging literature on scale-ups (DeSantola and Gulati 2017). Formal work in this literature has shown that digital firms tend to be narrow in vertical scope and large in scale (Giustiziero et al. 2021), that foreign acquirers may affect scaling decisions (Hellmann and Thiele 2022), and that scaling involves substantial amounts of risk-taking and pivoting with the help of venture capital firms (Norbäck, Persson, and Tåg 2022). The literature has also analysed several key aspects of scaling such as standardizing and automating processes (Coviello 2019), timing (Cubero and Segura 2020), and meeting organizational needs (Shepherd and Patzelt 2020). We point out that having loss tolerant financial backers may be key for financing a scale-up process.

2.2 Data

2.2.1 Sample construction

We use data from the Swedish Companies Registration Office that covers the population of limited liability companies between 1998 and 2019. The strength of the Swedish census data comes from the fact that all limited liability companies in Sweden must submit annual reports to the Companies Registration Office by law.[1] Companies have strong incentives to submit accurate information because non-compliance or submitting incorrect information can result in liquidation and unlimited liability for board members. In addition, the limited liability company is the most prevalent type of business enterprise in Sweden, principally because formation requires relatively little effort and because it is the only type of business enterprise that offers limited liability to all shareholders.[2] We merge data on venture capital investments and exits from Pitchbook, ThomsonOne, and Preqin. For investment or exit events that occur in more than one of these databases, we use Pitchbook as a base and then fill in missing information first from ThomsonOne and then from Preqin.[3] Our focus is on how investments from venture capitalists from different countries relate to future company outcomes. We therefore manually collect the location of the headquarters for those venture capital investors for whom this information is missing.

We construct our sample, a company-fiscal year panel for companies that receive venture capital funding, in the following way. First, we restrict observations to those for companies that ever receive venture capital investment. Second, for observations with both unconsol-

[1] Årsredovisningslag [1995:1554] 8 sec. 3 and Bokföringslag [1999:1078] 6 sec. 2.

[2] Formation requires only one person and a minimum share capital of SEK 25,000 (approximately USD 2,500).

[3] We choose this order of third-party provider databases as it reflects their relative coverage of venture capital events.

idated and consolidated financial statements, we use the consolidated version because it reflects the company's overall economic activity. Third, we exclude observations with an accounting type for which we do not know how financial statements are constructed because we use income statement and balance sheet items to construct cash flow statements. Please see the appendix in Montag (2021) for details on the construction of cash flow statements. Fourth, we annualise flow as well as growth stock variables to account for differences in fiscal period lengths. Last, depending on the skewness of their distributions, we winsorize variables at the 1st and 99th or 5th and 95th percentiles, respectively, to alleviate the potential impact of outliers. Table 2.1 lists definitions for all variables used in the analysis.

2.2.2 Descriptive statistics

Table 2.2 presents descriptive statistics. Panel A shows summary statistics at the company-fiscal year level. Column 1 reports these for the full sample, which consists of 21,419 company-fiscal years for 1,862 distinct companies. Out of these 254 (13.6%) companies, with 2,860 (13.4%) company-fiscal years, ever receive VC funding from a US investor. Columns 2 and 3 report summary statistics for those companies that never and ever receive US VC funding separately. We then take the observations for companies that ever receive US VC funding and split them into not yet US VC backed and US VC backed (Columns 4 and 5). We also include the statistical significance of t-tests for the difference in means between "Never US VC" and "Ever US VC" (asterisks in Column 3) as well as "Not yet US VC backed" and "US VC backed" (asterisks in Column 5). Companies that ever receive US VC funding have more and larger VC investment rounds. They are also less profitable, both in absolute and relative terms, and use more cash for operating activities. In addition, they are less likely to have an overdraft facility and, conditional on having one, they have a lower granted amount

and use a lower fraction of it. Relatedly, they also have less debt in the form of bank loans, both in absolute terms and as a fraction of total book assets. Further, they have higher sales growth and are more likely to exit, both by IPO and acquisition, as well as to fail. A similar pattern persists when comparing companies that are US VC backed with those that are not yet US VC backed (Columns 4 and 5 of Panel A in Table 2.2) and when computing pairwise correlations between the variables (Table 2.3).

Panels B and C of Table 2.2 present the distribution of industries and geographies at the company level, respectively, and Panel D shows the distribution of VC investment rounds. Like Panel A, we report statistics for the full sample as well as for companies that never and ever receive US VC funding separately. In Panels B to D, we report the output of χ^2-tests for the difference in the respective distributions between "Never US VC" and "Ever US VC". For brevity, we report industries and counties with less than 10% of all companies together as "other" in Panels B and C, and fourth and later rounds jointly in Panel D. Importantly, we use all levels of these categorical variables in the χ^2-tests. A higher (lower) fraction of companies that ever receive US VC funding operate in the "information and communication" ("manufacturing") sector. In addition, a higher fraction of these companies has their headquarters in Stockholm and a higher fraction of their VC investments are later rounds.

To get a sense of how persistent these unconditional differences between companies that never and ever receive US VC funding are, we focus on companies which register during our sample period and plot cumulative measures for some of these variables from birth over time. We do this for VC funding (Figure 2.1), net profit (Figure 2.2), cash from operations (Figure 2.3), and sales (Figure 2.4). Companies that ever receive US VC funding have higher cumulative VC funding from birth onwards, with the difference increasing as companies

become older. These companies also have higher cumulative net losses and cash used for operating activities during their first ten fiscal years, again with the differences increasing over time. In addition, these companies have higher cumulative sales, although only from fiscal year 6 onwards. Prior to that, companies that ever receive US VC funding have lower cumulative sales.

Taken together, the descriptive statistics in Tables 2.2 and 2.3 as well as Figures 2.1 to 2.4 are consistent with the notion that companies that ever receive US VC funding are less profitable, use more cash in their operations, have higher sales growth, and receive more capital from VC investments. In addition, these differences become larger as companies become older.

2.3 Empirical strategy

Our research question is in how far USVCs have an investment style that differs with respect to tolerance for financial losses relative to other VC investors. Our empirical strategy focuses on documenting these differences, rather than establishing causal selection or treatment effects.[4]

We divide our analysis into several parts. First, we examine which company characteristics are associated with receiving initial funding from a USVC. This part of the analysis speaks to the preferences of USVCs for specific portfolio company characteristics. Second, we look

[4]Kahn and Whited (2018) discuss the difference between identification and establishing causality. Disentangling selection and treatment effects when studying the effects of VC investments empirically is difficult. Sorensen (2007) estimates a structural model and finds that selection effects are almost twice as important as treatment effects for the likelihood of VC-backed companies going public. This is consistent with a survey of VC investors by Gompers et al. (2020) which documents that 72% of VC investors rate deal flow or selection as most important for value creation in their investments. Taking selection as given, Bernstein, Giroud, and Townsend (2016) find positive effects of VC monitoring on portfolio company outcomes. The authors use introductions of direct flights between the headquarters of VCs and already invested-in portfolio companies as shocks to monitoring costs.

at the relationship between USVC investment and subsequent VC fundraising. Third, we examine the relationship between USVC funding and future company outcomes, with a focus on subsequent cumulative profit and exit events. Importantly, in this last step we estimate two different estimating equations, one without and with controlling for subsequent VC funding. These latter two parts of the analysis characterise the path of portfolio companies following USVC investment, and explicitly examine the importance of subsequent VC funding for future company outcomes.

For most of our empirical analysis, we estimate the following two equations

$$Y_{i,t+n} = \alpha + \beta\, VC_{i,t} + \gamma\, USVC_{i,t} + \tau Z_{i,t-1} + \delta_r + \delta_j + \delta_c + \delta_y + \varepsilon_{i,t+n} \tag{2.1}$$

$$Y_{i,t+n} = \alpha + \beta\, VC_{i,t} + \gamma\, USVC_{i,t} + \tau Z_{i,t-1} + \varphi SF_{i,t+n} + \delta_r + \delta_j + \delta_c + \delta_y + \varepsilon_{i,t+n} \tag{2.2}$$

in which i is a company and t is a fiscal year. The dependent variable is $Y_{i,t+n}$ which measures company outcomes between fiscal years t and $t+n$. We report results for the next three and five fiscal years, but results are similar when using different measurement periods (e.g., two or four fiscal years). $VC_{i,t}$ is a dummy variable that equals one if a company receives VC funding, $Z_{i,t-1}$ is a vector of company control variables, δ_r are prior VC round fixed effects, δ_j are industry fixed effects, δ_c are county fixed effects, and δ_y are calendar year fixed effects. The vector of company control variables, $Z_{i,t-1}$, includes the log of sales, cumulative net profit, the log of company age, the log of cumulative VC funding, and the cumulative number of VC rounds with unknown funding amounts. The last control variable accounts for the fact that the amount of capital raised is sometimes unknown and thereby ensures that the coefficient estimate of cumulative prior VC funding is conditional on both the number of prior VC rounds and the prevalence of missing funding amounts amongst these rounds.

The coefficients of interest in Equations 2.1 and 2.2 are γ and φ. $USVC_{i,t}$ is a dummy variable that equals one if a company receives VC funding from a US investor. Its coefficient, γ, captures the differential relationship between receiving funding from a USVC and company outcomes. $SF_{i,t+n}$ is the cumulative VC funding that a company receives during the measurement period of the dependent variable.[5] We are particularly interested in how far the coefficient estimate γ of $USVC_{i,t}$ differs between Equations 2.1 and 2.2. That is, how much of the relationship between receiving USVC investment and company outcomes can be explained by subsequent VC fundraising.

The inclusion of prior VC rounds, industry, county, and calendar year fixed effects implies that γ measures the correlation between receiving US VC funding and company outcomes, comparing companies that have the same number of prior VC rounds, operate in the same industry, have their headquarters in the same county, and whose fiscal years during which they receive VC funding end in the same calendar year.

2.4 Results

2.4.1 Do USVCs invest in firms with higher losses?

As a first step of our analysis, we look at the investment decision of USVCs. Table 2.4 presents results for regressions of initial US VC funding on company characteristics. The dependent variable is a dummy variable that equals one if a company receives VC funding from a US investors for the first time. The unit of analysis is a company-VC round. We cluster standard errors by company.

[5] We also control for the number of subsequent VC rounds with unknown funding amounts. The reason is the same as for the control variable that counts the number past VC rounds with unknown funding amounts.

Table 2.4 shows that, relative to other VCs, USVCs invest in companies with higher cumulative net losses, and which are more likely to operate in the information and communication sector and to be headquartered in the greater Stockholm area. This evidence suggests that USVCs already have a higher tolerance for losses and riskier industries at the investment stage.

2.4.2 Is USVC funding associated with subsequent VC investments?

As a next step, we study in how far receiving funding from a USVC relates to subsequent VC investments. Table 2.5 presents results for regressions of future on current VC funding. The dependent variables are a dummy variable that equals one if a company receives VC funding and the log of the VC funding amount, measured during the next three and five fiscal years. We construct the dependent variables using all VC rounds (Panel A) and US VC rounds only (Panel B). The unit of analysis is a company-fiscal year. We exclude observations before a company's first VC round because we are interested in the relationship between current and subsequent VC funding. We cluster standard errors by company.

The results show that receiving VC funding is strongly positively associated with receiving additional VC funding going forward. The VC round coefficient is positive and statistically significant at the 1% level in all models in Panels A and B. The magnitudes of these associations become much stronger when a company receives VC funding from a US investor. Specifically, the association with receiving additional VC funding during the next three fiscal years increases by approximately 33% and the association with the subsequent funding amount doubles. These differential associations of receiving US VC funding become even larger when looking at subsequent US VC funding (Panel B). Taken together, the results in

Table 2.5 suggest that USVCs help companies access follow-on VC funding, especially from US investors.

2.4.3 Is USVC funding associated with higher subsequent losses?

We next investigate the relationship between receiving VC funding and future company earnings, with a focus on the role of subsequent fundraising. Table 2.6 presents results for regressions of company earnings on VC funding. The dependent variables are cumulative net profit (Panel A) and cumulative cash from operations (Panel B), measured during the next three and five fiscal years. The unit of analysis is a company-fiscal year. We cluster standard errors by company.

Table 2.6 shows that current VC investment is strongly associated with subsequent cumulative net losses and cash used in operations. The VC round coefficient is negative and statistically significant at the 1% level in all models in Panels A and B. The association with subsequent net losses and cash used in operations is even stronger for receiving US funding (models 1 and 3), but this differential association becomes insignificant once we control for subsequent VC funding (models 2 and 4). These results suggest that whilst receiving funding by a USVC is strongly associated with higher subsequent cumulative losses, this relationship can be explained by subsequent VC funding.

We then examine in how far receiving VC funding is related to earnings outcomes in the tails of the distribution. The outcomes of companies in a VC fund's portfolio are typically highly skewed and looking at earnings dispersion allows us to differentiate between an association of VC funding with a shift in average earnings (Table 2.6) and a higher propensity of earning outcomes in the tails (Table 2.7). Table 2.7 presents results for regressions of company earnings dispersion on VC funding. The dependent variables are dummy variables

that equal one if a company's cumulative net profit (Panels A and B) and cumulative cash from operations (Panels C and D) are in the top or bottom decile, measured during the next three and five fiscal years. The unit of analysis is a company-fiscal year. We cluster standard errors by company.

The results show that receiving VC funding is not associated with earning outcomes in the top decile and strongly positively associated with earning outcomes in the bottom decile. This pattern holds both for net profit and cash from operations. Receiving investment by a USVC doubles (triples) a company's propensity to have net profits (cash from operations) in the bottom decile in subsequent fiscal years. Similar to Table 2.6, once we control for subsequent VC funding, the economic and statistical significance of the USVC coefficient halves, becoming insignificant in the net profit regressions.

2.4.4 Is USVC funding associated with better exits?

Having established that USVCs invest in companies with higher levels of cumulative past losses and that these companies raise more follow-on VC funding which allows them to have more subsequent cumulative losses, we next investigate in how far receiving funding from USVCs relates to exit outcomes. This speaks to whether USVCs place riskier bets or have deeper pockets. Specifically, if receiving funding from a USVC is associated with a lower probability of exit, but a higher exit value conditional on exit, this would imply that USVCs make riskier investments and have a higher tolerance for risk. If, on the other hand, USVC investment is associated with an equal or higher probability of exit, then USVCs have deeper pockets and a higher tolerance for losses. Table 2.8 presents results for regressions of exit outcomes on VC funding. The dependent variables are dummy variables that equal one if a company has any exit (Panel A), an IPO (Panel B), an acquisition (Panel C), and a failure

(Panel D) event during the next fiscal year, as well as the log of the capital raised in an IPO (Panel E). The unit of analysis is a company-fiscal year in Panels A to D and an IPO event in Panel E. The variables of interest are dummy variables that equal one if a company is VC backed and US VC backed in the current fiscal year in Panels A to D and a dummy variable that equals one if a company is US VC backed at the beginning of the fiscal year during which the IPO event happens in Panel E. Standard errors are clustered by company in Panels A to D and heteroscedasticity robust in Panel E. The regressions in Panels A to D of Table 2.8 are best thought of as a discrete time duration model. A particular company can only have a single exit event which is why we use VC-backed dummies, rather than VC-investment dummies as in Tables 2.4 to 2.7 which have time-varying company outcomes as dependent variables.

Table 2.8 shows that USVC-backed companies are approximately twice as likely to have a successful exit event. This result is stronger for acquisitions than for IPOs. We also find that USVC-backed companies are not more likely to fail, and we find some suggestive evidence that USVC-backed companies raise more capital in IPOs.

2.4.5 Is USVC funding associated with more reliance on equity financing?

As a next step, we utilise the granularity of our dataset to examine in how far the equity funding from VC investors functions as a complement to or substitute for debt financing. It is not clear ex-ante in which direction the relationship should go. On the one hand, banks might be more willing to lend to companies that receive VC funding because VC investment functions as a signal that the company is more likely to receive follow-on funding (our results in Table 2.5). On the other hand, VC funding might be large enough to lower companies'

reliance on debt financing and thereby eases the burden of meeting debt repayment schedules, which is especially important for loss-making companies. We look at two outcome variables, overdraft facilities and bank loans. Table 2.9 presents results for regressions of overdraft facilities on VC funding. The dependent variables are a dummy variable that equals one if a company has an overdraft facility (Panel A), the log of the overdraft amount granted (Panel B), and the fraction of the granted overdraft amount used (Panel C). We measure the dependent variables at the end of the next three and five fiscal years. The unit of analysis is a company-fiscal year, and we restrict observations in Panels B and C to those for companies with an overdraft facility. We cluster standard errors by company.

The results in Panel A of Table 2.9 show that VC investment is associated with a lower propensity of having an overdraft facility, especially so for investments from USVCs. Interestingly, current and subsequent VC funding are associated with a higher granted overdraft amount when conditioning on companies with an overdraft facility at the end of three (models 1 and 2) or five (models 3 and 4) fiscal years (Panel B). There is no differential association for investments by USVCs with the granted amount of overdraft facilities, however, Panel C shows that USVC investment is related to a subsequent lower usage of granted overdraft facilities. Overall, the results suggest that VC funding and overdraft facilities function as substitutes for the average company and as complement for the subset of companies with an overdraft facility following VC investment. For companies that receive funding from a USVC investor, the evidence points towards a pure substitution story, even for the subset companies with an overdraft facility.

Table 2.10 presents results for regressions of bank loans on VC funding. The dependent variable is the log of bank loans (Panel A) and the fraction of banks loans of total assets (Panel B), measured at the end of the next three and five fiscal years. The unit of analysis

is a company-fiscal year. We cluster standard errors by company.

Table 2.10 shows that whilst subsequent VC funding is associated with a higher absolute amount of bank loans (models 2 and 4 in Panel A), both current and subsequent VC funding are associated with a lower relative amount of banks loans as fraction of total book assets (Panel B). Similar to the evidence for overdraft facilities in Table 2.9, USVC rounds are associated with both lower absolute and relative amounts of bank loans.

2.5 Robustness

We perform several robustness checks. The earnings dispersion results are qualitatively similar when looking at top/bottom quartiles instead of deciles (Table 2.11). The results in Tables 2.5, 2.6, 2.7, 2.9, and 2.10 are robust to using a round-to-round sample in which we restrict observations to fiscal years with a VC round (Tables 2.12 to 2.16). We also look at the relationship between VC funding and sales growth. We find that VC funding is associated with higher subsequent sales (Table 2.17). There is some evidence that USVC rounds are associated with even higher subsequent sales, although this association disappears once we control for subsequent funding. This is like our baseline results for earnings. We also find that current and subsequent VC funding are positively (negatively) associated with sales outcomes in the top (bottom) decile/quartile (Table 2.18).

2.6 Summary

We investigate if US venture capitalists have a distinct investment style that is more tolerant of financial losses when investing abroad. Using Swedish data on all private firms for over two decades, we found that USVCs already have a higher tolerance for losses at the investment

stage (Table 2.4) and they help their portfolio companies to raise more follow-on VC funding (Table 2.5), which allows their portfolio companies to sustain a higher level of losses (Tables 2.6 and 2.7). USVC-backed companies are also more likely to exit successfully (Table 2.8), which implies that their higher level of losses of is not driven by a higher tolerance for risk of USVCs but rather by deeper pockets which allow USVCs to sustain losses for longer. Finally, companies backed by USVCs rely less on overdraft facilities and bank loans (Tables 2.9 and 2.10), consistent with the notion that equity is more suitable than debt for loss-making companies. Our paper thus highlights a novel benefit of encouraging USVCs to invest locally, sheds light on why most unicorn start-ups tends to be USVC backed and offers a potential explanation for why entrepreneurial ecosystems outside of the US have so far generated so few unicorns.

2.7 References

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2.8 Figures

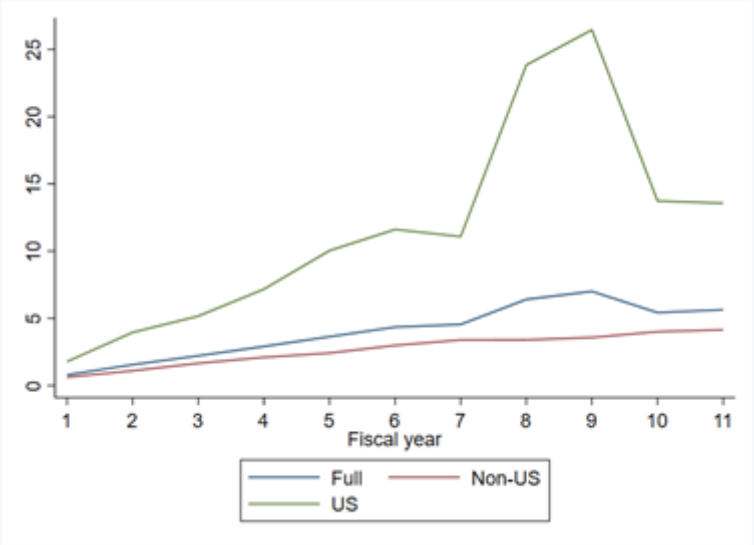


Figure 2.1. Cumulative VC funding since company registration. This figure shows cumulative VC funding (mil USD) by fiscal year since company registration. The blue line shows this for the full sample, and the red (green) line for the subsample of companies that never (ever) receive VC funding from a US investor. When constructing this graph, we only use observations for companies which register during our sample period so that we can measure cumulative VC funding from birth over time.

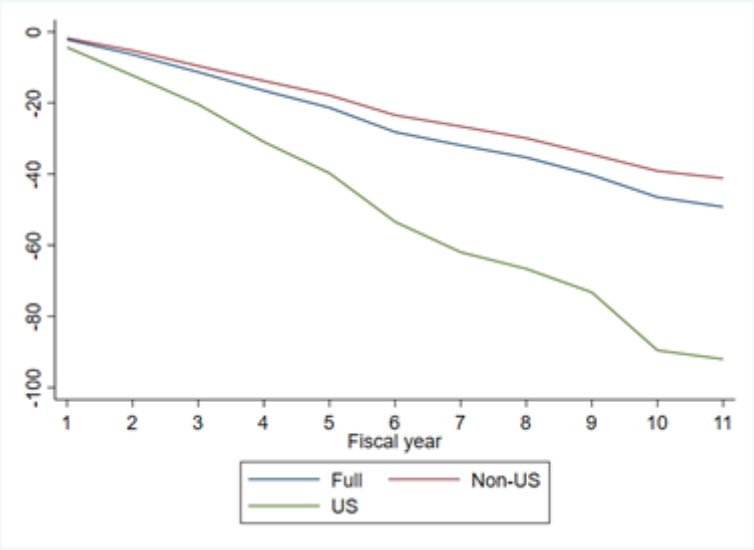


Figure 2.2. Cumulative net profit since company registration. This figure shows cumulative net profit (mil SEK) by fiscal year since company registration. The blue line shows this for the full sample, and the red (green) line for the subsample of companies that never (ever) receive VC funding from a US investor. When constructing this graph, we only use observations for companies which register during our sample period so that we can measure cumulative net profit from birth over time.

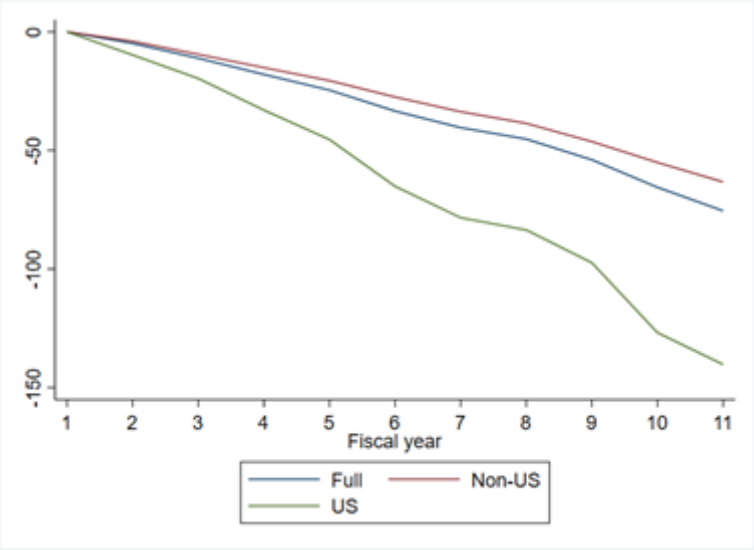


Figure 2.3. Cumulative operating cash since company registration. This figure shows cumulative cash from operations (mil SEK) by fiscal year since company registration. The blue line shows this for the full sample, and the red (green) line for the subsample of companies that never (ever) receive VC funding from a US investor. When constructing this graph, we only use observations for companies which register during our sample period so that we can measure cumulative cash from operations from birth over time.

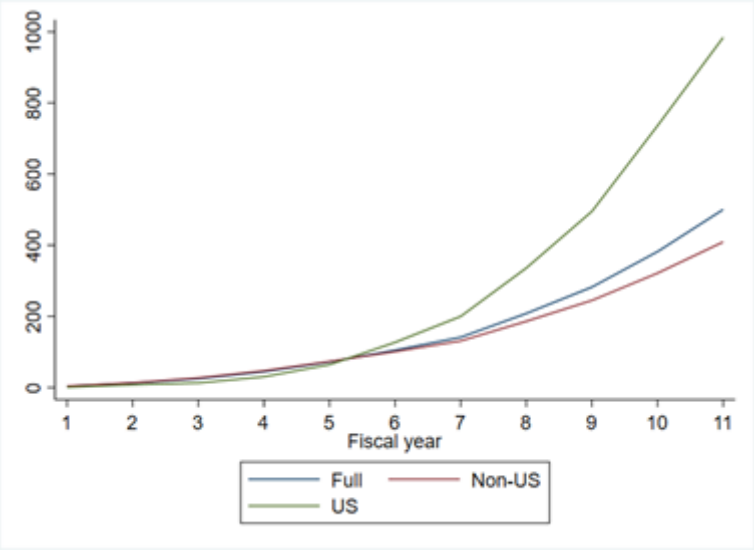


Figure 2.4. Cumulative sales since company registration. This figure shows cumulative sales (mil SEK) by fiscal year since company registration. The blue line shows this for the full sample, and the red (green) line for the subsample of companies that never (ever) receive VC funding from a US investor. When constructing this graph, we only use observations for companies which register during our sample period so that we can measure cumulative sales from birth over time.

2.9 Tables

Table 2.1
Variable definitions

This table lists definitions for all variables we construct from the raw data available from the Swedish companies' registrations office.

Variable	Definition
USVC round	A dummy variable that equals one if a company receives VC funding from a US investor
VC round	A dummy variable that equals one if a company receives VC funding from any investor
VC round size	The amount of funding a company receives in a VC round
Prior VC rounds	The number of a company's prior VC funding rounds
Net profit	A company's net profit or loss
Cash from operations	A company's cash from operations
Overdraft dummy	A dummy variable that equals one if a company has an overdraft facility
Overdraft	The amount of a company's granted overdraft facility
Overdraft used	The fraction of a company's granted overdraft facility that is drawn
Bank loans	The book value of a company's bank loans
Bank loans ratio	The fraction of a company's book value of banks loans of total book assets
Sales	A company's sales
Exit	A dummy variable that equals one if a company has an exit event (IPO or acquisition)
IPO	A dummy variable that equals one if a company goes public
Acquisition	A dummy variable that equals one if a company gets acquired
Failure	A dummy variable that equals one if a company goes bankrupt, is liquidated, is reorganized, or is removed from the company registry
IPO size	The capital raised by a company in an IPO
Age	The number of fiscal years since a company's registration
Industry	The primary industry in which a company operates (18 in total)
County	The county in which a company's headquarters are located (21 in total)
Calendar year	The calendar year during which a company's particular fiscal year ends

Table 2.2
Descriptive statistics

This table presents descriptive statistics. Panel A shows these at the company-fiscal year level, Panels B and C at the company level, and Panel D at the VC round level. In Panel A, we report standard deviations in parentheses and the statistical significance of *t*-tests for the difference in means between "Never US VC" and "Ever US VC" as well as "Not yet US VC backed" and "US VC backed". *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Panels B to D report the output of χ^2-tests for the difference in distributions of these categorial variables between "Never US VC" and "Ever US VC". For brevity, we report industries and counties with less than 10% of all companies together as "other" (Panels B and C). Similarly, we report fourth and later rounds jointly in Panel D. Importantly, we use all levels of these categorical variables in the χ^2-tests.

Panel A: Summary statistics

	Full	Never US VC	Ever US VC	Not yet US VC backed	US VC backed
USVC round	0.016	0.000	0.122***	0.000	0.195***
	(0.127)	(0.000)	(0.327)	(0.000)	(0.396)
VC round	0.138	0.129	0.200***	0.119	0.249***
	(0.345)	(0.335)	(0.400)	(0.323)	(0.432)
VC rnd size (mil USD)	0.540	0.293	2.128***	0.422	3.165***
	(11.635)	(10.861)	(15.279)	(11.230)	(17.152)
Net profit (mil SEK)	-2.821	-2.265	-6.433***	-4.485	-7.599***
	(11.635)	(10.861)	(15.279)	(11.230)	(17.152)
Net margin (%)	-289.396	-271.879	-406.125***	-361.540	-431.734*
	(750.167)	(728.338)	(873.189)	(834.337)	(894.020)
Opera cash (mil SEK)	-6.200	-5.342	-11.777***	-6.973	-14.074***
	(962.301)	(786.478)	(1705.631)	(231.511)	(2139.205)
Overdraft dummy	0.267	0.285	0.148***	0.191	0.121***
	(0.442)	(0.452)	(0.355)	(0.394)	(0.327)
Overdraft (mil SEK)	2.523	2.749	1.058***	0.720	1.260**
	(10.101)	(10.531)	(6.478)	(4.270)	(7.488)
Overdraft used (%)	34.723	35.063	30.454**	36.727	24.527***
	(37.935)	(37.932)	(37.756)	(38.586)	(36.050)
Bank loans (mil SEK)	4.155	4.439	2.313***	1.627	2.724**
	(19.839)	(20.425)	(15.381)	(10.309)	(17.726)
Bank loans ratio (%)	7.428	7.973	3.888***	5.894	2.694***
	(16.126)	(16.672)	(11.370)	(14.020)	(9.246)
Sales (mil SEK)	131.524	130.319	139.340	27.875	206.070***
	(816.363)	(734.166)	(1222.252)	(112.921)	(1539.223)
Sales growth (%)	52.585	49.529	73.027***	90.397	65.134***
	(142.420)	(139.146)	(161.189)	(170.440)	(156.229)
Exit	0.014	0.013	0.025***	0.002	0.039***
	(0.119)	(0.112)	(0.157)	(0.043)	(0.194)
IPO	0.004	0.003	0.008***	0.001	0.012***
	(0.062)	(0.057)	(0.089)	(0.031)	(0.110)
Acquisition	0.011	0.010	0.017***	0.001	0.027***
	(0.102)	(0.097)	(0.130)	(0.031)	(0.162)
Failure	0.017	0.018	0.012***	0.000	0.019***
	(0.129)	(0.132)	(0.108)	(0.000)	(0.137)
IPO size (mil USD)	0.427	0.041	2.930	0.030	4.670
	(50.355)	(1.382)	(137.785)	(0.993)	(174.280)
Observations	21,419	18,559	2,860	1,071	1,789

Panel B: Industries

	Full		Never US VC		Ever US VC	
	Companies	%	Companies	%	Companies	%
Information and communication	593	32%	474	29%	119	47%
Manufacturing	251	13%	229	14%	22	9%
Professional, scientific and technical activities	506	27%	448	28%	58	23%
Wholesale and retail trade; repair of motor vehicles and motorcycles	202	11%	180	11%	22	9%
Other	310	17%	277	17%	33	13%
Observations	1862		1608		254	
			Pearson $\chi^2 = 43.0769$		p-value = 0.001	

Panel C: Counties

	Full		Never US VC		Ever US VC	
	Companies	%	Companies	%	Companies	%
Skåne	229	12%	197	12%	32	13%
Stockholm	857	46%	705	44%	152	60%
Västra Götaland	281	15%	249	15%	32	13%
Other	495	27%	457	28%	38	15%
Observations	1862		1608		254	
			Pearson $\chi^2 = 52.3282$		p-value = 0.000	

Panel D: Rounds

	Full		Never US VC		Ever US VC	
	Rounds	%	Rounds	%	Rounds	%
1st round	1862	63%	1608	67%	254	44%
2nd round	612	21%	475	20%	137	24%
3rd round	255	9%	176	7%	79	14%
4th+ round	235	8%	133	6%	102	18%
Observations	2964		2392		572	
			Pearson $\chi^2 = 155.8376$		p-value = 0.000	

Table 2.3
Correlation matrix

This table presents pairwise correlations. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

		1	2	3	4	5	6	7	8	9	10	11	12	13
USVC round	1	1.000												
VC round	2	0.368***	1.000											
VC round size	3	0.326***	0.287***	1.000										
Net profit	4	-0.130***	-0.200***	-0.112***	1.000									
Operating cash	5	-0.117***	-0.153***	-0.117***	0.648***	1.000								
Overdraft amount	6	-0.020**	-0.030***	0.000	0.056***	-0.087***	1.000							
Bank loans	7	-0.006	-0.013	0.029***	0.026***	-0.129***	0.349***	1.000						
Bank loans ratio	8	-0.028***	-0.015*	-0.018*	0.023**	0.021**	0.062***	0.304***	1.000					
Sales	9	-0.006	-0.032***	0.024***	0.143***	0.012	0.272***	0.229***	-0.015*	1.000				
Exit	10	-0.004	-0.012	-0.003	-0.041***	-0.046***	-0.010	-0.017*	-0.032***	0.008	1.000			
IPO	11	-0.001	0.001	0.006	-0.053***	-0.060***	0.001	-0.009	-0.016*	0.028***	0.530***	1.000		
Acquisition	12	-0.004	-0.015*	-0.007	-0.015*	-0.016*	-0.013	-0.014	-0.028***	-0.008	0.844***	-0.007	1.000	
Failure	13	-0.009	0.026***	0.007	-0.051***	-0.032***	-0.018*	-0.015*	0.008	-0.019**	-0.017*	-0.009	-0.014	1.000

Table 2.4
Initial selection into US venture capital funding

This table presents results for regressions of initial US VC funding on company characteristics. The dependent variable is a dummy variable that equals one if a company receives VC funding from a US investors for the first time. The unit of analysis is a company-VC round. We use all VC rounds and first VC rounds in models 1 and 2, respectively. We control for lagged values of the log of sales, cumulative net profit, the log of company age, the log of cumulative VC funding, and cumulative rounds with missing VC funding. We also include prior VC rounds, industry, county, and calendar year fixed effects. We report the coefficient estimates for industries and counties with at least 10% of all companies. The baseline level for industry and county fixed effects is "Information and communication" and "Stockholm", respectively. Table 2.1 contains definitions for all variables. *t*-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) All rounds	(2) 1st round
Sales (log)	-0.0008	-0.0016
	(-0.697)	(-1.082)
Cum net profit	-0.0004*	-0.0004
	(-1.901)	(-1.083)
Age (log)	-0.0004	0.0106
	(-0.047)	(0.948)
Cum funding (log)	0.0156	
	(1.007)	
Cum missing funding	0.0074	
	(0.460)	
1 prior round	-0.0370**	
	(-1.994)	
2 prior rounds	-0.0507*	
	(-1.714)	
3 prior rounds	-0.0785*	
	(-1.951)	
4 prior rounds	-0.0688	
	(-1.173)	
>=5 prior rounds	-0.0428	
	(-0.554)	
Manufacturing	-0.0575***	-0.0722***
	(-3.083)	(-3.064)
Wholesale and retail trade; repair of motor vehicles and motorcycles	-0.0437*	-0.0187
	(-1.937)	(-0.605)
Professional, scientific and technical activities	-0.0552***	-0.0601***
	(-3.109)	(-2.622)
Skåne	-0.0224	-0.0427
	(-1.100)	(-1.593)
Västra Götaland	-0.0397**	-0.0413*
	(-2.313)	(-1.738)
Other industry FEs	Yes	Yes
Other county FEs	Yes	Yes
Calendar year FEs	Yes	Yes
Observations	2370	1470

Table 2.5
Associations with subsequent funding rounds

This table presents results for regressions of future on current VC funding. The dependent variables are a dummy variable that equals one if a company receives VC funding and the log of the VC funding amount, measured during the next three (models 1 and 2) and five (models 3 and 4) fiscal years. We construct these using all VC rounds and US VC rounds only in Panels A and B, respectively. The unit of analysis is a company-fiscal year, and we exclude observations before a company's first VC round. The variables of interest are dummy variables that equal one if a company receives any VC funding and US VC funding in the current fiscal year. We control for lagged values of the log of sales, cumulative net profit, the log of company age, the log of cumulative VC funding, and cumulative rounds with missing VC funding. We also include prior VC rounds, industry, county, and calendar year fixed effects. Table 2.1 contains definitions for all variables. *t*-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: All VC rounds				
	(1) VC round by t+3	(2) Subsequent funding by t+3	(3) VC round by t+5	(4) Subsequent funding by t+5
VC round	0.2392***	0.4563***	0.2421***	0.4809***
	(12.798)	(9.775)	(12.045)	(8.781)
USVC round	0.0743**	0.4874***	0.0497	0.5467***
	(2.281)	(3.505)	(1.262)	(2.859)
Prior funding	0.0132	0.1108***	0.0020	0.1099***
	(1.616)	(4.293)	(0.174)	(3.041)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	8110	8110	5956	5956

Panel B: US VC rounds				
	(1) US VC round by t+3	(2) Subsequent US funding by t+3	(3) US VC round by t+5	(4) Subsequent US funding by t+5
VC round	0.0474***	0.1421***	0.0592***	0.1690***
	(4.298)	(4.178)	(4.112)	(4.066)
USVC round	0.2176***	0.6707***	0.1841***	0.6995***
	(6.764)	(5.728)	(4.706)	(5.113)
Prior funding	0.0137***	0.0658***	0.0132**	0.0720***
	(3.055)	(3.740)	(2.176)	(3.431)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	8110	8110	5956	5956

Table 2.6
Relationship between VC funding and company earnings

This table presents results for regressions of company earnings on VC funding. The dependent variables are cumulative net profit (Panel A) and cumulative cash from operations (Panel B), measured during the next three (models 1 and 2) and five (models 3 and 4) fiscal years. The unit of analysis is a company-fiscal year. The variables of interest are dummy variables that equal one if a company receives any VC funding and US VC funding in the current fiscal year. We control for lagged values of the log of sales, cumulative net profit, the log of company age, the log of cumulative VC funding, and cumulative rounds with missing VC funding. We also include prior VC rounds, industry, county, and calendar year fixed effects. In addition, models 2 and 4 control for cumulative VC funding during the measurement period of the dependent variable. Table 2.1 contains definitions for all variables. *t*-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Cumulative net profit				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
VC round	-13.5778***	-11.4375***	-17.1486***	-14.6743***
	(-13.380)	(-13.350)	(-9.566)	(-9.620)
USVC round	-12.8560***	-5.2042	-19.5920***	-7.0543
	(-3.568)	(-1.592)	(-3.023)	(-1.225)
Cum net profit	0.0760***	0.0744***	0.0867***	0.0807***
	(6.122)	(6.321)	(3.794)	(3.798)
Prior funding	-1.7794	-0.4991	-1.3228	0.3629
	(-1.349)	(-0.426)	(-0.527)	(0.165)
Subsequent funding		-13.6990***		-20.2590***
		(-14.401)		(-14.503)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	13177	13177	10561	10561

Panel B: Cumulative cash from operations				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
VC round	-16.1289***	-13.3098***	-22.5969***	-19.4046***
	(-12.784)	(-12.633)	(-10.201)	(-10.359)
USVC round	-19.3312***	-9.1300*	-26.6186***	-10.0282
	(-4.514)	(-1.862)	(-3.565)	(-1.175)
Cum net profit	0.1081***	0.1060***	0.1338***	0.1261***
	(5.661)	(5.860)	(3.849)	(3.768)
Prior funding	-5.9804***	-4.2809***	-7.9201***	-5.6956**
	(-4.175)	(-3.262)	(-3.056)	(-2.395)
Subsequent funding		-18.2228***		-26.7596***
		(-16.526)		(-14.509)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	13177	13177	10561	10561

Table 2.7
Relationship between VC funding and company earnings dispersion

This table presents results for regressions of company earnings dispersion on VC funding. The dependent variables are dummy variables that equal one if a company's cumulative net profit (Panels A and B) and cumulative cash from operations (Panels C and D) are in the top or bottom decile, measured during the next three (models 1 and 2) and five (models 3 and 4) fiscal years. The unit of analysis is a company-fiscal year. The variables of interest are dummy variables that equal one if a company receives any VC funding and US VC funding in the current fiscal year. We control for lagged values of the log of sales, cumulative net profit, the log of company age, the log of cumulative VC funding, and cumulative rounds with missing VC funding. We also include prior VC rounds, industry, county, and calendar year fixed effects. In addition, models 2 and 4 control for cumulative VC funding during the measurement period of the dependent variable. Table 2.1 contains definitions for all variables. *t*-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Cumulative net profit top decile				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
VC round	-0.0114*	-0.0090	-0.0003	0.0013
	(-1.672)	(-1.316)	(-0.029)	(0.146)
USVC round	-0.0142	-0.0077	-0.0273	-0.0217
	(-0.613)	(-0.350)	(-1.012)	(-0.836)
Cum net profit	0.0006***	0.0006***	0.0004**	0.0004**
	(3.958)	(3.954)	(2.413)	(2.401)
Prior funding	0.0562***	0.0575***	0.0558***	0.0566***
	(4.374)	(4.478)	(3.648)	(3.708)
Subsequent funding		-0.0125**		-0.0092
		(-2.316)		(-1.571)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	13177	13177	10561	10561

Panel B: Cumulative net profit bottom decile				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
VC round	0.1229***	0.1005***	0.1068***	0.0900***
	(10.409)	(9.876)	(7.823)	(7.640)
USVC round	0.1425***	0.0626*	0.1287***	0.0423
	(3.839)	(1.754)	(2.821)	(0.990)
Cum net profit	-0.0005***	-0.0004***	-0.0004***	-0.0003***
	(-4.553)	(-4.666)	(-3.398)	(-3.267)
Prior funding	0.0580***	0.0446***	0.0433***	0.0317***
	(5.527)	(5.002)	(3.406)	(2.921)
Subsequent funding		0.1431***		0.1394***
		(15.899)		(16.347)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	13177	13177	10561	10561

Panel C: Cumulative cash from operations top decile				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
VC round	-0.0139*	-0.0111	-0.0170**	-0.0151*
	(-1.896)	(-1.509)	(-1.966)	(-1.721)
USVC round	-0.0277	-0.0188	-0.0178	-0.0105
	(-1.583)	(-1.065)	(-0.816)	(-0.494)
Cum net profit	0.0006***	0.0006***	0.0007***	0.0007***
	(4.555)	(4.558)	(4.219)	(4.204)
Prior funding	0.0398***	0.0414***	0.0449***	0.0459***
	(4.460)	(4.606)	(3.011)	(3.072)
Subsequent funding		-0.0162***		-0.0120**
		(-3.453)		(-2.249)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	13177	13177	10561	10561

Panel D: Cumulative cash from operations bottom decile				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
VC round	0.0894***	0.0699***	0.0893***	0.0744***
	(8.465)	(7.448)	(6.888)	(6.452)
USVC round	0.2020***	0.1324***	0.1704***	0.0935**
	(5.766)	(3.512)	(3.963)	(2.201)
Cum net profit	-0.0006***	-0.0006***	-0.0005***	-0.0004***
	(-4.184)	(-4.296)	(-2.897)	(-2.742)
Prior funding	0.0596***	0.0480***	0.0540***	0.0437***
	(5.661)	(5.048)	(3.998)	(3.660)
Subsequent funding		0.1247***		0.1241***
		(16.006)		(15.303)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	13177	13177	10561	10561

Table 2.8
Relationship between VC funding and exit outcomes

This table presents results for regressions of exit outcomes on VC funding. The dependent variables are dummy variables that equal one if a company has any exit (Panel A), an IPO (Panel B), an acquisition (Panel C), and a failure (Panel D) event during the next fiscal year, as well as the log of the capital raised in an IPO (Panel E). The unit of analysis is a company-fiscal year in Panels A to D and an IPO event in Panel E. The variables of interest are dummy variables that equal one if a company is VC backed and US VC backed in the current fiscal year in Panels A to D and a dummy variable that equals one if a company is US VC backed at the beginning of the fiscal year during which the IPO event happens in Panel E. We control for lagged values of the log of sales, cumulative net profit, the log of company age, the log of cumulative VC funding, and cumulative rounds with missing VC funding. We also include prior VC rounds, industry, county, and calendar year fixed effects. Model 2 additionally controls for cumulative VC funding during the measurement period of the dependent variable. Model 3 further controls for cumulative net profit during the measurement period of the dependent variable. Table 2.1 contains definitions for all variables. *t*-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Exit			
	(1)	(2)	(3)
	t+1	t+1	t+1
VC backed	0.0124***	0.0128***	0.0117***
	(3.702)	(3.788)	(3.461)
USVC backed	0.0155**	0.0161**	0.0159**
	(2.160)	(2.235)	(2.217)
Cum net profit	-0.0001***	-0.0001***	-0.0001**
	(-2.711)	(-2.702)	(-2.355)
Prior funding	0.0067**	0.0071**	0.0070**
	(2.355)	(2.455)	(2.423)
Subsequent funding		-0.0071***	-0.0086***
		(-3.195)	(-3.710)
Subs cum net profit			-0.0003*
			(-1.936)
Controls & FEs	Yes	Yes	Yes
Observations	16073	16073	16073

Panel B: IPO			
	(1)	(2)	(3)
	t+1	t+1	t+1
VC backed	0.0006	0.0004	-0.0004
	(0.410)	(0.287)	(-0.278)
USVC backed	0.0059	0.0060	0.0058
	(1.453)	(1.477)	(1.443)
Cum net profit	-0.0000**	-0.0000**	-0.0000*
	(-2.249)	(-2.247)	(-1.851)
Prior funding	0.0032*	0.0033*	0.0032*
	(1.785)	(1.790)	(1.744)
Subsequent funding		-0.0012	-0.0023
		(-0.728)	(-1.315)
Subs cum net profit			-0.0002**
			(-2.568)
Controls & FEs	Yes	Yes	Yes
Observations	16073	16073	16073

Panel C: Acquisition			
	(1)	(2)	(3)
	t+1	t+1	t+1
VC backed	0.0118***	0.0124***	0.0121***
	(3.875)	(4.017)	(3.922)
USVC backed	0.0097*	0.0102*	0.0101*
	(1.658)	(1.736)	(1.729)
Cum net profit	-0.0000*	-0.0000*	-0.0000*
	(-1.859)	(-1.856)	(-1.688)
Prior funding	0.0035	0.0038*	0.0038*
	(1.598)	(1.745)	(1.726)
Subsequent funding		-0.0059***	-0.0063***
		(-4.097)	(-4.145)
Subs cum net profit			-0.0001
			(-0.603)
Controls & FEs	Yes	Yes	Yes
Observations	16073	16073	16073

Panel D: Failure			
	(1)	(2)	(3)
	t+1	t+1	t+1
VC backed	0.0266***	0.0273***	0.0255***
	(5.265)	(5.424)	(5.070)
USVC backed	-0.0041	-0.0043	-0.0046
	(-0.789)	(-0.834)	(-0.907)
Cum net profit	-0.0001***	-0.0001***	-0.0001***
	(-3.626)	(-3.614)	(-2.925)
Prior funding	-0.0051***	-0.0052***	-0.0055***
	(-2.696)	(-2.755)	(-2.939)
Subsequent funding		0.0028	0.0004
		(1.096)	(0.146)
Subs cum net profit			-0.0005***
			(-3.964)
Controls & FEs	Yes	Yes	Yes
Observations	16073	16073	16073

Panel E: IPO size			
	(1)	(2)	(3)
USVC backed	1.1188**	0.7297	-0.0317
	(2.092)	(1.412)	(-0.067)
Sales (log)		-0.0302	-0.0093
		(-0.870)	(-0.337)
Cum net profit		-0.0049**	0.0010
		(-2.073)	(0.439)
Age (log)		0.4108	0.5056*
		(1.241)	(1.788)
1 prior round			-0.7167
			(-1.306)
2 prior rounds			-1.9606***
			(-4.065)
3 prior rounds			-2.4746***
			(-3.785)
4 prior rounds			-1.9014***
			(-2.934)
>=5 prior rounds			-1.5923**
			(-2.474)
Prior funding			0.7534***
			(3.889)
Cum missing size			0.3006
			(1.155)
Industry FEs	Yes	Yes	Yes
County FEs	Yes	Yes	Yes
Calendar year FEs	Yes	Yes	Yes
Observations	55	55	55

Table 2.9
Relationship between VC funding and overdraft facilities

This table presents results for regressions of overdraft facilities on VC funding. The dependent variables are a dummy variable that equals one if a company has an overdraft facility (Panel A), the log of the overdraft amount granted (Panel B), and the fraction of the granted overdraft amount used (Panel C). We measure the dependent variables at the end of the next three (models 1 and 2) and five (models 3 and 4) fiscal years. The unit of analysis is a company-fiscal year, and we restrict observations in Panels B and C to those for companies with an overdraft facility. The variables of interest are dummy variables that equal one if a company receives any VC funding and US VC funding in the current fiscal year. We control for lagged values of the log of sales, cumulative net profit, the log of company age, the log of cumulative VC funding, and cumulative rounds with missing VC funding. We also include prior VC rounds, industry, county, and calendar year fixed effects. In addition, models 2 and 4 control for cumulative VC funding during the measurement period of the dependent variable. Table 2.1 contains definitions for all variables. *t*-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Overdraft granted dummy				
	(1) t+3	(2) t+3	(3) t+5	(4) t+5
VC round	-0.0157	-0.0148	-0.0402***	-0.0396***
	(-1.366)	(-1.302)	(-2.891)	(-2.841)
USVC round	-0.0466*	-0.0440*	-0.0717***	-0.0696**
	(-1.949)	(-1.791)	(-2.725)	(-2.566)
Cum net profit	-0.0000	-0.0000	0.0002	0.0002
	(-0.104)	(-0.108)	(0.802)	(0.796)
Prior funding	-0.0408***	-0.0404***	-0.0407***	-0.0404***
	(-3.801)	(-3.775)	(-3.037)	(-3.021)
Prior overdraft (log)	0.1539***	0.1539***	0.1070***	0.1070***
	(18.518)	(18.502)	(10.723)	(10.717)
Subsequent funding		-0.0048		-0.0035
		(-0.746)		(-0.449)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	13177	13177	10561	10561

Panel B: Overdraft amount granted (conditional on overdraft granted)				
	(1) t+3	(2) t+3	(3) t+5	(4) t+5
VC round	0.1898***	0.1709***	0.1971***	0.1879***
	(4.056)	(3.667)	(3.390)	(3.148)
USVC round	0.0677	0.1558	0.0363	0.0756
	(0.343)	(0.837)	(0.122)	(0.307)
Cum net profit	0.0034***	0.0036***	0.0042***	0.0045***
	(3.991)	(4.201)	(3.650)	(3.935)
Prior funding	0.2187***	0.2125***	0.2486***	0.2503***
	(3.159)	(3.211)	(2.867)	(3.213)
Prior overdraft (log)	0.5411***	0.5327***	0.4538***	0.4427***
	(18.107)	(17.913)	(13.076)	(12.977)
Subsequent funding		0.2110***		0.2788***
		(5.666)		(6.975)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	4132	4132	3352	3352

Panel C: Fraction of granted overdraft amount used (conditional on overdraft granted)				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
VC round	-2.2520	-1.7046	-0.3359	-0.1114
	(-1.189)	(-0.921)	(-0.153)	(-0.050)
USVC round	-10.6329*	-11.1510**	-3.9309	-3.7961
	(-1.953)	(-2.050)	(-0.410)	(-0.399)
Cum net profit	-0.0238	-0.0262	-0.0047	-0.0062
	(-0.884)	(-0.974)	(-0.146)	(-0.191)
Prior funding	-4.1326**	-3.9829**	-3.0514	-3.0281
	(-2.193)	(-2.101)	(-1.299)	(-1.285)
Prior overdraft (log)	3.8949***	4.0096***	2.5525***	2.6227***
	(4.346)	(4.452)	(2.646)	(2.708)
Subsequent funding		-3.2948***		-1.8384
		(-2.648)		(-1.405)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	4132	4132	3352	3352

Table 2.10
Relationship between VC funding and bank loans

This table presents results for regressions of bank loans on VC funding. The dependent variable is the log of bank loans (Panel A) and the fraction of banks loans of total assets (Panel B), measured at the end of the next three (models 1 and 2) and five (models 3 and 4) fiscal years. The unit of analysis is a company-fiscal year. The variables of interest are dummy variables that equal one if a company receives any VC funding and US VC funding in the current fiscal year. We control for lagged values of the log of sales, cumulative net profit, the log of company age, the log of cumulative VC funding, and cumulative rounds with missing VC funding. We also include prior VC rounds, industry, county, and calendar year fixed effects. In addition, models 2 and 4 control for cumulative VC funding during the measurement period of the dependent variable. Table 2.1 contains definitions for all variables. *t*-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Bank loans amount				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
VC round	0.0019	-0.0062	-0.0333	-0.0440
	(0.080)	(-0.262)	(-0.986)	(-1.302)
USVC round	-0.0245	-0.0586	-0.0886	-0.1394**
	(-0.335)	(-0.819)	(-1.361)	(-2.073)
Cum net profit	0.0005	0.0005	0.0004	0.0005
	(1.256)	(1.286)	(0.791)	(0.856)
Prior funding	0.0357	0.0306	0.0251	0.0187
	(1.324)	(1.121)	(0.754)	(0.560)
Prior bank loans (log)	0.5203***	0.5180***	0.4145***	0.4113***
	(18.265)	(18.100)	(12.121)	(11.984)
Subsequent funding		0.0592***		0.0820***
		(3.248)		(3.759)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	13177	13177	10561	10561

Panel B: Bank loans leverage ratio				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
VC round	-0.8164**	-0.6858*	-0.7150*	-0.6839
	(-2.272)	(-1.923)	(-1.658)	(-1.588)
USVC round	-1.2352*	-0.7921	-1.1771*	-0.8995
	(-1.860)	(-1.162)	(-1.760)	(-1.295)
Cum net profit	-0.0017	-0.0018	-0.0013	-0.0015
	(-0.467)	(-0.507)	(-0.277)	(-0.307)
Prior funding	-0.4291	-0.3613	-0.0829	-0.0541
	(-1.631)	(-1.360)	(-0.267)	(-0.173)
Prior bank loans (log)	3.6902***	3.7197***	2.6177***	2.6410***
	(13.983)	(14.059)	(9.655)	(9.734)
Subsequent funding		-0.8401***		-0.4886**
		(-4.352)		(-2.447)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	13092	13092	10493	10493

2.10 Appendix

Table 2.11
Relationship between VC funding and company earnings dispersion

This table presents results for regressions of company earnings dispersion on VC funding. The dependent variables are dummy variables that equal one if a company's cumulative net profit (Panels A and B) and cumulative cash from operations (Panels C and D) are in the top or bottom quartile, measured during the next three (models 1 and 2) and five (models 3 and 4) fiscal years. The unit of analysis is a company-fiscal year. The variables of interest are dummy variables that equal one if a company receives any VC funding and US VC funding in the current fiscal year. We control for lagged values of the log of sales, cumulative net profit, the log of company age, the log of cumulative VC funding, and cumulative rounds with missing VC funding. We also include prior VC rounds, industry, county, and calendar year fixed effects. In addition, models 2 and 4 control for cumulative VC funding during the measurement period of the dependent variable. Table 2.1 contains definitions for all variables. *t*-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Cumulative net profit top quartile				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
VC round	-0.0843***	-0.0765***	-0.0667***	-0.0606***
	(-8.013)	(-7.458)	(-5.307)	(-4.923)
USVC round	-0.0356	-0.0079	-0.0635**	-0.0350
	(-1.295)	(-0.309)	(-2.065)	(-1.239)
Cum net profit	0.0005***	0.0005***	0.0005**	0.0005**
	(2.712)	(2.700)	(2.230)	(2.192)
Prior funding	0.0428***	0.0474***	0.0422**	0.0460***
	(2.976)	(3.376)	(2.389)	(2.683)
Subsequent funding		-0.0497***		-0.0464***
		(-7.133)		(-6.327)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	13177	13177	10561	10561

Panel B: Cumulative net profit bottom quartile				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
VC round	0.2107***	0.1831***	0.1826***	0.1614***
	(15.952)	(15.353)	(11.792)	(11.837)
USVC round	0.0912**	-0.0102	0.1414***	0.0292
	(2.331)	(-0.260)	(3.311)	(0.604)
Cum net profit	-0.0007***	-0.0007***	-0.0006***	-0.0006***
	(-5.071)	(-5.093)	(-3.772)	(-3.593)
Prior funding	0.0388***	0.0220*	0.0364**	0.0214
	(2.910)	(1.862)	(2.281)	(1.507)
Subsequent funding		0.1807***		0.1808***
		(16.782)		(17.824)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	13177	13177	10561	10561

Panel C: Cumulative cash from operations top quartile				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
VC round	-0.1113***	-0.1030***	-0.0959***	-0.0904***
	(-10.953)	(-10.124)	(-8.056)	(-7.624)
USVC round	-0.0159	0.0189	-0.0306	0.0034
	(-0.657)	(0.700)	(-1.061)	(0.107)
Cum net profit	0.0006***	0.0006***	0.0008***	0.0008***
	(3.873)	(3.858)	(4.269)	(4.237)
Prior funding	0.0099	0.0155	0.0184	0.0229
	(0.933)	(1.428)	(1.196)	(1.487)
Subsequent funding		-0.0606***		-0.0543***
		(-9.495)		(-7.438)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	13177	13177	10561	10561

Panel D: Cumulative cash from operations bottom quartile				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
VC round	0.1834***	0.1568***	0.1584***	0.1378***
	(14.074)	(13.187)	(10.337)	(10.115)
USVC round	0.1214***	0.0233	0.1856***	0.0763
	(3.121)	(0.484)	(4.469)	(1.387)
Cum net profit	-0.0009***	-0.0009***	-0.0007***	-0.0006***
	(-5.017)	(-5.046)	(-3.114)	(-2.957)
Prior funding	0.0711***	0.0549***	0.0742***	0.0596***
	(5.320)	(4.349)	(4.855)	(4.026)
Subsequent funding		0.1747***		0.1760***
		(18.315)		(17.580)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	13177	13177	10561	10561

Table 2.12
Associations with subsequent funding rounds – Round-to-round subsample

This table presents results for regressions of future on current VC funding in a round-to-round subsample, which only includes fiscal years during which a company receives VC funding. The dependent variables are a dummy variable that equals one if a company receives VC funding and the log of the VC funding amount, measured during the next three (models 1 and 2) and five (models 3 and 4) fiscal years. We construct these using all VC rounds and US VC rounds only in Panels A and B, respectively. The unit of analysis is a company-fiscal year with a VC round, and we exclude observations before a company's first VC round. The variables of interest are dummy variables that equal one if a company receives any VC funding and US VC funding in the current fiscal year. We control for lagged values of the log of sales, cumulative net profit, the log of company age, the log of cumulative VC funding, and cumulative rounds with missing VC funding. We also include prior VC rounds, industry, county, and calendar year fixed effects. Table 2.1 contains definitions for all variables. *t*-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: All VC rounds

	(1) VC round by t+3	(2) Subsequent funding by t+3	(3) VC round by t+5	(4) Subsequent funding by t+5
USVC round	0.0469	0.3012***	0.0226	0.3467**
	(1.341)	(2.713)	(0.572)	(2.328)
Prior funding	0.0169	0.3403***	0.0090	0.3900***
	(0.986)	(4.326)	(0.429)	(3.025)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	1881	1881	1436	1436

Panel B: US VC rounds

	(1) US VC round by t+3	(2) Subsequent US funding by t+3	(3) US VC round by t+5	(4) Subsequent US funding by t+5
USVC round	0.1990***	0.5042***	0.1695***	0.4841***
	(5.788)	(5.614)	(4.248)	(4.317)
Prior funding	0.0504***	0.2582***	0.0504**	0.2794***
	(3.205)	(4.044)	(2.383)	(3.713)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	1881	1881	1436	1436

Table 2.13

Relationship between VC funding and company earnings – Round-to-round sample

This table presents results for regressions of company earnings on VC funding in a round-to-round subsample, which only includes fiscal years during which a company receives VC funding. The dependent variables are cumulative net profit (Panel A) and cumulative cash from operations (Panel B), measured during the next three (models 1 and 2) and five (models 3 and 4) fiscal years. The unit of analysis is a company-fiscal year with a VC round. The variables of interest are dummy variables that equal one if a company receives any VC funding and US VC funding in the current fiscal year. We control for lagged values of the log of sales, cumulative net profit, the log of company age, the log of cumulative VC funding, and cumulative rounds with missing VC funding. We also include prior VC rounds, industry, county, and calendar year fixed effects. In addition, models 2 and 4 control for cumulative VC funding during the measurement period of the dependent variable. Table 2.1 contains definitions for all variables. *t*-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Cumulative net profit				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
USVC round	-7.4222**	-3.2773	-12.7382**	-5.8406
	(-2.205)	(-1.072)	(-2.036)	(-1.108)
Cum net profit	0.1569***	0.1553***	0.1879***	0.1838***
	(3.993)	(3.792)	(3.133)	(2.948)
Prior funding	-6.7564***	-2.0748	-8.5243**	0.5583
	(-3.249)	(-1.040)	(-2.167)	(0.150)
Subsequent funding		-13.9843***		-22.1277***
		(-10.031)		(-10.344)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	1881	1881	1436	1436

Panel B: Cumulative cash from operations				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
USVC round	-13.0049***	-7.5271**	-18.9823**	-10.0113
	(-3.275)	(-1.967)	(-2.553)	(-1.485)
Cum net profit	0.2693***	0.2685***	0.3096***	0.3051***
	(6.105)	(6.051)	(4.453)	(4.220)
Prior funding	-9.0743***	-2.8863	-12.5304***	-1.2288
	(-2.991)	(-0.840)	(-2.954)	(-0.230)
Subsequent funding		-18.3966***		-27.9175***
		(-10.315)		(-8.620)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	1881	1881	1436	1436

Table 2.14
Relationship between VC funding and company earnings dispersion – Round-to-round sample

This table presents results for regressions of company earnings dispersion on VC funding in a round-to-round subsample, which only includes fiscal years during which a company receives VC funding. The dependent variables are dummy variables that equal one if a company's cumulative net profit (Panels A and B) and cumulative cash from operations (Panels C and D) are in the top or bottom decile, measured during the next three (models 1 and 2) and five (models 3 and 4) fiscal years. The unit of analysis is a company-fiscal year with a VC round. The variables of interest are dummy variables that equal one if a company receives any VC funding and US VC funding in the current fiscal year. We control for lagged values of the log of sales, cumulative net profit, the log of company age, the log of cumulative VC funding, and cumulative rounds with missing VC funding. We also include prior VC rounds, industry, county, and calendar year fixed effects. In addition, models 2 and 4 control for cumulative VC funding during the measurement period of the dependent variable. Table 2.1 contains definitions for all variables. *t*-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Cumulative net profit top decile				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
USVC round	0.0033	0.0079	-0.0168	-0.0092
	(0.170)	(0.424)	(-0.706)	(-0.403)
Cum net profit	0.0007**	0.0007**	0.0008***	0.0008***
	(2.483)	(2.468)	(2.727)	(2.757)
Prior funding	0.0296*	0.0348**	0.0312	0.0410**
	(1.853)	(2.222)	(1.498)	(1.984)
Subsequent funding		-0.0159**		-0.0240***
		(-2.401)		(-3.297)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	1881	1881	1436	1436

Panel B: Cumulative net profit bottom decile				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
USVC round	0.0829**	0.0354	0.0785	0.0318
	(2.153)	(1.003)	(1.646)	(0.768)
Cum net profit	-0.0011***	-0.0011***	-0.0013***	-0.0013***
	(-3.002)	(-2.774)	(-3.171)	(-2.908)
Prior funding	0.1253***	0.0717***	0.0745***	0.0115
	(5.842)	(3.280)	(2.656)	(0.427)
Subsequent funding		0.1595***		0.1524***
		(10.264)		(10.827)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	1881	1881	1436	1436

Panel C: Cumulative cash from operations top decile				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
USVC round	-0.0224	-0.0149	-0.0210	-0.0130
	(-1.339)	(-0.892)	(-1.007)	(-0.638)
Cum net profit	0.0008***	0.0008***	0.0006**	0.0006**
	(3.896)	(3.931)	(2.301)	(2.333)
Prior funding	0.0409***	0.0495***	0.0276*	0.0373**
	(2.847)	(3.046)	(1.795)	(2.272)
Subsequent funding		-0.0254***		-0.0243***
		(-4.464)		(-4.244)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	1881	1881	1436	1436

Panel D: Cumulative cash from operations bottom decile				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
USVC round	0.1519***	0.1139***	0.1265***	0.0832**
	(4.269)	(3.346)	(2.869)	(2.114)
Cum net profit	-0.0019***	-0.0019***	-0.0013***	-0.0012***
	(-5.306)	(-5.398)	(-3.275)	(-3.073)
Prior funding	0.0893***	0.0463*	0.1036***	0.0475*
	(3.887)	(1.879)	(4.712)	(1.747)
Subsequent funding		0.1280***		0.1373***
		(9.235)		(9.884)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	1881	1881	1436	1436

Table 2.15

Relationship between VC funding and overdraft facilities – Round-to-round sample

This table presents results for regressions of overdraft facilities on VC funding in a round-to-round subsample, which only includes fiscal years during which a company receives VC funding. The dependent variables are a dummy variable that equals one if a company has an overdraft facility (Panel A), the log of the overdraft amount granted (Panel B), and the fraction of the granted overdraft amount used (Panel C). We measure the dependent variables at the end of the next three (models 1 and 2) and five (models 3 and 4) fiscal years. The unit of analysis is a company-fiscal year with a VC round, and we restrict observations in Panels B and C to those for companies with an overdraft facility. The variables of interest are dummy variables that equal one if a company receives any VC funding and US VC funding in the current fiscal year. We control for lagged values of the log of sales, cumulative net profit, the log of company age, the log of cumulative VC funding, and cumulative rounds with missing VC funding. We also include prior VC rounds, industry, county, and calendar year fixed effects. In addition, models 2 and 4 control for cumulative VC funding during the measurement period of the dependent variable. Table 2.1 contains definitions for all variables. *t*-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Overdraft granted dummy				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
USVC round	-0.0627**	-0.0609**	-0.0879***	-0.0901***
	(-2.354)	(-2.248)	(-3.162)	(-3.234)
Cum net profit	0.0005*	0.0005*	0.0010***	0.0010***
	(1.730)	(1.731)	(2.911)	(2.915)
Prior funding	-0.0200	-0.0180	-0.0300	-0.0329
	(-1.175)	(-1.054)	(-1.451)	(-1.592)
Prior overdraft (log)	0.1632***	0.1632***	0.0898***	0.0899***
	(10.510)	(10.520)	(5.029)	(5.043)
Subsequent funding		-0.0062		0.0070
		(-0.699)		(0.750)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	1881	1881	1436	1436

Panel B: Overdraft amount granted (conditional on overdraft granted)				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
USVC round	0.1477	0.1869	0.0951	0.0869
	(0.718)	(0.928)	(0.284)	(0.257)
Cum net profit	0.0022*	0.0025*	0.0041	0.0041
	(1.665)	(1.842)	(1.642)	(1.613)
Prior funding	0.2879**	0.2774*	0.3090	0.2576
	(1.984)	(1.933)	(1.344)	(1.186)
Prior overdraft (log)	0.5357***	0.5351***	0.3557***	0.3516***
	(10.026)	(9.971)	(5.396)	(5.255)
Subsequent funding		0.1187		0.1218
		(1.637)		(1.519)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	501	501	359	359

Panel C: Fraction of granted overdraft amount used (conditional on overdraft granted)				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
USVC round	-11.8919*	-13.3235**	-14.2607	-19.9449
	(-1.734)	(-1.968)	(-1.092)	(-1.590)
Cum net profit	0.0183	0.0088	0.0480	0.0249
	(0.376)	(0.179)	(0.749)	(0.399)
Prior funding	-7.2104*	-6.6561	8.6772	9.9284*
	(-1.751)	(-1.568)	(1.389)	(1.688)
Prior overdraft (log)	5.1585***	5.2457***	4.6776*	4.6869**
	(3.125)	(3.110)	(1.903)	(1.989)
Subsequent funding		-5.5527***		-3.1627
		(-2.955)		(-1.521)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	501	501	359	359

Table 2.16
Relationship between VC funding and bank loans – Round-to-round sample

This table presents results for regressions of bank loans on VC funding in a round-to-round subsample, which only includes fiscal years during which a company receives VC funding. The dependent variable is the log of bank loans (Panel A) and the fraction of banks loans of total assets (Panel B), measured at the end of the next three (models 1 and 2) and five (models 3 and 4) fiscal years. The unit of analysis is a company-fiscal year with a VC round. The variables of interest are dummy variables that equal one if a company receives any VC funding and US VC funding in the current fiscal year. We control for lagged values of the log of sales, cumulative net profit, the log of company age, the log of cumulative VC funding, and cumulative rounds with missing VC funding. We also include prior VC rounds, industry, county, and calendar year fixed effects. In addition, models 2 and 4 control for cumulative VC funding during the measurement period of the dependent variable. Table 2.1 contains definitions for all variables. *t*-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Bank loans amount				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
USVC round	-0.0234	-0.0281	-0.1068	-0.1299*
	(-0.365)	(-0.438)	(-1.502)	(-1.764)
Cum net profit	0.0012	0.0012	0.0008	0.0008
	(1.279)	(1.266)	(0.707)	(0.704)
Prior funding	0.0578	0.0525	0.0247	0.0063
	(1.015)	(0.960)	(0.428)	(0.108)
Prior bank loans (log)	0.5111***	0.5112***	0.3912***	0.3915***
	(10.327)	(10.348)	(6.536)	(6.549)
Subsequent funding		0.0147		0.0538*
		(0.532)		(1.786)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	1881	1881	1436	1436

Panel B: Bank loans leverage ratio				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
USVC round	-1.3631*	-1.0657	-1.5026**	-1.3765*
	(-1.937)	(-1.497)	(-2.053)	(-1.841)
Cum net profit	0.0099*	0.0094*	0.0064	0.0060
	(1.739)	(1.656)	(0.716)	(0.671)
Prior funding	-0.1020	0.2024	0.2325	0.3986
	(-0.269)	(0.530)	(0.485)	(0.794)
Prior bank loans (log)	2.6821***	2.7272***	1.8304***	1.8438***
	(7.906)	(8.182)	(4.721)	(4.807)
Subsequent funding		-1.0051***		0.0538*
		(-4.571)		(1.786)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	1865	1865	1418	1418

Table 2.17
Relationship between VC funding and sales growth

This table presents results for regressions of company sales on VC funding. The dependent variables are the log of cumulative sales (Panel A) and sales growth (Panel B), measured during the next three (models 1 and 2) and five (models 3 and 4) fiscal years. The unit of analysis is a company-fiscal year. The variables of interest are dummy variables that equal one if a company receives any VC funding and US VC funding in the current fiscal year. We control for lagged values of the log of sales, cumulative net profit, the log of company age, the log of cumulative VC funding, and cumulative rounds with missing VC funding. We also include prior VC rounds, industry, county, and calendar year fixed effects. In addition, models 2 and 4 control for cumulative VC funding during the measurement period of the dependent variable. Table 2.1 contains definitions for all variables. *t*-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Cumulative sales				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
VC round	0.6293***	0.5505***	0.4735***	0.4206***
	(5.108)	(4.596)	(3.399)	(3.126)
USVC round	0.8141**	0.4780	0.5733	0.2039
	(2.402)	(1.521)	(1.443)	(0.533)
Cum net profit	0.0095***	0.0095***	0.0102***	0.0104***
	(5.034)	(5.069)	(4.464)	(4.526)
Prior funding	0.1720	0.1190	0.1451	0.0969
	(1.173)	(0.802)	(0.826)	(0.544)
Subsequent funding		0.5836***		0.5853***
		(8.266)		(7.850)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	13177	13177	10561	10561

Panel B: Sales growth				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
VC round	0.2633***	0.2233***	0.0531	0.0184
	(4.209)	(3.658)	(0.651)	(0.230)
USVC round	0.2244	0.0793	0.3161	0.1466
	(1.168)	(0.429)	(1.166)	(0.558)
Cum net profit	0.0002	0.0002	0.0000	0.0001
	(0.254)	(0.330)	(0.015)	(0.103)
Prior funding	-0.0214	-0.0488	-0.1191*	-0.1459**
	(-0.529)	(-1.195)	(-1.833)	(-2.226)
Subsequent funding		0.2516***		0.2780***
		(6.728)		(6.098)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	11282	11282	9065	9065

Table 2.18
Relationship between VC funding and sales growth dispersion

This table presents results for regressions of company sales dispersion on VC funding. The dependent variables are dummy variables that equal one if a company's cumulative sales are in the top decile (Panel A), bottom decile (Panel B), top quartile (Panel C), and bottom quartile (Panel D), measured during the next three (models 1 and 2) and five (models 3 and 4) fiscal years. The unit of analysis is a company-fiscal year. The variables of interest are dummy variables that equal one if a company receives any VC funding and US VC funding in the current fiscal year. We control for lagged values of the log of sales, cumulative net profit, the log of company age, the log of cumulative VC funding, and cumulative rounds with missing VC funding. We also include prior VC rounds, industry, county, and calendar year fixed effects. In addition, models 2 and 4 control for cumulative VC funding during the measurement period of the dependent variable. Table 2.1 contains definitions for all variables. *t*-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Cumulative sales top decile				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
VC round	0.0137*	0.0094	0.0186*	0.0157
	(1.753)	(1.246)	(1.919)	(1.616)
USVC round	0.0511*	0.0337	0.0169	-0.0025
	(1.767)	(1.305)	(0.546)	(-0.093)
Cum net profit	0.0014***	0.0014***	0.0014***	0.0014***
	(6.268)	(6.272)	(5.417)	(5.424)
Prior funding	0.1031***	0.1003***	0.1013***	0.0988***
	(6.788)	(6.537)	(5.614)	(5.398)
Subsequent funding		0.0305***		0.0308***
		(4.316)		(4.003)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	13177	13177	10561	10561

Panel B: Cumulative sales bottom decile				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
VC round	-0.0283***	-0.0258***	-0.0266***	-0.0242***
	(-3.855)	(-3.577)	(-3.094)	(-2.884)
USVC round	-0.0282	-0.0176	-0.0306	-0.0158
	(-1.601)	(-1.016)	(-1.402)	(-0.699)
Cum net profit	-0.0002**	-0.0002**	-0.0002	-0.0002*
	(-2.300)	(-2.327)	(-1.609)	(-1.674)
Prior funding	0.0322***	0.0339***	0.0259***	0.0278***
	(4.020)	(4.205)	(2.734)	(2.942)
Subsequent funding		-0.0184***		-0.0237***
		(-4.579)		(-4.987)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	13177	13177	10561	10561

Panel C: Cumulative sales top quartile				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
VC round	0.0273**	0.0209*	0.0300**	0.0261**
	(2.480)	(1.920)	(2.360)	(2.019)
USVC round	-0.0115	-0.0394	-0.0107	-0.0420
	(-0.368)	(-1.339)	(-0.283)	(-1.142)
Cum net profit	0.0012***	0.0012***	0.0011***	0.0011***
	(5.748)	(5.728)	(4.406)	(4.412)
Prior funding	0.1187***	0.1143***	0.1197***	0.1157***
	(8.319)	(7.946)	(7.097)	(6.758)
Subsequent funding		0.0482***		0.0492***
		(6.548)		(5.859)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	13177	13177	10561	10561

Panel D: Cumulative sales bottom quartile				
	(1)	(2)	(3)	(4)
	t+3	t+3	t+5	t+5
VC round	-0.0411***	-0.0368***	-0.0359***	-0.0322***
	(-4.223)	(-3.876)	(-2.882)	(-2.676)
USVC round	-0.0362	-0.0165	-0.0419	-0.0144
	(-1.169)	(-0.524)	(-1.113)	(-0.359)
Cum net profit	-0.0000	-0.0000	-0.0000	-0.0000
	(-0.286)	(-0.322)	(-0.086)	(-0.179)
Prior funding	-0.0093	-0.0062	-0.0170	-0.0134
	(-0.999)	(-0.669)	(-1.456)	(-1.130)
Subsequent funding		-0.0338***		-0.0435***
		(-5.416)		(-6.182)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	13177	13177	10561	10561

Chapter 3

Attention, please! Outside expertise and entrepreneurial success

ABSTRACT

I examine whether and how outside expertise of directors matters for start-up companies. I exploit the fact that some directors sit on multiple boards simultaneously and study the effects of director attention on a focal company's performance and growth. Identification comes from leveraging distraction events at directors' other companies that plausibly shock their attention. I find that an increase in a company's fraction of directors who are distracted leads to a decline in return on assets (ROA) and sales growth, especially if distracted directors are more experienced. Effect sizes represent 8% and 11% of the sample median of ROA and sales growth, which is larger than what prior literature has documented for public companies.

"Sometimes you'd be surprised by what blind spots exist in early-stage businesses. Bringing in someone senior can head off some of those blind spots before they become a problem."

– Simon Guild, experience as director at 20+ start-ups

3.1 Introduction

An entrepreneur typically has an idea but not all the resources that are necessary to execute the idea successfully. Whilst it is well documented that entrepreneurs are financially constrained (Black and Strahan 2002; Schmalz, Sraer, and Thesmar 2017), we have a much more limited understanding of other constraints that entrepreneurs might face. Most entrepreneurs are first-time founders and might therefore, as the introductory quote suggests, benefit from advice by someone who is more seasoned.

A natural way for entrepreneurs to access senior leadership and guidance is by appointing directors who "have been there before". Even for public companies, however, suitable directors are a scarce resource with smaller companies facing higher search costs (Knyazeva, Knyazeva, and Masulis 2013). Presumably, these frictions are even larger for start-ups, which implies that forming a board with experienced members requires considerable effort from the entrepreneur.

Even so, directors are busy, many work full-time at other companies, and often receive little or no compensation for their start-up board duties. It is therefore not clear if directors at start-ups add significant value. In this paper, I examine whether outside expertise in the form of directors matters for start-up company performance and growth.

An ideal experiment would be to randomly allocate directors to some companies and not to others. This would remove endogenous director-company matching and enable us to estimate the value that directors add. However, it is difficult to find an empirical setting that

sufficiently resembles this thought experiment. A related, and arguably more feasible, experiment would be to focus on already appointed directors and to randomly shock the attention of some of those directors. If a director adds value by providing outside expertise, then the director's total contribution should be a function of the attention given to a company. This experiment would allow us to estimate the value-add of directors, conditional on endogenous board composition. In this paper, I design an empirical strategy that approximates this second thought experiment.

I exploit the fact that some directors sit on multiple boards simultaneously and measure distraction events at those directors' other companies that plausibly shock their attention. The intuition is that a "shocked" director diverts attention towards the "distracting" company, which leaves the director with less available attention for the focal company. Under the identifying assumption that distraction events are not correlated to the performance and growth of the other companies on whose boards a "shocked" director sits (and conditional on all control variables in the estimating equation), I can use these events to identify the effect of changes in director attention on company performance and growth.

Data availability is a challenge when trying to approximate this experiment empirically. It requires information about individual directors and financial performance of companies since founding. I therefore collect data on the population of Swedish companies between 1998 and 2019, and construct a company-fiscal year panel that follows start-up companies from registration over time. The main strength of the Swedish data comes from the fact that all business enterprises must be registered with the Swedish Companies Registration Office before starting to operate. To the best of my knowledge, such data is neither available in the US nor in the UK.

I find that an increase in a company's fraction of directors who are distracted leads to

a decline in return on assets (ROA) and sales growth. For every additional director who becomes distracted, ROA and sales growth decrease by 0.5 and 0.75 percentage points (pp), respectively. These effect sizes represent 8% and 11% of the sample median of ROA and sales growth, and are larger than what prior literature has documented for public companies. This finding rejects the statistical null hypothesis that director attention is uncorrelated with company performance and growth, and it is inconsistent with a theory according to which the board of directors at start-ups only has a signalling function.

As a next step, I explore whether the results differ by prior experience of directors. I use the number of other companies at which a director was a manager or board member in the past as a proxy for prior experience. I find that company performance and growth suffer to a greater extent when more experienced directors are distracted. I also examine whether there is a differential effect for prior entrepreneurial experience by only counting prior manager or director spells at start-ups. The idea is that this specific experience yields expertise that is arguably more relevant. Consistent with this argument, I find that company performance and growth suffer even more when directors with more prior entrepreneurial experience are distracted. These effects become even stronger when I only count prior spells at companies that operate in the same industry as the focal company, lending further support to the expertise interpretation.

A potential methodological concern with my empirical strategy is that I regress a company level outcome variable on a distraction variable that I initially calculate at the director level, before aggregating it at the company-fiscal year level. I therefore examine whether I can find any evidence that director attention shocks correlate with director level outcome variables. Specifically, I test for whether distracted directors are more likely to leave a company's board. All else equal, distracted directors are 0.3% and 0.4% more likely to depart from a

company's board in the next fiscal year and the fiscal year thereafter, respectively. These coefficient estimates correspond to a 4% and 6% increase from the unconditional probability of director departure of 6%.

A potential endogeneity concern with my empirical strategy is that director quality might drive the results. More specifically, I use declining company performance relative to industry peers as distraction event to measure shocks to director attention in the baseline specification. The intuition is that companies benchmark their performance against that of similar companies, and deteriorating relative performance will likely shift a director's attention. However, company performance might be correlated with director quality. To address this concern, I run regressions at the director-company-fiscal year level which allows me to include director fixed effects which absorb time-invariant director characteristics. All results hold with similar coefficient estimates when including director fixed effects. This implies that director quality is unlikely to fully explain my results.

An alternative story that could potentially explain the baseline results is directors having a "bad year". More formally, there might be unobserved shocks to directors that simulataneously drive changes in the distraction as well as company performance and growth variables. An example would be a director going through a divorce as a result of which the director gives less attention to all professional duties. To address this concern, I use CEO turnover as an alternative distraction event. It seems unlikely that CEO turnover is systematically correlated with directors experiencing a "bad year". An additional benefit is that CEO turnover, compared to relative company performance, is arguably less likely correlated with director quality. A disadvantage of using CEO turnover is that this event occurs less frequently and therefore offers less variation to identify off. The main results are qualitatively unchanged when using CEO turnover as distraction event.

I use mergers and acquisitions (M&As) as another alternative distraction event, which is also arguably less likely correlated with director quality than relative company performance. A feature of M&As is that the board of the target company is usually dissolved, which lends itself to an instrumental variable specification in which I instrument the change in the number of other board seats (a common proxy for director "busyness" in the literature) with M&As of other companies a director sits on. This approach is similar in spirit to the baseline empirical strategy in that it looks at the effect of shocks to director attention on company performance and growth. An added benefit is to test for whether my results are robust to different model choices that address the same identification problem. I find results that are qualitatively similar to the baseline results.

All of the results presented so far are conditional on board composition. To explore the director-company matching more explicitly, I utilize the granularity of the data in my sample by training a machine learning algorithm that predicts the appointment of non-executive directors who sit on multiple boards based on lagged company characteristics. The results suggest that companies which appoint directors who sit on multiple boards are larger, faster growing, less profitable, and have more experienced directors who sit on more other boards. The board characteristic variables have the largest statistical and economic signifiance, which points towards the potential importance of director networks for the appointment of directors who sit on multiple boards.

This paper contributes to a burgeoning literature on boards of directors of private companies. Extant work focuses on director appointments and board composition after a company has raised outside equity, typically by a venture capital (VC) fund. Using a sample of companies that have raised at least series A financing, Venugopal and Yerramilli (2020) finds that non-employee director appointments are related to social connections and complementary

skill sets between founders and directors. Companies that appoint non-employee directors are more likely to raise VC financing, have more patents, and are more likely to exit. Ewens and Malenko (2022) documents that control on boards of directors of VC-backed companies shifts from entrepreneurs to shared to VCs over time. The authors argue that independent directors play a tie-breaking role on boards with shared control. Baltrunaite and Karmaziene (2021) shows that an increase in the supply of non-local directors leads to appointments of higher (lower) quality directors at higher (lower) quality Italian private companies, consistent with positive assortative matching. I complement these papers by showing that the board of directors matters for company performance and growth already before a start-up's first outside equity investment and also for start-ups in general, not just for those that attract VC funding.

This paper also contributes to a literature on advice and entrepreneurial outcomes. Hellmann and Puri (2002) provides evidence that start-ups benefit from VC investment along several professionalization measures. These findings suggest that VC investors add value to start-ups in a capacity beyond one of a traditional financial intermediary. Bernstein, Giroud, and Townsend (2016) shows that the introduction of a direct flight between the headquarters of a VC firm and an existing portfolio company correlates with increases in patent-based innovation measures and the probability of a successful exit of the portfolio company. The authors conduct a survey of venture capitalists which confirms that a reduction in travel time leads to more valuable interaction between the VC and the portfolio company. Consistent with this, a separate survey by Gompers et al. (2020) documents that 87% of venture capitalists say that they add value to portfolio companies by providing strategic advice.[1] Gonzalez-Uribe and Leatherbee (2018) finds that, conditional on admission to an accelera-

[1]Da Rin, Hellmann, and Puri (2013) provides a comprehensive survey of the VC literature.

tor, access to entrepreneurial capital, which the authors define as "set of skills and resources needed to start and grow nascent businesses", positively correlates with future fundraising and employment growth.[2] Chatterji et al. (2019) shows that advice received by peers with a formal approach to managing people correlates with future employment-based company size and survival. I add to existing studies by highlighting a different channel through which start-ups can receive valuable advice, namely non-executive directors.

3.2 Data

3.2.1 Sample construction

Data availability is a challenge when studying the relationship between outside expertise in the form of directors and start-up performance and growth empirically. It requires information about individual directors and financial performance of companies since founding.

I use data from Sweden to overcome these challenges. The main strength of the Swedish data comes from the fact that all business enterprises must be registered with the Swedish Companies Registration Office before starting to operate.[3] I collect data on the population of Swedish limited liability companies between 1998 and 2019. I focus on limited liability companies for two reasons. First, it is the most common form of business enterprise in Sweden. Formation is relatively easy and it is the only company form that offers limited liability to all shareholders.[4] Second, Swedish law requires all limited liability companies to submit annual reports to the Companies Registration Office.[5] Non-compliance or submitting incorrect infor-

[2]Bone et al. (2019) provides a review of the literature on accelerators and incubators.

[3]Sole traders (self-employed) are an exception because they can opt to only register with the Swedish Tax Agency.

[4]Formation requires only one person and a minimum share capital of SEK 25,000 (≈USD 2,500).

[5]Årsredovisningslag [1995:1554] 8 sec. 3 and Bokföringslag [1999:1078] 6 sec. 2.

mation results in liquidation and unlimited liability for board members. Companies therefore have strong incentives to submit accurate information. To the best of my knowledge, such data is neither available in the US nor in the UK.[6]

I collate data from different sources to construct a company-fiscal year panel that follows start-up companies from birth over time. My principal data source is the Swedish Companies Registration Office which has information on annual reports, boards of directors, and company events (e.g., mergers or bankruptcies). I merge data on external equity financing events from Pitchbook, ThomsonOne, and Preqin.

To construct the sample, I start with the annual reports data from the Swedish Companies Registration Office and restrict it to limited liability companies. I only keep annual reports which follow an accounting type for which I know how income statement and balance sheet are constructed.[7] If a company provides both consolidated and unconsolidated financial statements for a given fiscal year, I use the consolidated version to capture the company's overall economic activity. These filters keep 96% of the observations, primarily because Swedish law requires only limited liability companies to submit annual reports. I only keep companies that are registered during the sample period because I am interested in studying the life cycle of start-up companies. This drops 44% of the remaining observations. I also restrict the sample to companies that have an employee in at least one fiscal year to focus the sample on potential employer companies. This drops 69% of the remaining observations.

I then augment the annual reports panel with several other datasets. First, I merge

[6]Whilst data on annual reports and boards of directors for all limited companies is publicly available in the UK from Companies House, micro-entities and small companies can submit abridged accounts which contain less information. This makes it difficult to measure the growth of start-up companies, particularly in the initial years after founding.

[7]I keep annual reports which follow either the nature of expense or cost of sales accounting type.

company name, location, and industry information by assigning each update submitted to the Companies Registration Office to the corresponding fiscal year in the annual reports panel during which the update occurred. For each company-fiscal year observation, I then keep the latest available information at fiscal year end. I assign municipalities to counties by using the most recent national classification system. I standardize industry classifications to the latest version of the Swedish standard (SNI 2007) because most company-fiscal years fall under that version.

Second, I add information on liquidations, mergers, bankruptcies, and re-organizations by assigning each event recorded by the Companies Registration Office to the corresponding fiscal year in the annual reports panel during which the event occurred. If a company has multiple events of the same type during a fiscal year, I keep the earliest available record. For each company, I assign events that occur after the latest fiscal year with annual reports data to the last fiscal year in the annual reports panel.

Third, I add information on executives and the board of directors at fiscal year end by tracking key personnel appointments and removals filed with the Companies Registration Office. I assign individuals to four mutually exclusive categories: executives, non-executive directors, employee representatives, and non-executive deputy directors. I classify an individual holding a top management position (CEO or vice CEO) as executive. An executive might also serve as a director on the board or be a deputy director. I classify a (deputy) director who is neither an executive nor an employee representative as non-executive (deputy) director. I only treat executive directors and non-executive directors as members of the board because these are appointed by the owners of the company.[8] Employee representatives are appointed by the labour union and deputy directors only attend board meetings when a

[8]Regulatory requirements (e.g., minimum number of directors) also use this definition of board membership.

regular director is unavailable. I differentiate between executive and non-executive directors because executive directors are employees of the company, and I would like to isolate the effect of outside expertise.

Fourth, I merge data on external equity financing events from Pitchbook, ThomsonOne, and Preqin by machting on company name and city. I use the Pitchbook data as base because it has the highest number of investment rounds, and fill in missing variables for existing financing events or add previously missing financing events with data from ThomsonOne and then Preqin (in order of decreasing coverage).

I annualise flow as well as growth stock variables to account for differences in fiscal period lengths. This is important in the context of my study because 93% of fiscal periods that are shorter or longer than 12 months are first fiscal years of companies. I winsorize all growth variables at the 1st and 99th percentiles to alleviate the potential impact of outliers.

I use shocks to the attention of incumbent non-executive directors who sit on multiple boards simultaneously for identification.[9] I therefore restrict the sample used in most of the analysis to observations for companies with at least one "shockable" director, that is an incumbent non-executive director who sits on the board of at least one other company. Given this sample inclusion restriction, one might worry about the importance of the analysis sample relative to the full sample of all start-up companies. Even though the analysis sample includes 28% of company-fiscal years and 34% of distinct companies of the full sample, it captures a meaningful fraction of economic activity of the full sample, representing 79% of assets, 75% of sales, and 66% of employment. Table 3.20 lists the filters applied to the raw data to construct the sample and shows how many unique companies and company-fiscal year observations are left after each step.

[9]Section 3.3 discusses the empirical strategy in more detail.

3.2.2 Descriptive statistics

Table 3.1 shows descriptive statistics for the sample used in most of the analysis (Panel A) and the full sample of start-up companies (Panel B). The unit of observation is a company-fiscal year. There are 65,198 and 189,499 distinct companies in the analysis and full sample, respectively. All measures of company size are right-skewed. In the analysis sample, the average company has assets of 64 million Swedish krona ($\approx$ 6.4 million US dollars), sales of 56 million Swedish krona, and 24 employees; whilst the median company has assets of 3 million Swedish krona, sales of 6 million Swedish krona, and 4 employees. The respective figures in the full sample are 2-3x lower. Companies in the analysis sample are slightly older than the ones in the full sample (mean age of 6.9 vs 5.5 years). The analysis sample inclusion filter mentioned in the preceding paragraph explains part of this gap. By restricting the analysis sample to observations for companies with at least one "shockable" director, I drop all first fiscal year observations because a company cannot have an incumbent director during its first fiscal year. The distributions of the board variables have smaller tails than the company size variables. In the analysis sample, the average (median) board consists of two (two) members with 55% (60%) of incumbent non-executive directors being distracted. Figures in the full sample are again lower, with an average board size of 1.5 and 15% of distracted incumbent non-executive directors.

Insert Table 3.1 about here.

All companies in my sample have a board of directors because Swedish limited liability companies must set up a board with at least one director at registration. Swedish corporate governance has a unitary structure with a single board of directors. If there are two or more directors, the shareholders must appoint a chairman. CEO duality is allowed - that is, a

single person can be both chairman and CEO.[10]

3.3 Empirical strategy

An ideal experiment to test whether outside expertise in the form of directors matters for start-up company performance and growth would be to randomly assign directors to some companies but not to others. This would ensure that the estimation of the value-add of directors is free from the otherwise endogenous matching of directors and companies. Unfortunately, it is quite difficult to find an empirical setting that sufficiently approximates this thought experiment.

A related experiment would be to concentrate on directors who have already been appointed, and to randomly shock the attention of some of those directors. If a director adds value by providing outside expertise, then the director's total contribution should be a function of the attention given to a company. This approach would allow for the estimation of the value-add of directors, taking board composition as given. I use the data available to me, particularly annual reports and information on boards of directors, to design an empirical strategy that gets me as close to this second thought experiment as possible.

I exploit the fact that some directors sit on multiple boards simultaneously and measure company-level events that plausibly shock those directors' attention. The intuition of this approach is that a "shocked" director diverts attention towards the company experiencing

[10] At registration, the founders choose between a private and public limited liability company type which differ in the required minimum share capital and the ability to distribute shares. Only 0.7% of companies in the analysis sample are public. Shareholders can change the company type at the annual general meeting any time after registration. Public companies have a minimum share capital of 500,000 Swedish krona, whereas private companies require 25,000 Swedish krona. Private companies must neither advertise their shares to the open market nor have more than 200 shareholders. Public companies do not have such restrictions. Furthermore, only public limited liability companies can apply for their shares to be listed on an exchange. Boards of public companies must consist of at least three directors, one of which must be appointed chairman. CEO duality is not allowed for public companies.

the distraction event, which results in less available attention for the other companies on whose boards the director sits.[11] Under the identifying assumption that distraction events are not correlated to the performance and growth of the other companies on whose boards a "shocked" director sits (and conditional on all control variables in the estimating equation), I can use these events to identify the effect of changes in director attention on company performance and growth.

I focus on shocks to non-executive directors because I would like to isolate the effect of outside expertise. Executive directors are employees of the company and including shocks to executive directors would thus introduce noise in the measurement of outside expertise. In addition, I only include shocks to incumbent directors (i.e., non-executive directors who have been with a company for at least one fiscal year) to ensure that personnel changes do not affect variable measurement. This means that directors joining or leaving a company's board or director replacements are not part of the identifying variation.

I use declining company performance relative to industry peers as distraction event in the baseline specification.[12] The intuition is that companies benchmark their performance against that of similar companies, and deteriorating relative performance will likely shift a director's attention. Following Masulis and Zhang (2019), I calculate relative company performance as the difference between a company's ROA and median industry ROA, and

[11] An implicit assumption of this approach is that directors have limited attention and cannot simply increase their attention to a particular company in response to a distraction event without decreasing their attention to other companies on whose boards they sit. In a global survey of 1,074 directors, McKinsey (2016) finds that, on average, directors would like to spend 15% more time on work related to their directorships than they currently do. This evidence is consistent with the notion that directors are attention-constrained with respect to their board duties.

[12] A potential concern is that company performance may be related to director quality. I therefore repeat the analysis at the director-company-fiscal year level in which I include director fixed effects that account for time-invariant director quality (Tables 3.6 and 3.7). I also construct alternative distraction variables using CEO turnover events, which are arguably less likely related to director quality (Table 3.8). In addition, I run an instrumental variable specification (Section 3.5.4). All of these alternative approaches yield similar results to the baseline specification.

define a company-fiscal year as distraction if relative company performance is lower than in the previous period.[13] I consider the entire fiscal year to be a distraction. For each director who sits on multiple boards simultaneously, I then calculate the total number of distracted days at company i in fiscal year t by adding all days of distraction fiscal years at other companies that overlap with fiscal year t at company i. I define director x at company i in fiscal year t as distracted if the total number of distracted days is at least as long as half the length of fiscal year t. Whilst I am interested in studying whether outside expertise in the form of directors matters for start-up company performance and growth, directors can serve on the board of any company, not just start-ups. I therefore consider board memberships at any Swedish limited liability company when constructing the distraction variables for directors at start-ups.

I estimate the following equation

$$Y_{i,t} = \alpha + \beta Distracted_{i,t} + \gamma Z_{i,t-1} + \tau NewNED_{i,t} + \delta_i + \delta_a + \delta_{j,y} + \epsilon_{i,t} \tag{3.1}$$

in which i is a company and t is a fiscal year. The dependent variable is $Y_{i,t}$ which measures company performance or growth. $Z_{i,t-1}$ is a vector of company control variables, $NewNED_{i,t}$ is an indicator variable for new non-executive directors, δ_i are company fixed effects, δ_a are company age fixed effects, and $\delta_{j,y}$ are industry-calendar year fixed effects. The vector of company control variables includes lagged values of board size, the fraction of non-executive directors who sit on at least one other board, leverage ratio, total assets quintile, sales quintile, and employment quintile. I use company size quintiles to account for non-linearities

[13] Examples of other papers that study directors at public companies and use distraction events for identification are Renjie and Verwijmeren (2020) and Stein and Zhao (2019). Relatedly, Kempf, Manconi, and Spalt (2017) and Liu et al. (2020) use distraction events to examine the effects of shocks to investor attention at public companies.

in the relationship between company size and growth that linear control variables cannot capture.[14] More specifically, I compute sales growth as the percentage change in sales at time t relative to $t-1$. This measure is sensitive to small values in the denominator. Consistent with this, the standard deviation of sales growth is 1.5x times higher in the smallest sales quintile compared to the largest sales quintile. I also include an indicator variable for when a company appoints new non-executive directors in fiscal year t to control for director appointments that might be mechanically correlated with increases in company growth. An example of this is an external equity fundraising round in which the investor obtains a board seat.

The coefficient of interest is β in Equation 3.1. $Distracted_{i,t}$ is the fraction of a company's non-executive directors that are distracted. The inclusion of company, company age, and industry-calendar year fixed effects implies that the identification comes from variation within companies, company age (year integers), and industry-calendar years. Put differently, β measures the correlation between a company's fraction of distracted non-executive directors and growth, controlling for time-invariant company characteristics and comparing companies of the same age that operate in the same industry-calendar year pair (in addition to the vector of company control variables). 3.11 contains definitions for all variables that I use in the analysis.

3.4 Results

Table 3.2 presents results for ordinary least squares (OLS) estimation of Equation 3.1 using ROA and sales growth as dependent variable in columns 1 and 2, respectively. The unit of analysis is a company-fiscal year. I cluster standard errors by company.

The coefficient on the fraction of distracted incumbent non-executive directors, β, is

[14] Table 3.14 shows that the baseline results go through when using continuous company size controls.

negative and statistically significant at the 1% level in both models. The estimates are also economically significant—if a company's fraction of distracted incumbent non-executive directors increases from 0 to 100%, ROA and sales growth decrease by 1 and 1.5pp on average, respectively. On average, a company has two incumbent non-executive directors, which means that for every additional incumbent non-executive director who becomes distracted, ROA and sales growth decrease by 0.5pp and 0.75pp, respectively. A 0.5pp decrease in ROA represents 11% of the variable's sample mean and 8% of its median. For sales growth, a change of 0.75pp amounts to 3% of the mean and 11% of the median. This result rejects the statistical null hypothesis that director attention is uncorrelated with company performance and growth, and it is difficult to reconcile with a story in which the board of directors at start-ups only has a signalling function. This suggests that how much value a director adds to a company depends, at least in part, on the level of the director's attention.

Insert Table 3.2 about here.

The economic significance of my baseline results is higher than what prior literature has documented for public companies.[15] In contrast to public companies, start-ups are often run by founders who combine majority ownership of the equity and management of the company. In addition, private companies face fewer regulatory restrictions relating to board composition. The combination of less severe agency conflicts and more regulatory flexibility may point towards a relatively more important advising role of boards for private than for public companies. The fact that the effect size in my sample of start-ups is higher than what prior work has found for public companies is consistent with this argument.

[15]In a sample of US public companies, Masulis and Zhang (2019) shows that for every additional independent director who becomes distracted, ROA decreases by 0.3pp, which is equal to 2% of the sample mean and median.

I next examine whether the results differ by prior experience of directors. I therefore decompose the baseline variable of interest into two parts, one for directors with less and one for directors with more prior experience:

$$Distracted_{i,t} = Distracted_{i,t}^{LOW} + Distracted_{i,t}^{HIGH} \tag{3.2}$$

I do the decomposition in the following way. For every company-fiscal year, I classify each director into either below or above median prior experience. I use the number of other companies at which a director was either a manager or a board member in the past as proxy for experience. I compute a separate cut-off value (i.e., median prior experience) for each calendar year to account for the fact that average prior spells increase mechanically over the sample period. For every company-fiscal year, I then calculate the percentages of distracted incumbent non-executive directors with below and above median prior experience, that is $Distracted_{i,t}^{LOW}$ and $Distracted_{i,t}^{HIGH}$.

I implement the decomposition twice, using a different type of prior experience in each instance. First, prior total experience counts all companies at which an individual was a manager or director in the past. Second, prior entrepreneurial experience counts only those companies at which an individual was a manager or director already during the first fiscal year. The intuition for the latter is that people in senior leadership positions at company registration are likely founding members.

Table 3.3 shows the results from the estimation using the prior experience decomposition. All coefficients have negative signs and are statistically significant at the 1% level, except for $Distracted_{i,t}^{LOW}$ using prior total experience in the regression of sales growth which is significant at the 5% level. Coefficient estimates for the fraction of distracted directors with above median prior experience (both total and entrepreneurial) are higher than those for di-

rectors with below median prior experience, with all differences being statistically significant at the 1% level, except for the difference between the prior total spells coefficients which is marginally statistically significant. In addition, all prior entrepreneurial experience coefficients (columns 3 and 4) are higher than their respective prior total experience counterparts (columns 1 and 2).

Taken together, these findings show two things. First, company performance and growth suffer to a greater extent when more experienced directors are distracted. Second, they suffer even more when directors with specific, arguably more relevant, expertise (here prior manager or director spells at start-ups) are distracted.

Insert Table 3.3 about here.

To investigate the specific experience results in more detail, I repeat the decomposition in Equation 3.2 counting only prior spells at companies that operate in the same industry as the focal company. The rationale is that prior experience in the same industry might be more valuable. Table 3.4 presents the results. All coefficients have negative signs and are statistically significant at the 1% level, except for $Distracted_{i,t}^{LOW}$ using prior total same-industry experience in the regression of sales growth which is significant at the 10% level. Coefficient estimates show a similar pattern as in Table 3.3. All above median prior experience coefficients are higher than their below median prior experience counterparts. The differences between $Distracted_{i,t}^{LOW}$ and $Distracted_{i,t}^{HIGH}$ are statistically significant for the prior same-industry entrepreneurial experience decomposition, and marginally insignificant when using prior total same-industry experience. Interestingly, the estimates for $Distracted_{i,t}^{HIGH}$ using prior entrepreneurial same-industry experience are even higher than the ones using prior entrepreneurial experience reported in Table 3.3. This evidence lends additional support

to the notion that company performance and growth suffer more when more experienced directors with specific, arguably more relevant, expertise are distracted.

Insert Table 3.4 about here.

3.5 Extensions and robustness

3.5.1 Director level outcomes

A potential methodological concern with my empirical strategy is that the unit of analysis in the baseline specification is at the company-fiscal year level, even though the distraction variable essentially varies at the director-company-fiscal year level. To address this, I change the unit of analysis to the director-company-fiscal year level, which allows me to test whether attention shocks correlate with outcome variables at the director level. Specifically, I examine whether distracted directors are more likely to depart a company's board by regressing a dummy variable that equals one if a director leaves a company's board during the next fiscal year or the fiscal year thereafter on a distracted dummy. I include the same control variables as in Table 3.2, except for company fixed effects because I am interested in within-director variation.[16] The unit of analysis is a director-company-fiscal year. I double-cluster standard errors by director and company. Table 3.5 shows the results. I find that distracted directors are 0.3% and 0.4% more likely to depart a company's board in $t+1$ and $t+2$, respectively. These coefficient estimates represent a 4% and 6% increase relative to the unconditional probability of a director leaving a company's board of 6%.

Insert Table 3.5 about here.

[16]Results are similar, albeit weaker, when using company fixed effects instead.

3.5.2 Within-director variation

A potential endogeneity concern with my empirical strategy is that director quality is an omitted variable that causes changes in both a company's fraction of distracted directors and company performance and growth. In the baseline specification, I use declining industry-adjusted company performance as distraction event. It is conceivable that directors of lower (higher) quality cause companies to perform worse (better). This would imply that director quality affects both the likelihood that I define a director as distracted (through declining relative performance at other companies on whose boards the director sits) and changes in performance and growth at the focal company.

I therefore change the unit of observation to a director-company-fiscal year so that I can run regressions with director fixed effects, which control for time-invariant director characteristics. Tables 3.6 and 3.7 show that these regressions yield similar results to the baseline specification, which implies that unobserved director quality is unlikely to fully explain the findings.

Insert Table 3.6 about here.

Insert Table 3.7 about here.

A related concern might be that the distraction variable rarely changes for any given director over time. More loosely speaking, some directors might always be distracted while others are never distracted. The identifying variation in the regressions with director fixed effects comes from within-director changes in distraction. The fact that these results are similar to the ones for the baseline specification implies that there is meaningful variation in the distraction variable at the director level.

3.5.3 Alternative distraction events

Another potential endogeneity concern is that unobserved shocks to individual directors cause changes in both director distraction and company performance and growth. More loosely speaking, directors experiencing a "bad year" could drive the main results. For example, a director might go through a divorce and therefore reduce the attention given to all professional duties.

To address this concern, I use an alternative distraction event, CEO turnover, for which a systematic correlation with directors having a "bad year" seems improbable. Another advantage of using CEO turnover as a distraction event is that CEO turnover seems less likely correlated with director quality than relative company performance. However, CEO turnover is a relatively rare event and thus generates less variation to idetify off.

The intuition of this approach is the same as for the baseline version that uses declining relative company performance: a "shocked" director diverts attention towards the company experiencing the distraction event, which results in less available attention for the other companies on whose boards the director sits. The difference is that I now use CEO turnover as distraction event.[17] Table 3.8 presents results for the baseline estimation (Panel A) and the experience decomposition (Panel B). Coefficient estimates and significance levels in the models with ROA as dependent variable are similar to those that use declining relative company performance as distraction event. For the sales growth models, only the coefficient for the fraction of distracted incumbent non-executive directors with above median prior entrepreneurial experience is statistically significant, and is of similar size to the corresponding coefficient in Table 3.3.

Insert Table 3.8 about here.

[17] Section 3.3 explains how I construct the distraction variable in more detail.

3.5.4 Instrumental variable specification

This section uses an alternative distraction event, mergers and acquisitions (M&As), and employs a different empirical strategy for identification. This has two benefits. First, M&As appear less likely to be correlated with director quality than industry-adjusted company performance, but also occur less frequently. Second, it allows me to test whether the main results are robust to using an alternative model choice. I exploit the fact that the board of the target company in M&As is typically dissolved by using an instrumental variable specification (IV) in which I instrument the change in the number of other board seats (a common proxy for director "busyness" in the literature) with M&As of other companies a director sits on. The IV and baseline empirical strategies both use shocks to director attention for identification but employ different models to test for the effects on company performance and growth.

Using the raw measure of a director's other board seats for causal inference is problematic because it is likely positively correlated with director quality. Higher quality directors are probably more sought after by companies and therefore sit on more boards simultaneously. Importantly, I argue here that the number of other boards a director sits on, and not the distraction events that I use earlier in the paper, is endogenous.

The intuition for using M&As as shocks to director attention is as follows. After an acquisition, the board of directors of the target company is usually dissolved and its directors can then, all else equal, devote more time to other companies on whose boards they sit. The identifying assumption is that acquisitions and the growth of the shocked director's other companies are uncorrelated. Hauser (2018) uses this identification strategy to study boards of directors of public companies in the US.[18]

[18]Using the same identification strategy, Brown, Dai, and Zur (2019) extend the findings in Hauser (2018)

I use a first-differenced specification because M&As should correlate with the change in, rather than the level of, the number of other board seats of a director.

I estimate the following system of first-differenced 2SLS equations

$$\Delta Boards_{i,t} = \alpha + \beta_1 M\&As_{i,t} + \gamma \Delta Z_{i,t-1} + \tau_1 NoNED_{i,t-1} + \tau_2 NewNED_{i,t} + \tau_3 NewNED_{i,t+1} + \delta_a + \delta_c + \delta_{j,y} + \epsilon_{i,t} \quad (3.3)$$

$$\Delta Y_{i,t+1} = \alpha + \beta_2 \Delta \widehat{Boards}_{i,t} + \gamma \Delta Z_{i,t-1} + \tau_1 NoNED_{i,t-1} + \tau_2 NewNED_{i,t} + \tau_3 NewNED_{i,t+1} + \delta_a + \delta_c + \delta_{j,y} + \epsilon_{i,t} \quad (3.4)$$

in which Equation 3.3 is the first stage and Equation 3.4 is the second stage. In both equations, i is a company and t is a fiscal year. The dependent variable in the second stage is $\Delta Y_{i,t+1}$ which measures the cumulative change in company performance or growth in the next fiscal year relative to the pre-shock level. $\gamma \Delta Z_{i,t-1}$ is a vector of lagged first-differenced company control variables, δ_a are company age fixed effects, δ_c are county fixed effects, and $\delta_{j,t}$ are industry-calendar year fixed effects. The vector of company control variables includes lagged first-differenced values of board size, the fraction of non-executive directors who sit on at least one other board, leverage ratio, log of total assets, log of sales, and log of employment. I also include the following indicator variables. A first one ($NoNED_{i,t-1}$) for when a company has no non-executive directors in the previous period. A second ($\tau_2 NewNED_{i,t}$) and third one ($NewNED_{i,t+1}$) for when a company appoints new non-executive directors in fiscal year t or $t+1$, respectively. The specification in first differences controls for time-invariant

by showing that the effects are stronger for companies that lose fewer board connections as a result of a director's M&A shock.

company characteristics and is analogous to a specification in levels with company fixed effects.

The coefficient of interest is β_2 in Equation 3.4. $\Delta Boards_{i,t}$ is the change in the number of other board seats of a company's directors which I instrument for using $M\&As_{i,t}$ which is the sum of M&As of other companies on whose boards a company's directors sit. 3.11 contains definitions for all variables that I use in the analysis.

A first-differenced specification also avoids the potential impact of changes in the composition of a company's directors on the measurement of $\Delta Boards_{i,t}$. By defining this variable as first difference at the company-director-fiscal year level and then aggregating it to the company-fiscal year level, I exclude fiscal years in which a director joins or leaves the board of a company. $\Delta Boards_{i,t}$ thus measures the change in the number of other board seats of a company's incumbent directors and effectively controls for time-invariant director characteristics. Situations in which a company, for example, replaces a director who sits on no other boards with a director who sits on relatively many other boards do not affect $\Delta Boards_{i,t}$. In this hypothetical example, $\Delta Boards_{i,t}$ would only start measuring the change in the number of other board seats of the newly appointed director in the second fiscal year of her spell at this company.

A potential concern with this identification strategy is that shocked directors immediately replace their "lost" board seat. Figure 3.1 shows cumulative changes in the number of other board seats of shocked directors around the acquisition of one of the companies on whose boards they sit. The median change is 0 in the fiscal year prior to the acquisition, -1 in the fiscal year of the acquisition, and 0 in the two fiscal years following the acquisition. This suggests that most directors do not immediately replace a board seat lost due to an acquisition, and provides graphical evidence for the relevance of the instrument.

Table 3.9 shows the results of the two-stage least squares (2SLS) estimation of Equations 3.3 and 3.4 in which I instrument the changes in other board seats of a company's directors with the sum of M&As of other companies on whose boards these directors sit. The unit of analysis is a company-fiscal year. I cluster standard errors by company. The F-statistic of the instrument in the first stages is well above the commonly used threshold of 10 (columns 1 and 3). In the second stages, I find that positive shocks to director attention lead to increases in ROA (column 2). I find no significant results for changes in sales (column 4). It is comforting that an alternative empirical specification yields similar results.

Insert Table 3.9 about here.

Table 3.10 shows the output for two separate sets of OLS regressions using the endogenous variable (columns 1 and 2) and the instrument as regressors (columns 3 and 4), respectively. The results confirm that it is problematic to use the non-instrumented change in the number of other board seats of a company's directors as regressor for causal inference.

Insert Table 3.10 about here.

3.5.5 Additional tests

I also do the following additional robustness tests. First, I construct the main variable of interest, $Distracted_{i,t}$, using only distraction events at companies that operate in a different industry than the focal company. I do this to control for potential heterogeneous exposures to industry-specific shocks across companies. The industry-calendar year fixed effects in the baseline specification control for average shocks, but companies can have different exposures to these shocks depending on how many of their directors also have board seats at other

companies in the same industry. Results are similar to the ones for the baseline specification when restricting distracting events to those at companies in other industries (Table 3.11).

Insert Table 3.11 about here.

Second, I use sales, instead of ROA, to calculate industry-adjusted company performance. As before, I then define declining relative company performance as a distraction event. Table 3.12 reports the results. I find similar coefficient estimates as in the baseline specification, which implies that results are robust to using an alternative company performance measure when defining distraction events.

Insert Table 3.12 about here.

Third, I use board size, instead of the total number of non-executive directors, in the denominator when computing the main variable of interest, $Distracted_{i,t}$. This controls for the presence of non-NEDs on the board more explicitly. Table 3.13 shows that results are similar to the baseline specification.

Insert Table 3.13 about here.

I also show that results hold when using continuous company size control variables (Table 3.14), when using the full sample (Table 3.15), and when restricting observations to the first ten fiscal years for each company (Table 3.16).

Insert Table 3.14 about here.

Insert Table 3.15 about here.

Insert Table 3.16 about here.

3.5.6 Director appointments

All of the results presented so far are conditional on board composition. A natural question to ask is: which company characteristics correlate with director appointments? To answer this question, I utilize the richness of the administrative data in my sample by using machine learning to predict the appointment of directors who sit on multiple boards based on a very large number of lagged company characteristics. The results from this prediction exercise speak to the external validity of the main finding in this paper. More specifically, I identify off the subset of directors who sit on multiple boards and the machine learning results can help to gauge in how far the main findings are generalizable to the population of start-up companies.

I use a random forest classifier algorithm to predict the appointment of directors who sit on multiple boards based on lagged company characteristics. The advantage of using a random forest estimator is that it allows for the creation of a feature importance plot which visualizes the set of variables that correlate most strongly with the target, here the appointment of a director who sits on multiple boards.

The goal of a random forest model is to achieve as high a prediction accuracy as possible whilst minimizing overfitting. A key ingredient for this is to split the sample into two parts, one to train the algorithm on (training set) and another one to test the model's prediction accuracy out-of-sample (test set).[19] Splitting the sample thus penalizes the random forest model for overfitting in the training set with a lower prediction accuracy in the test set.

Another important input for improving prediction accuracy is that the individual decision

[19]I use a test size of 25%, meaning that I use 75% of my sample to train the algorithm and 25% to test its prediction accuracy. This step requires human input which is why the random forest model belongs to the category of supervised machine learning techniques. An example of the other category, unsupervised machine learning, is clustering. A recent application of supervised machine learning in a finance context is Zheng (2021), who studies the US patent examination process.

trees that make up the random forest model are as uncorrelated to each other as possible. A random forest model is a combination of many individual decision trees and the model's prediction is the consensus from all individual trees. In my case, the random forest model predicts whether a particular appointment is of a director who also sits on other boards or not. The prediction that the model returns is the one which receives the most votes from individual decision trees.

Bagging and feature randomness are the two key characteristics of a random forest model to reduce the correlations between individual decision trees. Each decision tree draws a random sample with replacement of the training set (bagging). This ensures that all decision trees train on samples that have the same length as the training set but have different observations. As a result of this, the samples of individual decision trees will differ with respect to the values of variables that they include (feature randomness). Taken together, this reduces correlations between the predictions of individual decision trees. A random forest model, however, relies on some features in the data to have some predictive power, otherwise the principle garbage in-garbage out applies.

To implement the random forest classifier algorithm, I create a sample at the non-executive director appointment level. The target (machine learning term for dependent variable) is a dummy variable that equals one if the appointed director sits on the board of at least one other company. I use lagged values of company characteristics as features (machine learning term for regressors). These features fall broadly into three categories: financial statements, boards of directors, and other. Annual reports submitted to the Swedish Companies Registration Office include an income statement and a balance sheet but no cash flow statement. I therefore use income statement and balance sheet items to construct cash flow statements which show how a company spends or generates cash. 3.12 outlines how I con-

struct cash flow statements. This allows me to include variables from all financial statements, including the cash flow statement, as features in the random forest model.

I use two sets of features, one including and one excluding growth and cash flow variables. Including these variables involves trading off using more potentially important features and losing observations (all appointments during second fiscal years). The reason why adding growth and cash flow variables leads to losing appointments during second fiscal years is that the construction of these variables requires information from fiscal year t and $t-1$. Since I use lagged values of features, I need data from at least three fiscal years to be able to include growth and cash flow variables. I therefore run all the prediction exercises twice, once with and once without growth and cash flow variables as features.

Figures 3.2 and 3.3 show the feature importance plots from the random forest classifier algorithms that predict the appointment of directors who sit on multiple boards based on lagged company characteristics including and excluding growth and cash flow variables, respectively.[20] These graphs show which features correlate most strongly with the target. The most important features relate to company size, growth, profitability, and board of directors characteristics. The results with and without growth and cash flow variables as features are similar.

Insert Figure 3.2 about here.

Insert Figure 3.3 about here.

I next decompose the target to generate two additional targets, one dummy variable that equals one if the appointed director sits on one other board prior to the focal appointment

[20]The out-of-sample prediction accuracy of the two models is 74% and 75%, respectively. Both of these prediction accuracies are higher than the respective sample mean of the target in the test sets (70% and 67%), which implies that the algorithms add predictive power over and above using sample means.

and another dummy variable that equals one if the appointed director sits on at least two other boards prior to the focal appointment. This essentially splits the baseline target into two mutually exclusive targets, one for directors who sit on multiple boards only after the focal appointment and one for directors who already sit on multiple boards prior to the focal appointment. I again run each random forest model twice, once including and once excluding growth and cash flow variables. Figures 3.4 and 3.5 show the feature importance plots for the models predicting appointments of directors who sit on at least two other boards prior to the focal appointment, and Figures 3.6 and 3.7 show the feature importance plots for the models predicting appointments of directors who sit on one other boards prior to the focal appointment. The most important features relate to similar company characteristics as in the baseline random forest classifier models.

Insert Figure 3.4 about here.

Insert Figure 3.5 about here.

Insert Figure 3.6 about here.

Insert Figure 3.7 about here.

Whilst feature importance plots show which features correlate most strongly with the target, they do not show the directionality of the correlation between each feature and the target. I therefore look at means of features and t-tests for differences in means between groups of different types of appointments. Table 3.17 shows means of the ten most important features in Figure 3.2 for all non-executive director appointments as well as for appointments of directors who sit on at least one other board and no other board. For the latter two groups, I also report the differences in means and their t-statistic. The results suggest that companies

which appoint directors who sit on multiple boards are larger, faster growing, less profitable, and have more experienced directors who sit on more other boards.

Insert Table 3.17 about here.

Table 3.18 shows the same statistics for the subset of appointments of directors who sit on at least one other board as well as for appointments of directors who already sit on at least two other boards and only one other board before the focal appointment. I again report the differences in means and their t-statistic for the latter two groups. These results suggest that companies which appoint directors who sit on at least two other boards before the focal appointment are even larger, faster growing, less profitable, and have even more experienced directors who sit on more other boards.

Insert Table 3.18 about here.

As a next step, I run OLS regressions of a director appointment dummy on the ten most important features in Figure 3.2 to produce conditional correlations. These complement the unconditional means presented in Tables 3.17 and 3.18 by allowing for an easier interpretation of relative statistical and economic importance of individual company characteristics. I use standardized versions of the regressors to make it easier to read off each variable's relative economic importance. I also include industry, county, and calendar year fixed effects. Standard errors are heteroscedasticity robust and clustered by company. I run two separate regressions, the dependent variable in model 1 (2) is a dummy for the appointment of a non-executive director who sits on at least one (two) other board(s) after the focal appointment. In model 2, I restrict appointments to those of directors who sit on multiple boards. The unit of analysis is a non-executive director appointment. All else equal, the board characteristic variables have the highest statistical (t-statistics) and economic (coefficient estimates)

signifiance. The results point towards the potential importance of director networks for the appointment of directors who sit on multiple boards.

Insert Table 3.19 about here.

3.6 Conclusion

This paper examines whether outside expertise of directors matters for start-up company performance and growth. I use shocks to the attention of directors who sit on multiple boards simultaneously for identification. I find that a company's fraction of directors who are distracted leads to declines in ROA and sales growth, and that companies suffer to a greater extent when more experienced directors are distracted. Effect sizes amount to 8% and 11% of the sample median of ROA and sales growth, which is larger than what prior literature has documented for public companies. I complement existing studies by highlighting directors as a different channel through which start-ups in general, not just those that attract VC investment, can access valuable advice that matters for company performance and growth.

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3.8 Tables

Table 3.1
Descriptive statistics

This table presents descriptive statistics at the company-fiscal year level. Panels A and B show these for the sample used in the analysis and the full sample of start-up companies, respectively. I report assets and sales in millions of Swedish krona, and company age in years. >1 board (%) and Distracted (%) is the fraction of a company's incumbent non-executive directors that sits on at least one other board and that is distracted, respectively.

Panel A: Sample used in analysis

Variable	Obs	Mean	SD	25^{th}	Median	75^{th}
Assets (mil *kr*)	330,994	63.60	1,373.82	1.24	3.29	9.32
Sales (mil *kr*)	330,994	55.85	1,271.19	1.95	5.96	17.09
Employees	330,994	23.58	366.61	2.00	4.00	10.00
ROA (%)	330,800	4.56	32.26	−4.94	5.89	20.84
Sales gwth (%)	326,328	25.13	82.30	−7.17	6.96	29.49
Company age	330,994	6.91	4.18	3.00	6.00	10.00
Board size	330,994	2.12	1.41	1.00	2.00	3.00
Multi board (%)	330,994	91.08	19.82	100.00	100.00	100.00
Distracted (%)	330,994	55.31	44.91	0.00	60.00	100.00

Panel B: Full sample of start-up companies

Variable	Obs	Mean	SD	25^{th}	Median	75^{th}
Assets (mil *kr*)	1,198,258	22.31	778.53	0.57	1.32	3.50
Sales (mil *kr*)	1,198,258	20.51	691.88	1.07	2.42	6.59
Employees	1,198,258	9.83	198.91	1.00	2.00	5.00
ROA (%)	1,197,624	7.14	34.48	−467	7.78	25.17
Sales gwth (%)	997,805	21.60	76.27	−852	6.01	28.13
Company age	1,198,258	5.51	4.13	2.00	4.00	8.00
Board size	1,198,258	1.52	1.03	1.00	1.00	2.00
Multi board (%)	1,198,258	25.16	42.04	0.00	0.00	50.00
Distracted (%)	1,198,258	15.33	34.24	0.00	0.00	0.00

Table 3.2
Distraction shocks and company outcomes

This table presents results for regressions of company performance and growth on the fraction of distracted incumbent non-executive directors. The dependent variable is ROA and sales growth in models 1 and 2, respectively. The unit of analysis is a company-fiscal year. I control for lagged values of board size, the fraction of non-executive directors who also sit on other boards, leverage ratio, total assets quintile, sales quintile, and employment quintile. I also include an indicator variable for new non-executive directors as well as company, company age, and industry-calendar year fixed effects. 3.11 contains definitions for all variables. *t*-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) ROA	(2) Sales growth
Distracted (%)	-1.016^{***}	-1.504^{***}
	(−8.26)	(−4.51)
L.Board size	-0.579^{***}	0.523^{*}
	(−4.55)	(1.70)
L.Leverage ratio	0.166^{***}	0.179^{***}
	(32.25)	(12.90)
Controls	Yes	Yes
Company FEs	Yes	Yes
Company age FEs	Yes	Yes
Industry-calendar year FEs	Yes	Yes
Observations	316,620	312,364
Adj. R^2	0.441	0.331

Table 3.3
Distraction shocks by prior experience

This table presents results for regressions of company performance and growth on the fraction of distracted incumbent non-executive directors with below and above median prior total and entrepreneurial spells. The dependent variable is ROA in models 1 and 3 and sales growth in models 2 and 4. The unit of analysis is a company-fiscal year. I control for lagged values of board size, the fraction of non-executive directors who also sit on other boards, leverage ratio, total assets quintile, sales quintile, and employment quintile. I also include an indicator variable for new non-executive directors as well as company, company age, and industry-calendar year fixed effects. 3.11 contains definitions for all variables. *t*-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Prior total spells		Prior entrepreneurial spells	
	(1)	(2)	(3)	(4)
	ROA	Sales growth	ROA	Sales growth
Distracted (low tot)	−0.554***	−0.966**		
	(−3.30)	(−2.26)		
Distracted (high tot)	−1.384***	−1.935***		
	(−8.45)	(−4.25)		
Distracted (low entr)			−0.636***	−1.387***
			(−3.70)	(−3.16)
Distracted (high entr)			−1.467***	−3.116***
			(−8.93)	(−6.99)
L.Board size	−0.583***	0.519*	−0.583***	0.508*
	(−4.58)	(1.69)	(−4.58)	(1.66)
L.Leverage ratio	0.166***	0.179***	0.167***	0.180***
	(32.26)	(12.90)	(32.33)	(12.93)
Controls	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes
Observations	316,620	312,364	316,620	312,364
Adj. R^2	0.441	0.332	0.441	0.332
High=low *p*-value	0.000	0.099	0.000	0.003

Table 3.4
Distraction shocks by prior same-industry experience

This table presents results for regressions of company performance and growth on the fraction of distracted incumbent non-executive directors with below and above median prior total and entrepreneurial same-industry spells. The dependent variable is ROA in models 1 and 3 and sales growth in models 2 and 4. The unit of analysis is a company-fiscal year. I control for lagged values of board size, the fraction of non-executive directors who also sit on other boards, leverage ratio, total assets quintile, sales quintile, and employment quintile. I also include an indicator variable for new non-executive directors as well as company, company age, and industry-calendar year fixed effects. 3.11 contains definitions for all variables. t-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Prior total spells		Prior entrepreneurial spells	
	(1)	(2)	(3)	(4)
	ROA	Sales growth	ROA	Sales growth
Distracted (low ind)	−0.777***	−0.892*		
	(−4.10)	(−1.76)		
Distracted (high ind)	−1.166***	−1.887***		
	(−7.52)	(−4.54)		
Distracted (low ind entr)			−0.956***	−1.309***
			(−6.26)	(−3.16)
Distracted (high ind entr)			−1.507***	−4.217***
			(−7.85)	(−8.23)
L.Board size	−0.581***	0.519*	−0.584***	0.494
	(−4.56)	(1.69)	(−4.59)	(1.61)
L.Leverage ratio	0.166***	0.179***	0.167***	0.179***
	(32.26)	(12.90)	(32.30)	(12.92)
Controls	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes
Observations	316,620	312,364	316,620	312,364
Adj. R^2	0.441	0.332	0.441	0.332
High=low p-value	0.102	0.114	0.020	0.000

Table 3.5
Director departures

This table presents results for regressions of director departures on a dummy that equals one if an incumbent non-executive director is distracted. The dependent variable is a dummy variable that equals one if a director leaves a company's board within the next two fiscal years. The unit of analysis is a director-company-fiscal year. I restrict observations to incumbent non-executive directors. In model 2, I only include director-company pairs in which the director leaves the company's board. I control for lagged values of board size, the fraction of non-executive directors who also sit on other boards, leverage ratio, total assets quintile, sales quintile, and employment quintile. I also include an indicator variable for new non-executive directors as well as director, company age, and industry-calendar year fixed effects. 3.11 contains definitions for all variables. *t*-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by director and company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
	Departure	Departure
	t+1	t+2
Distracted	0.003***	0.004***
	(3.83)	(4.13)
L.Board size	0.017***	0.016***
	(23.31)	(18.83)
L.Leverage ratio	0.000***	0.000***
	(8.19)	(4.39)
Controls	Yes	Yes
FEs	Yes	Yes
Observations	472,850	366,533
Adj. R^2	0.126	0.130

Table 3.6
Director fixed effects

This table presents results for regressions of company performance and growth on a dummy that equals one if an incumbent non-executive director is distracted. The dependent variable is ROA and sales growth in models 1 and 2, respectively. The unit of analysis is a director-company-fiscal year. I restrict observations to incumbent non-executive directors. I control for lagged values of board size, the fraction of non-executive directors who also sit on other boards, leverage ratio, total assets quintile, sales quintile, and employment quintile. I also include an indicator variable for new non-executive directors as well as director, company, company age, and industry-calendar year fixed effects. 3.11 contains definitions for all variables. *t*-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by director and company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) ROA	(2) Sales growth
Distracted	-0.711^{***}	-1.230^{***}
	(-7.35)	(-4.50)
L.Board size	-0.362^{**}	-0.314
	(-2.41)	(-0.85)
L.Leverage ratio	0.185^{***}	0.142^{***}
	(33.51)	(8.59)
Controls	Yes	Yes
Director FEs	Yes	Yes
Company FEs	Yes	Yes
Company age FEs	Yes	Yes
Industry-calendar year FEs	Yes	Yes
Observations	468,457	461,614
Adj. R^2	0.475	0.340

Table 3.7
Director fixed effects and prior experience

This table presents results for regressions of company performance and growth on a dummy that equals one if an incumbent non-executive director with below and above median prior total and entrepreneurial spells is distracted. The dependent variable is ROA in models 1 and 3 and sales growth in models 2 and 4. The unit of analysis is a director-company-fiscal year. I restrict observations to incumbent non-executive directors. I control for lagged values of board size, the fraction of non-executive directors who also sit on other boards, leverage ratio, total assets quintile, sales quintile, and employment quintile. I also include an indicator variable for new non-executive directors as well as director, company, company age, and industry-calendar year fixed effects. 3.11 contains definitions for all variables. t-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by director and company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Prior total spells		Prior entrepreneurial spells	
	(1)	(2)	(3)	(4)
	ROA	Sales growth	ROA	Sales growth
Distracted (low total)	−0.550***	−0.999***		
	(−4.03)	(−2.77)		
Distracted (high total)	−0.825***	−1.395***		
	(−6.76)	(−3.94)		
Distracted (low entrepr)			−0.485***	−0.733**
			(−3.68)	(−2.09)
Distracted (high entrepr)			−0.883***	−1.612***
			(−7.12)	(−4.52)
Controls	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes
Observations	468,457	461,614	468,457	461,614
Adj. R^2	0.475	0.340	0.475	0.340
High=low p-value	0.107	0.395	0.018	0.053

Table 3.8
CEO turnover as distraction event

This table presents results for regressions of company performance and growth on the fraction of distracted incumbent non-executive directors. I use CEO turnover as distraction event. Panels A and B show baseline and prior spells results, respectively. The unit of analysis is a company-fiscal year. I include the same control variables as in Table 3.2. 3.11 contains definitions for all variables. t-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Baseline

	(1) ROA	(2) Sales growth
Distracted (%)	−0.997***	0.723
	(−4.79)	(1.24)
Controls & FEs	Yes	Yes
Observations	316,620	312,364
Adj. R^2	0.441	0.331

Panel B: Prior spells

	Prior total spells		Prior entrepreneurial spells	
	(1) ROA	(2) Sales growth	(3) ROA	(4) Sales growth
Distracted (low tot)	−0.463	−0.614		
	(−0.80)	(−0.40)		
Distracted (high tot)	−1.069***	0.903		
	(−4.78)	(1.43)		
Distracted (low entr)			−0.724*	0.815
			(−1.79)	(0.75)
Distracted (high entr)			−1.396***	−2.892***
			(−8.52)	(−6.52)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	316,620	312,364	316,620	312,364
Adj. R^2	0.441	0.331	0.441	0.332

Table 3.9
M&As as distraction event in IV specification

This table presents results for first-differenced 2SLS regressions of company performance and growth in which I instrument the changes in other board seats of a company's directors with the sum of M&As of other companies on whose boards these directors sit. The dependent variable is the change in ROA and the logarithm of sales in the next fiscal year in models 1 and 2, respectively. The unit of analysis is a company-fiscal year. I control for lagged first-differenced values of board size, the fraction of non-executive directors who sit on at least one other board, leverage ratio, log of total assets, log of sales, and log of employment. I also include company age, county, and industry-calendar year fixed effects as well as the following indicator variables. A first one for when a company has no non-executive directors in the previous period. A second and third one for when a company appoints new non-executive directors in fiscal year t or $t+1$, respectively. t-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	ΔROA		ΔSales	
	(1)	(2)	(3)	(4)
	1st	2nd	1st	2nd
M&As	−0.295***		−0.295***	
	(−16.19)		(−16.17)	
Δ Other boards		−2.098**		−0.046
		(−2.11)		(−1.61)
L.Δ Board size	0.044***	0.689***	0.044***	0.032***
	(11.27)	(5.81)	(11.30)	(11.54)
L.Δ Leverage ratio	−0.040***	71.639***	−0.040***	0.266***
	(−7.14)	(205.45)	(−7.11)	(35.13)
Controls	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes
Observations	705,553	705,553	706,166	706,166
Adj. R^2	0.013	0.178	0.013	0.018

Table 3.10
M&As as distraction event in naive second stage

This table presents results for OLS regressions of company performance and growth on the endogenous variable (columns 1 and 2) and the instrument (columns 3 and 4) from the IV specification in Table 3.9, respectively. The dependent variable is the change in ROA and the logarithm of sales in the next fiscal year in models 1 and 2, respectively. The unit of analysis is a company-fiscal year. I include the same control variables as in Table 3.9. *t*-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) ΔROA	(2) ΔSales	(3) ΔROA	(4) ΔSales
Δ Other boards	0.095*	0.017***		
	(1.69)	(11.58)		
M&As			0.619**	0.013
			(2.12)	(1.62)
L.Δ Board size	0.594***	0.029***	0.596***	0.030***
	(5.42)	(11.84)	(5.44)	(12.12)
L.Δ Leverage ratio	71.728***	0.268***	71.724***	0.268***
	(207.63)	(35.91)	(207.62)	(35.82)
Controls	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes
Observations	705,553	706,166	705,553	706,166
Adj. R^2	0.186	0.036	0.186	0.035

Table 3.11
Distractions in other industries

This table presents results for regressions of company performance and growth on the fraction of distracted incumbent non-executive directors. I only use distractions in other industries than the focal company's. Panels A and B show baseline and prior spells results, respectively. The unit of analysis is a company-fiscal year. I include the same control variables as in Table 3.2. 3.11 contains definitions for all variables. t-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Baseline

	(1) ROA	(2) Sales growth
Distracted (%)	−0.825***	−1.468***
	(−5.93)	(−3.87)
Controls & FEs	Yes	Yes
Observations	316,620	312,364
Adj. R^2	0.441	0.331

Panel B: Prior spells

	Prior total spells		Prior entrepreneurial spells	
	(1) ROA	(2) Sales growth	(3) ROA	(4) Sales growth
Distracted (low tot)	−0.349	−1.102**		
	(−1.62)	(−2.01)		
Distracted (high tot)	−1.060***	−1.650***		
	(−6.23)	(−3.45)		
Distracted (low entr)			−0.554***	−1.782***
			(−2.63)	(−3.27)
Distracted (high entr)			−1.430***	−3.090***
			(−8.69)	(−6.95)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	316,620	312,364	316,620	312,364
Adj. R^2	0.441	0.331	0.441	0.332

Table 3.12
Alternative relative performance measure

This table presents results for regressions of company performance and growth on the fraction of distracted incumbent non-executive directors. I use industry-adjusted sales to construct distraction events. Panels A and B show baseline and prior spells results, respectively. The unit of analysis is a company-fiscal year. I include the same control variables as in Table 3.2. 3.11 contains definitions for all variables. t-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Baseline

	(1) ROA	(2) Sales growth
Distracted (%)	−1.263***	−2.536***
	(−9.91)	(−7.30)
Controls & FEs	Yes	Yes
Observations	316,620	312,364
Adj. R^2	0.441	0.332

Panel B: Prior spells

	Prior total spells		Prior entrepreneurial spells	
	(1) ROA	(2) Sales growth	(3) ROA	(4) Sales growth
Distracted (low tot)	−0.855***	−1.611***		
	(−4.43)	(−3.30)		
Distracted (high tot)	−1.502***	−3.080***		
	(−9.31)	(−6.89)		
Distracted (low entr)			−0.928***	−1.659***
			(−4.92)	(−3.42)
Distracted (high entr)			−1.477***	−3.097***
			(−9.01)	(−6.96)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	316,620	312,364	316,620	312,364
Adj. R^2	0.441	0.332	0.441	0.332

Table 3.13
Alternative denominator for variable of interest

This table presents results for regressions of company performance and growth on the fraction of distracted incumbent non-executive directors on a company's board. Panels A and B show baseline and prior spells results, respectively. The unit of analysis is a company-fiscal year. I include the same control variables as in Table 3.2. 3.11 contains definitions for all variables. *t*-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Baseline

	(1) ROA	(2) Sales growth
Distracted (%)	−1.062***	−1.706***
	(−8.01)	(−4.76)
Controls & FEs	Yes	Yes
Observations	316,620	312,364
Adj. R^2	0.441	0.332

Panel B: Prior spells

	Prior total spells		Prior entrepreneurial spells	
	(1) ROA	(2) Sales growth	(3) ROA	(4) Sales growth
Distr (low tot)	−0.608***	−1.124**		
	(−3.43)	(−2.51)		
Distr (high tot)	−1.456***	−2.214***		
	(−8.10)	(−4.41)		
Distr (low entr)			−0.658***	−1.347***
			(−3.56)	(−2.85)
Distr (high entr)			−1.387***	−1.995***
			(−7.85)	(−4.20)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	316,620	312,364	316,620	312,364
Adj. R^2	0.441	0.332	0.441	0.332

Table 3.14
Alternative company size controls

This table presents results for regressions of company performance and growth on the fraction of distracted incumbent non-executive directors. Panels A and B show baseline and prior spells results, respectively. The unit of analysis is a company-fiscal year. I control for lagged values of the logarithms of total assets, sales, and employees. All other control variables are as in Table 3.2. t-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Baseline

	(1) ROA	(2) Sales growth
Distracted (%)	−0.934***	−1.115***
	(−7.60)	(−3.69)
Controls & FEs	Yes	Yes
Observations	316,620	312,364
Adj. R^2	0.442	0.448

Panel B: Prior spells

	Prior total spells		Prior entrepreneurial spells	
	(1) ROA	(2) Sales growth	(3) ROA	(4) Sales growth
Distracted (low tot)	−0.582***	−1.253***		
	(−3.48)	(−3.30)		
Distracted (high tot)	−1.214***	−1.005**		
	(−7.38)	(−2.35)		
Distracted (low entr)			−0.653***	−1.438***
			(−3.80)	(−3.60)
Distracted (high entr)			−1.326***	−2.474***
			(−8.04)	(−5.82)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	316,620	312,364	316,620	312,364
Adj. R^2	0.442	0.448	0.442	0.448

Table 3.15
Full sample

This table presents results for regressions of company performance and growth on the fraction of distracted incumbent non-executive directors using the full sample. Panels A and B show baseline and prior spells results, respectively. The unit of analysis is a company-fiscal year. I include the same control variables as in Table 3.2. 3.11 contains definitions for all variables. t-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Baseline

	(1) ROA	(2) Sales growth
Distracted (%)	−0.542***	−1.016***
	(−4.62)	(−3.26)
Controls & FEs	Yes	Yes
Observations	982,383	972,162
Adj. R^2	0.350	0.281

Panel B: Prior spells

	Prior total spells		Prior entrepreneurial spells	
	(1) ROA	(2) Sales growth	(3) ROA	(4) Sales growth
Distracted (low tot)	−0.253	−0.410		
	(−1.55)	(−1.02)		
Distracted (high tot)	−0.744***	−1.442***		
	(−4.84)	(−3.49)		
Distracted (low entr)			−0.347**	−0.505
			(−2.11)	(−1.23)
Distracted (high entr)			−0.960***	−2.654***
			(−6.03)	(−6.31)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	982,383	972,162	982,383	972,162
Adj. R^2	0.350	0.281	0.350	0.281

Table 3.16
First ten fiscal years only

This table presents results for regressions of company performance and growth on the fraction of distracted incumbent non-executive directors restricting observations to the first ten fiscal years for each company. Panels A and B show baseline and prior spells results, respectively. The unit of analysis is a company-fiscal year. I include the same control variables as in Table 3.2. 3.11 contains definitions for all variables. t-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Baseline

	(1) ROA	(2) Sales growth
Distracted (%)	-0.944^{***}	-1.530^{***}
	(-6.53)	(-3.81)
Controls & FEs	Yes	Yes
Observations	249,994	246,292
Adj. R^2	0.458	0.355

Panel B: Prior spells

	Prior total spells		Prior entrepreneurial spells	
	(1) ROA	(2) Sales growth	(3) ROA	(4) Sales growth
Distracted (low tot)	-0.604^{***}	-1.246^{**}		
	(-3.01)	(-2.43)		
Distracted (high tot)	-1.226^{***}	-1.766^{***}		
	(-6.39)	(-3.15)		
Distracted (low entr)			-0.539^{***}	-1.494^{***}
			(-2.67)	(-2.79)
Distracted (high entr)			-1.320^{***}	-3.424^{***}
			(-6.85)	(-6.28)
Controls & FEs	Yes	Yes	Yes	Yes
Observations	249,994	246,292	249,994	246,292
Adj. R^2	0.458	0.355	0.458	0.355

Table 3.17
Company characteristics and director appointments

This table presents descriptive statistics at the non-executive director appointment level. I report means of lagged company characteristics for all non-executive director appointments as well as for appointments of directors who sit on at least one other board and no other board. For the latter two groups, I also report the differences in means and their t-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The variables in this table are the ten most important features in the random forest model in Figure 3.2. I report income statement, balance sheet, and cash flow items in millions of Swedish krona, and average salaries in thousands of Swedish krona.

	All	Multiple boards	Single board	Difference	t-statistic
Sales	116.74	156.82	46.18	110.64***	(14.39)
Total current receivables	52.19	64.34	30.81	33.53***	(5.32)
Total current liabilities	66.17	85.89	31.46	54.43***	(9.53)
Total equity	48.37	64.62	19.78	44.84***	(11.36)
Cash from operations	−5.16	−7.48	−0.74	−6.74**	(−2.53)
Multiple boards ratio (dirs)	0.59	0.70	0.39	0.31***	(101.13)
Current directorships (dirs)	2.20	2.80	1.15	1.66***	(98.54)
Directorships (dirs)	4.40	5.56	2.36	3.21***	(93.32)
Entrepr exp (dirs)	1.92	2.39	1.09	1.30***	(75.32)
Assets growth (%)	33.52	35.24	30.25	4.99***	(5.38)
Observations	78,904	50,318	28,586	78,904	

Table 3.18
Appointments of directors who sit on multiple boards

This table presents descriptive statistics at the non-executive director appointment level. I restrict appointments to those of directors who sit on multiple boards. I report means of lagged company characteristics for this subset of non-executive director appointments as well as for appointments of directors who already sit on at least two other boards and only one other board before the focal appointment. For the latter two groups, I also report the differences in means and their t-statistics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The variables in this table are the ten most important features in the random forest model in Figure 3.2. I report income statement, balance sheet, and cash flow items in millions of Swedish krona, and average salaries in thousands of Swedish krona.

	Multiple boards	Already before	Only after	Difference	t-statistic
Sales	156.82	180.27	101.75	78.51***	(6.24)
Total current receivables	64.34	70.73	49.31	21.42**	(2.44)
Total current liabilities	85.89	97.58	58.44	39.15***	(4.66)
Total equity	64.62	73.23	44.37	28.86***	(4.90)
Cash from operations	−7.48	−7.88	−6.51	−1.37	(−0.37)
Multiple boards ratio (dirs)	0.70	0.73	0.62	0.11***	(27.64)
Current directorships (dirs)	2.80	3.17	1.94	1.24***	(50.66)
Directorships (dirs)	5.56	6.28	3.90	2.38***	(47.01)
Entrepr exp (dirs)	2.39	2.64	1.78	0.86***	(34.53)
Assets growth (%)	35.24	36.31	32.66	3.65***	(2.95)
Observations	50,318	35,291	15,027	50,318	

Table 3.19

Director appointments and conditional correlations

This table presents results for regressions of a director appointment dummy on lagged company characteristics. The dependent variable is a dummy for the appointment of a non-executive director who sits on at least one (two) other board(s) after the focal appointment in model 1 (2). In model 2, I restrict appointments to those of directors who sit on multiple boards. The unit of analysis is a non-executive director appointment. I use standardized versions of the ten most important features in the random forest model in Figure 3.2 as regressors. I include industry, county, and calendar year fixed effects. t-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Multiple boards	(2) Already before
Sales	0.004**	0.003
	(2.02)	(1.11)
Total current receivables	−0.008***	−0.005
	(−2.76)	(−1.08)
Total current liabilities	0.007**	0.004
	(2.18)	(0.64)
Total equity	0.000	0.000
	(0.04)	(0.29)
Cash from operations	−0.002	0.000
	(−1.26)	(0.26)
Multiple boards ratio (dirs)	0.120***	0.007*
	(42.56)	(1.88)
Current directorships (dirs)	0.038***	0.061***
	(11.80)	(16.84)
Directorships (dirs)	0.019***	0.024***
	(5.29)	(5.98)
Entrepr exp (dirs)	0.001	−0.006*
	(0.46)	(−1.82)
Assets growth (%)	0.007***	0.006**
	(3.80)	(2.43)

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Industry FEs	Yes	Yes
County FEs	Yes	Yes
Calendar year FEs	Yes	Yes
Observations	64,495	42,301
Adj. R^2	0.142	0.051

3.9 Figures

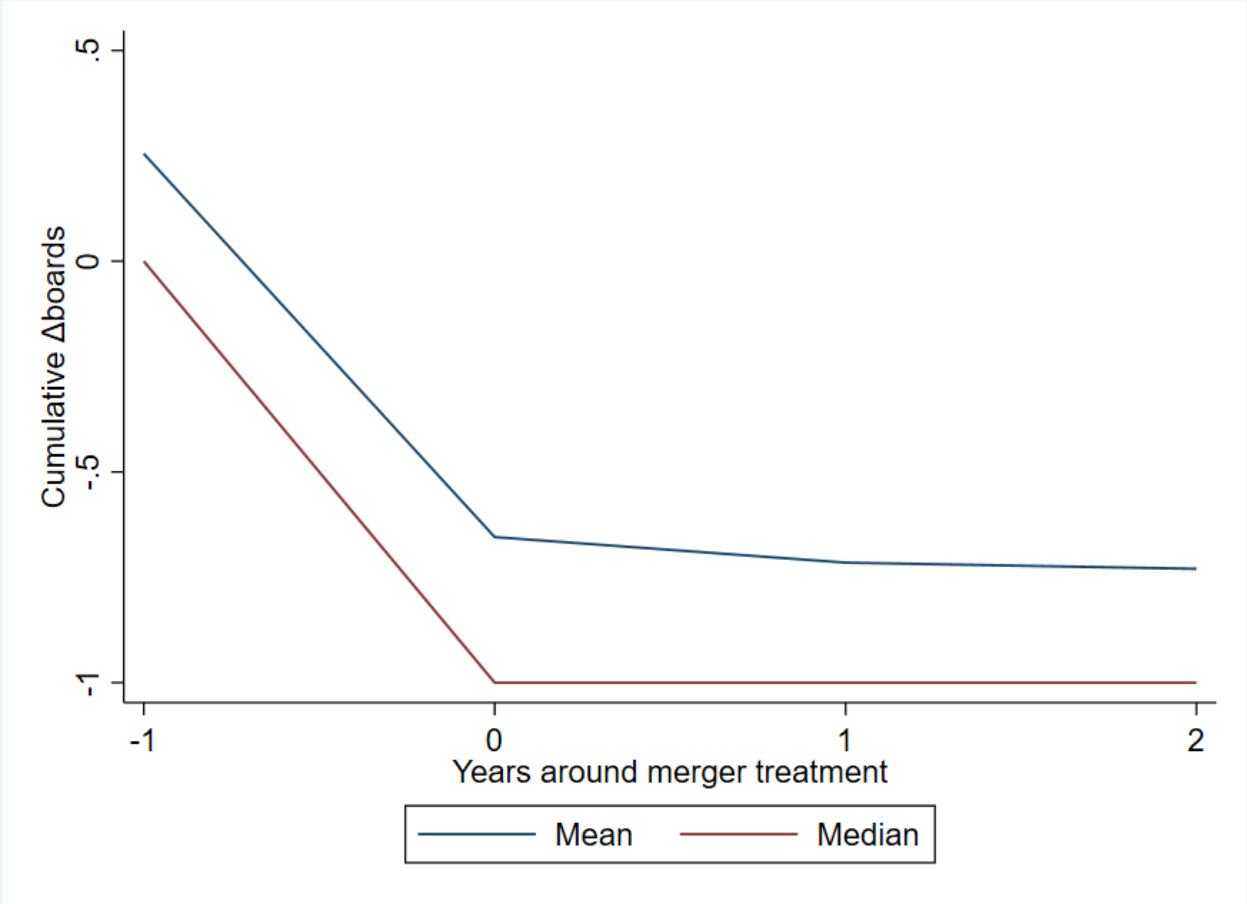


Figure 3.1. Cumulative changes in board seats around mergers. This figure shows cumulative changes in the number of board seats held by directors around merger treatment events. To avoid overlapping pre- and post-treatment periods, I construct this graph using data only for directors who are treated once.

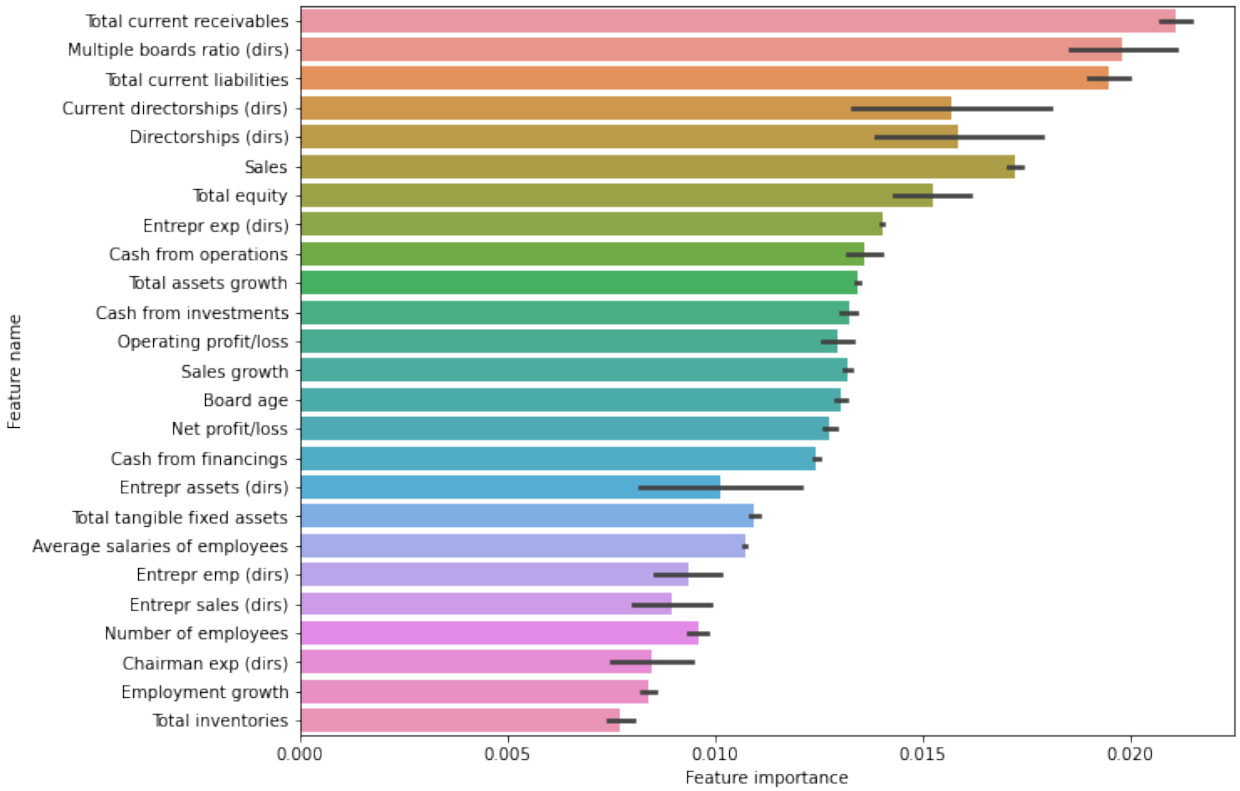


Figure 3.2. Predicting the appointment of non-executive directors who sit on multiple boards. This figure shows the feature importance plot of a random forest model that predicts the appointment of non-executive directors who also sit on the board of at least one other company. I use lagged company characteristics as features, including growth and cash flow variables. This increases the number of potentially important features in the random forest model but reduces the sample size by excluding director appointments during second fiscal years.

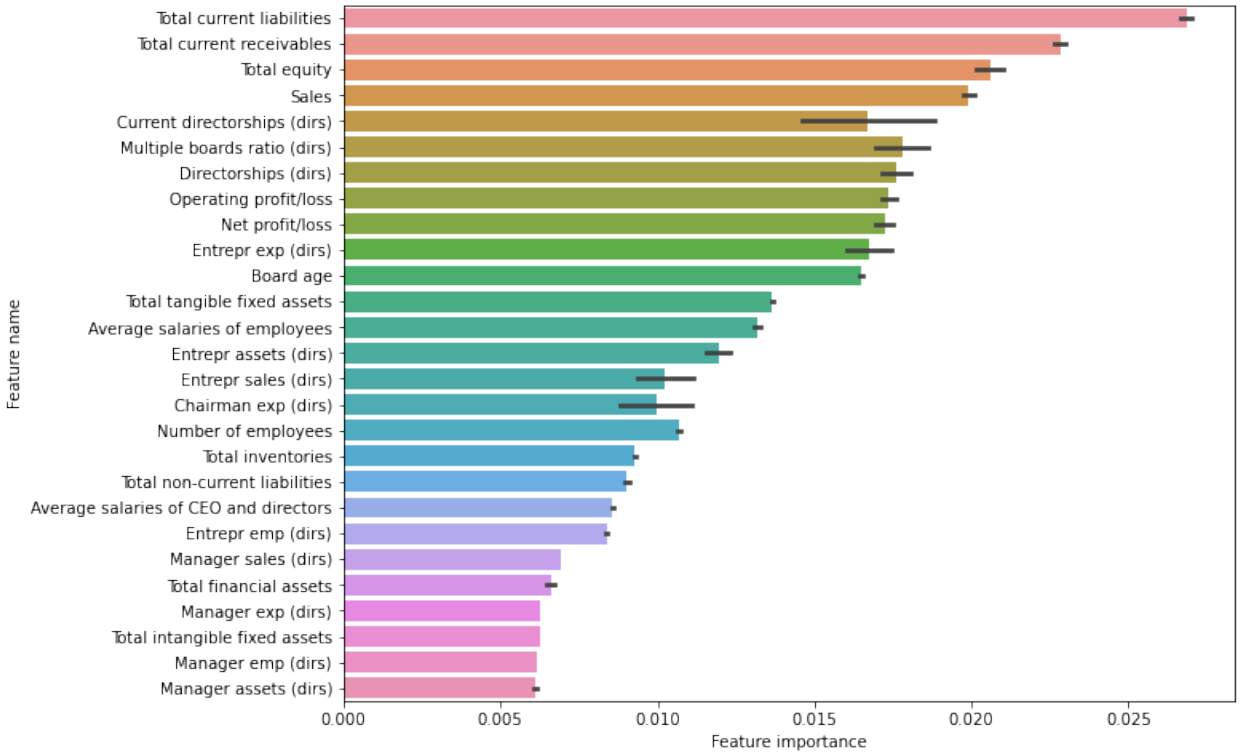


Figure 3.3. Predicting the appointment of non-executive directors who sit on multiple boards. This figure shows the feature importance plot of a random forest model that predicts the appointment of non-executive directors who also sit on the board of at least one other company. I use lagged company characteristics as features, excluding growth and cash flow variables. This reduces the number of potentially important features in the random forest model but increases the sample size by including director appointments during second fiscal years.

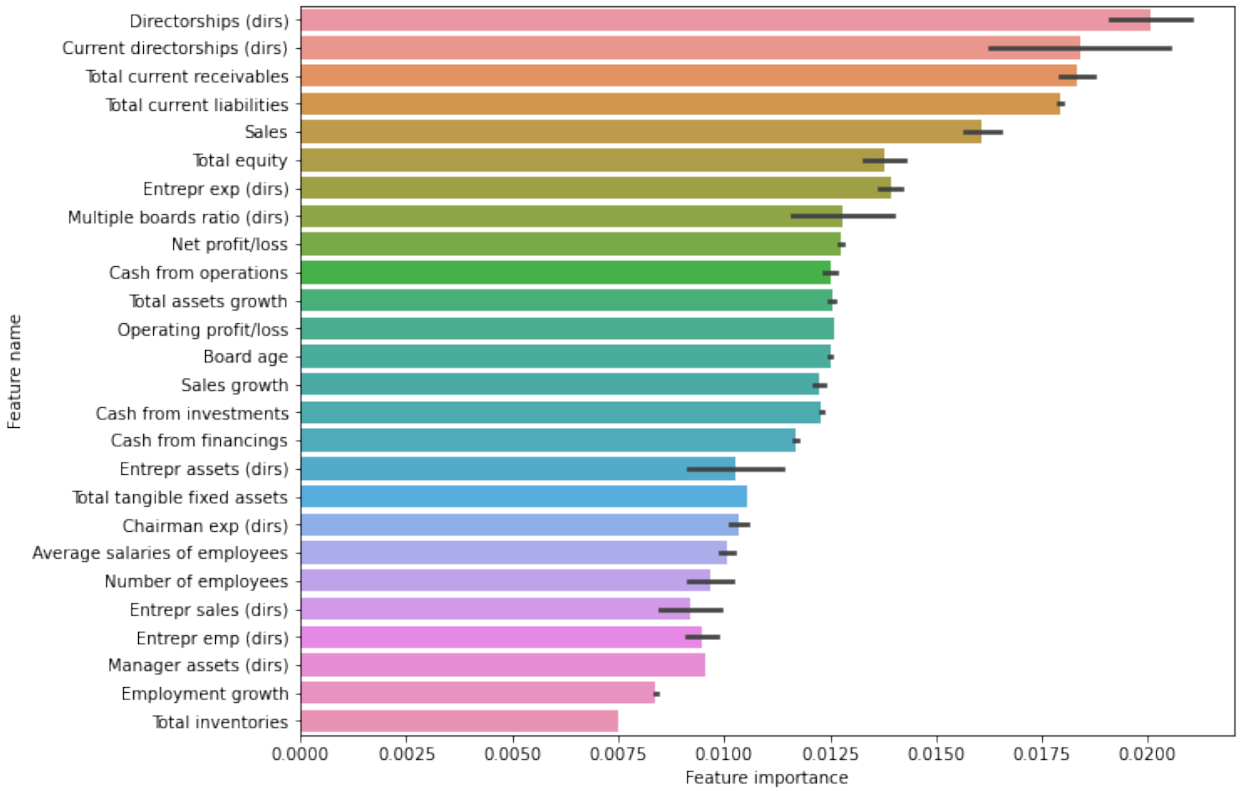


Figure 3.4. Predicting the appointment of non-executive directors who already sit on multiple boards prior to the focal appointment. This figure shows the feature importance plot of a random forest model that predicts the appointment of non-executive directors who also sit on the board of at least one other company, already before the focal appointment. I use lagged company characteristics as features, including growth and cash flow variables. This increases the number of potentially important features in the random forest model but reduces the sample size by excluding director appointments during second fiscal years.

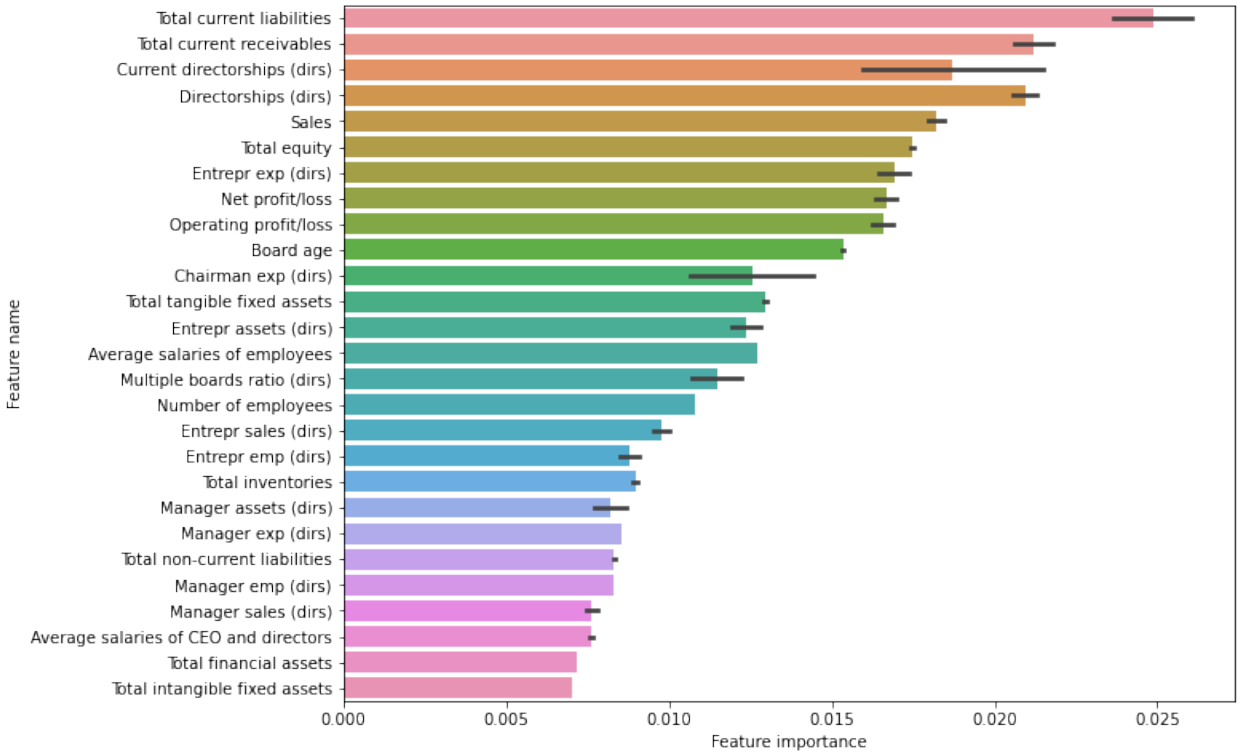


Figure 3.5. Predicting the appointment of non-executive directors who already sit on multiple boards prior to the focal appointment. This figure shows the feature importance plot of a random forest model that predicts the appointment of non-executive directors who also sit on the board of at least one other company, already before the focal appointment. I use lagged company characteristics as features, excluding growth and cash flow variables. This reduces the number of potentially important features in the random forest model but increases the sample size by including director appointments during second fiscal years.

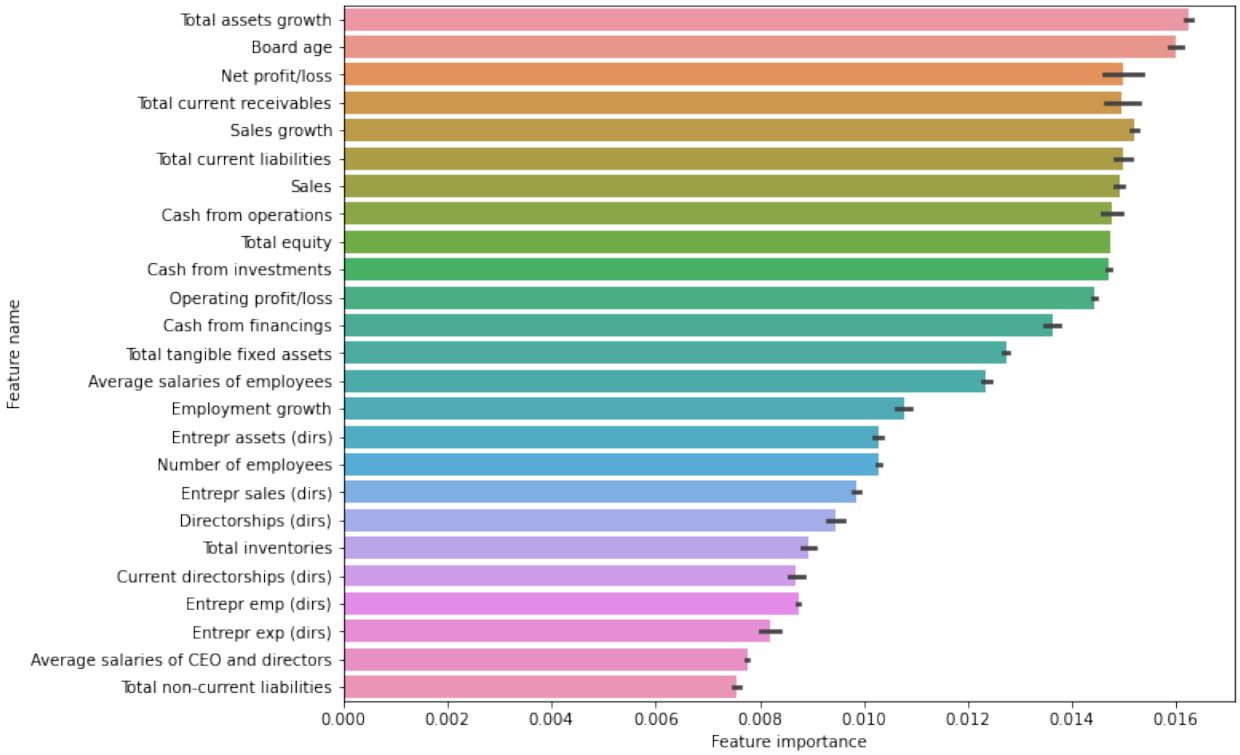


Figure 3.6. Predicting the appointment of non-executive directors who sit on multiple boards after the focal appointment. This figure shows the feature importance plot of a random forest model that predicts the appointment of non-executive directors who also sit on the board of at least one other company, only after the focal appointment. I use lagged company characteristics as features, including growth and cash flow variables. This increases the number of potentially important features in the random forest model but reduces the sample size by excluding director appointments during second fiscal years.

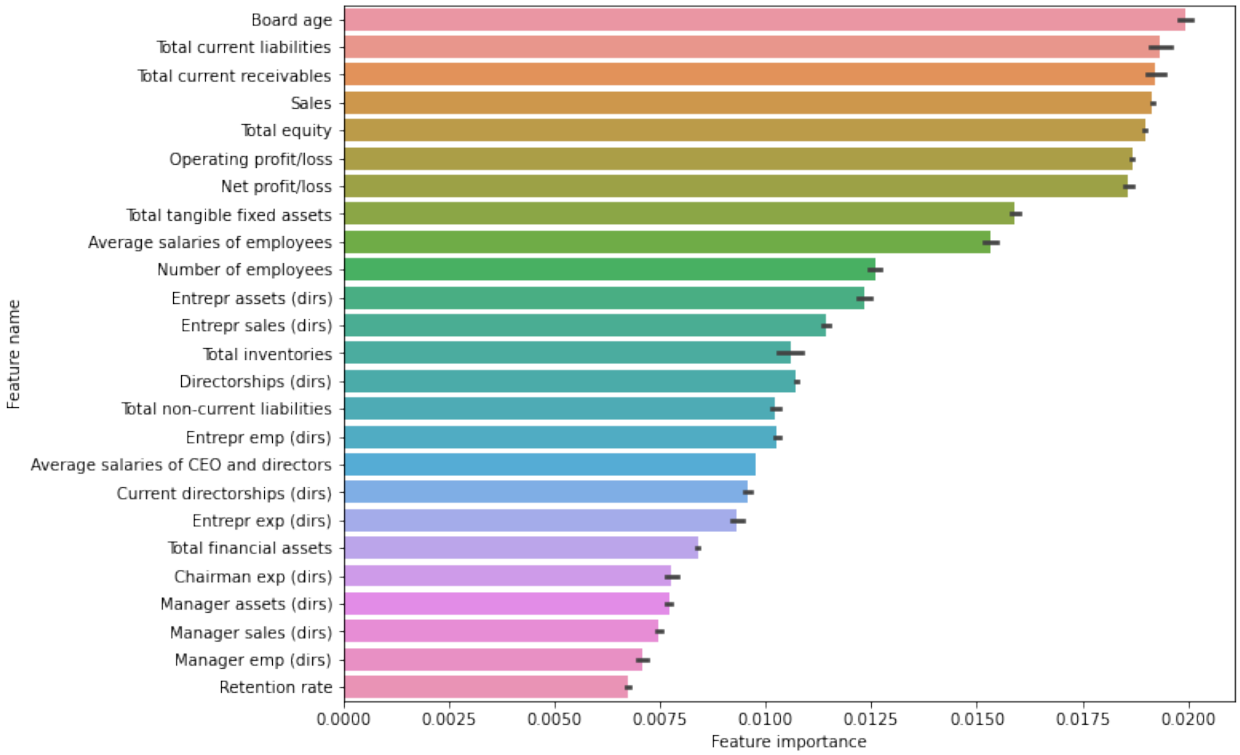


Figure 3.7. Predicting the appointment of non-executive directors who sit on multiple boards after the focal appointment. This figure shows the feature importance plot of a random forest model that predicts the appointment of non-executive directors who also sit on the board of at least one other company, only after the focal appointment. I use lagged company characteristics as features, excluding growth and cash flow variables. This reduces the number of potentially important features in the random forest model but increases the sample size by including director appointments during second fiscal years.

3.10 Appendix A: Sample construction filters

Table 3.20
Sample construction

This table lists the filters applied to the raw data to construct the sample. It also shows how many unique companies and company-fiscal year observations are left after each step.

Filter applied	# companies	# company-fiscal years
Full sample		
None: Raw data	895,395	8,388,539
Restrict to limited liability companies	873,573	8,306,832
Restrict to nature of expense and cost of sales accounting types	872,644	8,297,359
If both consolidated and unconsolidated financial statements are available, restrict to former	872,644	8,041,057
Restrict to years before 2020	867,986	7,983,607
Restrict to companies with known registration dates	867,502	7,982,336
Restrict to companies that are registered during the sample period	636,986	4,484,833
Restrict to companies that have employees in at least one fiscal year	205,152	1,385,172
Restrict to companies that provide their board composition for every fiscal year	189,586	1,198,874
Restrict to financial statement filings without gaps	189,499	1,198,258
Analysis sample		
Restrict to observations with at least one "shockable" director	65,198	330,994

3.11 Appendix B: Variable definitions

Table 3.21
Variable definitions

This table lists definitions for all variables.

Variable	Definition
Dependent	
ROA	A company's return on assets calculated as $\frac{EBITDA}{Total\ assets} * 100$
Sales growth	A company's sales growth calculated as $\frac{Sales_t - Sales_{t-1}}{Sales_{t-1}} * 100$
Departure	Dummy variable that equals one if a director leaves a company's board
Independent	
Distracted (%)	Fraction of a company's incumbent non-executive directors who are distracted
ΔOther boards	The sum of the changes in the number of all other board seats held by a company's directors relative to the previous fiscal year (I define this variable as first difference at the director-company-fiscal year level) (I calculate this variable using data on all limited liability companies in Sweden, not just start-ups, because directors of start-ups can be on the board of any other company)
M&As	The sum of acquisitions of other companies on whose boards a company's directors sit
Controls	
Total assets	A company's total book assets
Sales	A company's net sales
Employment	A company's number of employees
EBITDA	A company's EBITDA
Leverage ratio	A company's leverage ratio calculated as $\frac{Total\ debt}{Total\ assets}$
Board size	The number of a company's board members
Multi board (%)	Fraction of a company's non-executive directors who also sit on other boards
New NED	Indicator variable for when a company appoints new non-executive directors
No NED	Indicator variable for when a company has no non-executive directors
Age	The number of fiscal years since a company's registration
County	The county in which a company's headquarters are located (25 in total)
Industry	The primary industry in which a company operates (20 in total)
Calendar year	The calendar year during which a particular company's fiscal year ends

3.12 Appendix C: Financial statements

This section outlines the income statement and balance sheet items from the annual reports submitted to the Swedish Companies Registration Office and shows how I use these to construct cash flow statements.

I am interested in studying how companies manage cash flows. The annual reports submitted to the Companies Registration Office include an income statement and a balance sheet, neither of which directly shows how cash is spent or generated. The balance sheet shows the aggregate net change in cash from the previous to the current fiscal year. The income statement lists income and expense items that reflect economic activity regardless of when cash is exchanged.[21] It recognizes economic activity by matching revenue and expenses when a transaction occurs, and not when a payment is made.[22] I therefore use the income statement and balance sheet information to construct cash flow statements. Section 3.12.1 uses a stylized example to illustrate how the income statement and balance sheet record transactions, and how the timing of these can be different from when cash is exchanged.

To give some intuition for how I construct the cash flow statements, I use the property of the balance sheet that the total of the left-hand side (assets) is equal to the total of the right-hand side (liabilities and equity).

$$Assets = Liabilities + Equity \tag{3.5}$$

This implies that the changes from one fiscal year to the next must also be equal on both

[21] This is known as accrual accounting.
[22] This is known as matching principle.

sides of the balance sheet.

$$\Delta Assets = \Delta Liabilities + \Delta Equity \tag{3.6}$$

We can decompose the change in assets into the change in cash and the change in all other items, and then solve for the change in cash.

$$\Delta Cash = -\Delta Non\text{-}cash\ assets + \Delta Liabilities + \Delta Equity \tag{3.7}$$

The cash flow statement breaks down the net change in cash on the balance sheet into cash provided by or used for operating, investing, and financing activities during a fiscal year. To compute the net cash from operating activities, I take the net profit/loss from the income statement and adjust it by using non-cash items from the income statement as well as changes in current asset and current liability accounts from the balance sheet. For example, I add back depreciation expenses which decrease net profit but do not involve a cash outflow. Most adjustments to compute the net cash from financing activities involve summing up changes in non-current liability and equity accounts. I calculate the net cash from investing activities as a balancing amount by taking the net change in cash on the balance sheet and subtracting the sum of net cash from operating and financing activities. Figure 3.8 illustrates how I use items from the income statement and balance sheet account categories to construct the cash flow statement activities. Section 3.12.4 outlines all adjustments I make to construct cash flow statements.

A limitation of the data is that I can only observe net changes in balance sheet items and not all underlying transactions. Ideally, I would break down net changes in balance sheet items into transactions that involve cash and those that do not. I would then only use

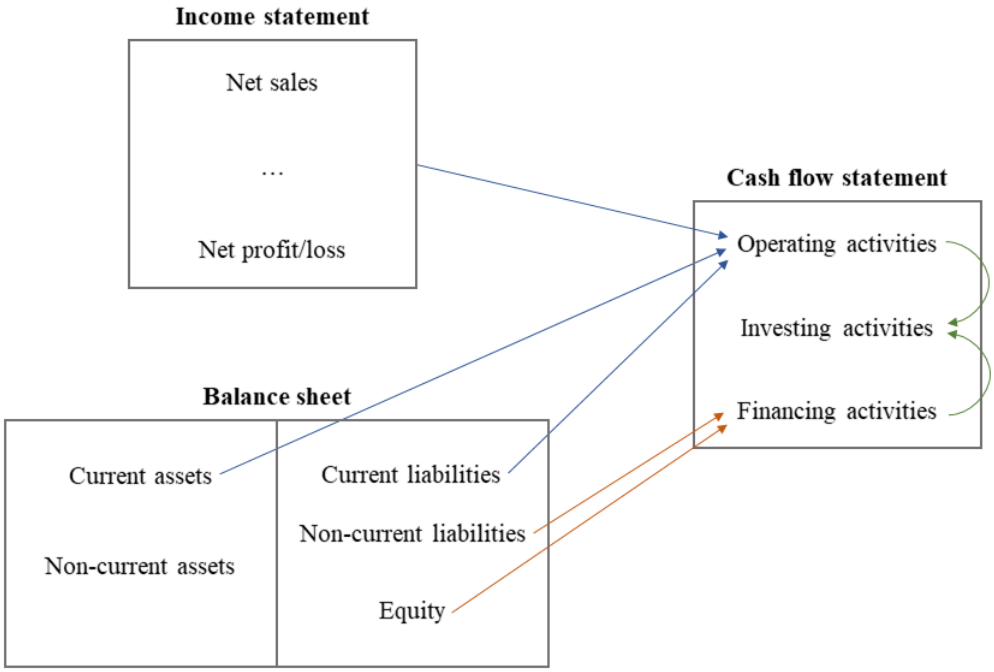


Figure 3.8. Financial statements. This figure illustrates how I use items from the income statement and balance sheet account categories to construct the cash flow statement activities.

transactions that involve cash and assign each to either operating, investing, or financing activities. For example, the net change in the balance sheet item machinery can combine the purchase of a new machine for cash (involves cash) and depreciation (does not involve cash). The purchase decreases *Cash* and increases *Non-cash assets* in Equation 3.7 by the same amount. Depreciation, on the other hand, decreases both *Non-cash assets* and *Equity* on the right-hand side of Equation 3.7, leaving cash unchanged. Using the net change in machinery when constructing the cash flow statement would understate the cash outflow from investing activities.

Using net changes in balance sheet items introduces the largest measurement error in the calculation of net cash from investing activities because non-cash transactions account

for a relatively large part of non-current assets. Net cash from operating and financing activities should be mostly unaffected. The biggest source of measurement error in net cash from operating activities is most likely the difference between observable tax expenses on the income statement and unobservable actual taxes paid (the effective tax rate). I do not expect this to have a significant effect because my sample consists of young companies for whom tax optimization is probably not that important. Using net changes in balance sheet items for constructing the cash flow statement should not affect the calculation of net cash from financing activities.

I compute net cash from investing activities by taking the net change in cash on the balance sheet and subtracting the sum of net cash from operating and financing activities. This minimizes the measurement error in breaking down the net change in cash into net cash from each of the three activity categories (operating, investing, financing) by trading off granularity in investing activities. I calculate net cash from investing activities as a balancing amount as opposed to the sum of cash from different investing activities.

Companies can choose between the nature of expense and cost of sales accounting types when preparing the income statement. The nature of expense method is easier to follow because it assigns expenses to categories (e.g., raw materials or depreciation), whereas the cost of sales method breaks down expenses according to their function (e.g., cost of goods sold or administrative expenses). The main drawback of the nature of expense method is that the income statement does not show a gross profit. Almost all income statements (96.7%) in my dataset follow the nature of expense method, and companies rarely switch accounting types (2.7%). Sections 3.12.2 and 3.12.2 outline income statement items for the nature of expense and cost of sales accounting types, respectively. Similarly, Sections 3.12.4 and 3.12.4 show how I construct cash flow statements for either accounting type.

Smaller companies have the option to submit abridged annual reports. I find that these companies often leave the most granular balance sheet items blank and only provide the total for that account category. For example, total inventories is much less likely to be missing than its two components work in progress and other inventories. I therefore use the total amounts of account categories instead of the respective component accounts to construct cash flow statements for smaller companies. Section 3.12.5 outlines all adjustments that I make when constructing cash flow statements for smaller companies.

3.12.1 Stylized example

This section uses a stylized example to illustrate how transactions are recorded on the balance sheet and income statement, and that the timing of these can be different from when cash is exchanged.

A company produces a good in period 1, sales the good on account in period 2, and receives payment for the sold good in period 3. In period 1, the asset side of the balance sheet shows a decrease in raw materials and a complementary increase in finished goods reflecting the production costs of the good. This is known as an asset swap because total assets remain unchanged. The income statement does not record anything. In period 2, the asset side of the balance sheet shows a decrease in finished goods by the production costs and an increase in accounts receivable by the sales price. This usually results in an increase of total assets because the sales price of a good is typically higher than its production costs. The income statement reports the sales price of the good as revenue and its production costs as expense. The sales profit appears as net income on the income statement and increases retained earnings (part of equity) on the balance sheet. Both sides of the balance sheet increase by the same amount, the sales profit. In period 3, the balance sheet shows another

asset swap with an increase in cash and a decrease in accounts receivable by the sales price. Again, the income statement does not record anything.

This stylized example shows that the company records a profit on the income statement and balance sheet at the time of the sale (period 2), and not when it receives the cash payment (period 3). I therefore create cash flow statements, which reflect when cash is exchanged, to study how companies manage cash flows.

3.12.2 Income statement

Nature of expense method

Item

Net sales

± Inventory change

± Capitalized work

+ Other operating income

− Raw materials and consumables

− Goods for resale

− Other external expenses

− Salaries and benefits

− Depreciation

± Financial items affecting comparability

− Other operating expenses

Operating profit/loss

± Profit/loss from group companies

+ Interest income from group companies

+ External interest income

+ Other financial income

− Interest expenses to group companies

− External interest expenses

− Other financial expenses

Profit/loss after net financial income

+ Extraordinary income

− Extraordinary expenses

± Group contributions

± Shareholders' contributions

± Appropriations

− Taxes

± Minority shareholdings

Net profit/loss

Cost of sales method

Item

Net sales

− Cost of goods sold

Gross profit/loss

− Selling expenses

− Administrative expenses

− R&D expenses

± Financial items affecting comparability

+ Other operating income

− Other operating expenses

Operating profit/loss

± Profit/loss from group companies

+ Interest income from group companies

+ External interest income

+ Other financial income

− Interest expenses to group companies

− External interest expenses

− Other financial expenses

Profit/loss after net financial income

+ Extraordinary income

− Extraordinary expenses

± Group contributions

± Shareholders' contributions

± Appropriations

− Taxes

± Minority shareholdings

Net profit/loss

3.12.3 Balance sheet

Item

Assets

Cash

Short-term investments

Accounts receivable

Current receivables from group/associated companies

Other current receivables

Total current receivables

Work in progress

Other inventories

Total inventories

Total current assets

Participation in group/associated companies

Long-term receivables from group/associated companies

Loans to partners and related parties

Other financial assets

Total financial assets

Buildings and land

Machinery

Equipment

Machinery and equipment

Other tangible fixed assets

Total tangible fixed assets

Subscribed capital unpaid

Capitalized R&D expenses

Patents, licenses, concessions etc.

Goodwill

Other intangible fixed assets

Total intangible fixed assets

Total fixed assets

Total assets

Liabilities and equity

Current liabilities to credit institutions

Accounts payable

Current liabilities to group/associated companies

Other current liabilities

Total current liabilities

Untaxed reserves

Minority shareholding

Provisions

Bonds

Non-current liabilities to credit institutions

Non-current liabilities to group/associated companies

Other non-current liabilities

Total non-current liabilities

Nominal share capital

Share premium reserve

Revaluation reserve

Other restricted equity

Profit/loss brought forward

Group contributions

Shareholders' contributions

Profit/loss for the year

Total equity

Total liabilities and equity

3.12.4 Cash flow statement

Nature of expense method

Item

OPERATING ACTIVITIES

Net profit/loss

+ Depreciation

− Group contributions

− Shareholders' contributions

− Appropriations

− Δ Accounts receivable

− Δ Current receivables from group/associated companies

− Δ Other current receivables

− Δ Work in progress

− Δ Other inventories

+ Δ Current liabilities to credit institutions

+ Δ Accounts payable

+ Δ Current liabilities to group/associated companies

+ Δ Other current liabilities

+ Δ Deferred taxes

Net cash provided by/used in operating activities

FINANCING ACTIVITIES

Group contributions

+ Shareholders' contributions

+ Appropriations

− Dividends

+ Δ Bonds

+ Δ Non-current liabilities to credit institutions

+ Δ Non-current liabilities to group/associated companies

+ Δ Other non-current liabilities

+ Δ Nominal share capital

+ Δ Share premium reserve

+ Δ Revaluation reserve

+ Δ Other restricted equity

Net cash provided by/used in financing activities

INVESTING ACTIVITIES

Δ Cash

− Net cash provided by/used in operating activities

− Net cash provided by/used in financing activities

Net cash provided by/used in investing activities

Cost of sales method

Item

OPERATING ACTIVITIES

Net profit/loss

+ Depreciation of cost of goods sold

+ Depreciation of selling expenses

+ Depreciation of administrative expenses

+ Depreciation of R&D expenses

+ Depreciation of other operating expenses

+ Unspecified depreciations

− Group contributions

− Shareholders' contributions

− Appropriations

− Δ Accounts receivable

− Δ Current receivables from group/associated companies

− Δ Other current receivables

− Δ Work in progress

− Δ Other inventories

+ Δ Current liabilities to credit institutions

+ Δ Accounts payable

+ Δ Current liabilities to group/associated companies

+ Δ Other current liabilities

+ Δ Deferred taxes

Net cash provided by/used in operating activities

FINANCING ACTIVITIES

Group contributions

+ Shareholders' contributions

+ Appropriations

− Dividends

+ Δ Bonds

+ Δ Non-current liabilities to credit institutions

+ Δ Non-current liabilities to group/associated companies

+ Δ Other non-current liabilities

+ Δ Nominal share capital

+ Δ Share premium reserve

+ Δ Revaluation reserve

+ Δ Other restricted equity

Net cash provided by/used in financing activities

INVESTING ACTIVITIES

Δ Cash

− Net cash provided by/used in operating activities

− Net cash provided by/used in financing activities

Net cash provided by/used in investing activities

3.12.5 Abridged annual reports: Cash flow statement

This section shows how I construct cash flow statements for companies that submit abridged annual reports to the Swedish Companies Registration Office.

Nature of expense method

Item

OPERATING ACTIVITIES

Net profit/loss

+ Depreciation

− Group contributions

− Shareholders' contributions

− Appropriations

− Δ Total current receivables

− Δ Total inventories

+ Δ Total current liabilities

+ Δ Deferred taxes

Net cash provided by/used in operating activities

FINANCING ACTIVITIES

Group contributions

+ Shareholders' contributions

+ Appropriations

− Dividends

+ Δ Bonds

+ Δ Total non-current liabilities

+ Δ Nominal share capital

+ Δ Share premium reserve

+ Δ Revaluation reserve

+ Δ Other restricted equity

Net cash provided by/used in financing activities

INVESTING ACTIVITIES

Δ Cash

− Net cash provided by/used in operating activities

− Net cash provided by/used in financing activities

Net cash provided by/used in investing activities

Cost of sales method

Item

OPERATING ACTIVITIES

Net profit/loss

+ Depreciation of cost of goods sold

+ Depreciation of selling expenses

+ Depreciation of administrative expenses

+ Depreciation of R&D expenses

+ Depreciation of other operating expenses

+ Unspecified depreciations

− Group contributions

− Shareholders' contributions

− Appropriations

− Δ Total current receivables

− Δ Total inventories

+ Δ Total current liabilities

+ Δ Deferred taxes

Net cash provided by/used in operating activities

FINANCING ACTIVITIES

Group contributions

+ Shareholders' contributions

+ Appropriations

− Dividends

+ Δ Bonds

+ Δ Total non-current liabilities

+ Δ Nominal share capital

+ Δ Share premium reserve

+ Δ Revaluation reserve

+ Δ Other restricted equity

Net cash provided by/used in financing activities

INVESTING ACTIVITIES

Δ Cash

– Net cash provided by/used in operating activities

– Net cash provided by/used in financing activities

Net cash provided by/used in investing activities

3.13 Appendix D: Complementary analyses

3.13.1 Persistence

I examine in how far the effects of shocks to director attention on company performance and growth persist over time. I therefore re-estimate Equation 3.1 by shifting the dependent variable forward in time. Table 3.22 presents the results. I measure the dependent variable at time t, t+1, and t+2 in columns 1, 2, and 3, respectively. The effect is mainly contemporaneous, with some evidence for a longer-lasting, albeit dissipating, effect on ROA at t+1.

Insert Table 3.22 about here.

Decomposing the fraction of distracted incumbent non-executive directors by prior experience yields slightly more nuanced results, both for prior spells in any industry (Table 3.23) and for those in the same industry as the focal company (Table 3.24). An increase in the fraction of more experienced directors who are distracted leads to a decline in ROA that persists longer, with the effect size decreasing over time. For sales growth, there is some evidence for a partial reversal of the negative contemporaneous effect during the next fiscal year. As in prior tables, the economic significance of coefficients is larger for directors with prior entrepreneurial experience, and even larger for those with same-industry prior spells.

Insert Table 3.23 about here.

Insert Table 3.24 about here.

3.13.2 Tables

Table 3.22
Persistence

This table presents results for regressions of company performance and growth on the fraction of distracted incumbent non-executive directors. I measure the dependent variable at time t, t+1, and t+2 in models 1, 2, and 3, respectively. Panels A and B show the results for ROA and sales growth, respectively. The unit of analysis is a company-fiscal year. I include the same control variables as in Table 3.2. 3.11 contains definitions for all variables. *t*-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: ROA			
	(1)	(2)	(3)
	t	t+1	t+2
Distracted (%)	−1.016***	−0.398***	−0.061
	(−8.26)	(−3.03)	(−0.44)
Controls	Yes	Yes	Yes
FEs	Yes	Yes	Yes
Observations	316,620	265,890	221,472
Adj. R^2	0.441	0.434	0.433
Panel B: Sales growth			
	(1)	(2)	(3)
	t	t+1	t+2
Distracted (%)	−1.504***	0.679**	0.107
	(−4.51)	(2.10)	(0.30)
Controls	Yes	Yes	Yes
FEs	Yes	Yes	Yes
Observations	312,364	262,976	219,124
Adj. R^2	0.331	0.117	0.070

Table 3.23
Persistence by prior experience

This table presents results for regressions of company performance and growth on the fraction of distracted incumbent non-executive directors with below and above median prior total and entrepreneurial spells. I measure the dependent variable at time t, t+1, and t+2 in models 1, 2, and 3, respectively. Panels A and B show the results for ROA and sales growth, respectively. The unit of analysis is a company-fiscal year. I include the same control variables as in Table 3.2. 3.11 contains definitions for all variables. *t*-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: ROA

	Prior total spells			Prior entrepreneurial spells		
	(1)	(2)	(3)	(4)	(5)	(6)
	t	t+1	t+2	t	t+1	t+2
Distracted (low tot)	−0.554***	0.147	0.181			
	(−3.30)	(0.82)	(0.92)			
Distracted (high tot)	−1.384***	−0.814***	−0.236			
	(−8.45)	(−4.67)	(−1.30)			
Distracted (low entr)				−0.636***	−0.009	0.102
				(−3.70)	(−0.05)	(0.54)
Distracted (high entr)				−1.467***	−0.807***	−0.421**
				(−8.93)	(−4.69)	(−2.26)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	316,620	265,890	221,472	316,620	265,890	221,472
Adj. R^2	0.441	0.434	0.433	0.441	0.434	0.433
High=low *p*-value	0.000	0.000	0.100	0.000	0.001	0.037

Panel B: Sales growth

	Prior total spells			Prior entrepreneurial spells		
	(1)	(2)	(3)	(4)	(5)	(6)
	t	t+1	t+2	t	t+1	t+2
Distracted (low tot)	−0.966**	0.475	−0.129			
	(−2.26)	(1.14)	(−0.28)			
Distracted (high tot)	−1.935***	0.835**	0.278			
	(−4.25)	(1.99)	(0.60)			
Distracted (low entr)				−1.387***	0.697*	0.307
				(−3.16)	(1.69)	(0.68)
Distracted (high entr)				−3.116***	1.547***	0.394
				(−6.99)	(3.68)	(0.85)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	312,364	262,976	219,124	312,364	262,976	219,124
Adj. R^2	0.332	0.117	0.070	0.332	0.117	0.070
High=low p-value	0.099	0.503	0.494	0.003	0.112	0.883

Table 3.24
Persistence by prior same-industry experience

This table presents results for regressions of company performance and growth on the fraction of distracted incumbent non-executive directors with below and above median prior total and entrepreneurial same-industry spells. I measure the dependent variable at time t, t+1, and t+2 in models 1, 2, and 3, respectively. Panels A and B show the results for ROA and sales growth, respectively. The unit of analysis is a company-fiscal year. I include the same control variables as in Table 3.2. 3.11 contains definitions for all variables. *t*-statistics are shown in parentheses, and standard errors are heteroscedasticity robust and clustered by company. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: ROA

	Prior total spells			Prior entrepreneurial spells		
	(1)	(2)	(3)	(4)	(5)	(6)
	t	t+1	t+2	t	t+1	t+2
Distracted (low ind)	−0.777***	−0.239	0.403*			
	(−4.10)	(−1.18)	(1.89)			
Distracted (high ind)	−1.166***	−0.498***	−0.356**			
	(−7.52)	(−3.04)	(−2.05)			
Distracted (low ind entr)				−0.956***	−0.352**	0.026
				(−6.26)	(−2.15)	(0.15)
Distracted (high ind entr)				−1.507***	−0.743***	−0.512**
				(−7.85)	(−3.68)	(−2.28)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	316,620	265,890	221,472	316,620	265,890	221,472
Adj. R^2	0.441	0.434	0.433	0.441	0.434	0.433
High=low *p*-value	0.102	0.303	0.004	0.020	0.117	0.047

Panel B: Sales growth

	Prior total spells			Prior entrepreneurial spells		
	(1)	(2)	(3)	(4)	(5)	(6)
	t	t+1	t+2	t	t+1	t+2
Distracted (low ind)	−0.892*	1.642***	−0.231			
	(−1.76)	(3.46)	(−0.43)			
Distracted (high ind)	−1.887***	0.073	0.322			
	(−4.54)	(0.18)	(0.75)			
Distracted (low ind entr)				−1.309***	0.986***	0.038
				(−3.16)	(2.58)	(0.09)
Distracted (high ind entr)				−4.217***	2.162***	0.703
				(−8.23)	(4.50)	(1.31)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	312,364	262,976	219,124	312,364	262,976	219,124
Adj. R^2	0.332	0.117	0.070	0.332	0.117	0.070
High=low p-value	0.114	0.007	0.383	0.000	0.040	0.296

Chapter 4

Separate account vs mutual fund investors: Manager selection and performance

ABSTRACT

Separate account investors outperform category-matched mutual fund investors yearly by 14-24 bps gross and 50-75 bps net. This outperformance is entirely explained by structural and reporting differences between the vehicles and by size differences between investors. Controlling for the average outperformance of separate accounts over their mutual fund twins, separate account investors perform at the same level as mutual fund investors, gross of fees, and slightly below them, net. Separate account investors choose products that, once adjusted, are more expensive than those chosen by mutual fund investors. Their fixed income picks do better whereas their equity picks do worse.

4.1 Introduction

Separate (or "segregated") accounts are the main means by which large institutional investors delegate the management of portfolios to asset managers. Their performance is closely scrutinized by practitioners and, increasingly, researchers. In the most comprehensive study to date Gerakos, Linnainmaa, and Morse (2021) show that investments in actively managed portfolios, which are predominantly separate accounts, significantly outperform strategy benchmarks as well as investments in mutual funds.[1] This outperformance is the result of differences both in gross performance and in fees and is consistent with the predictions of Gârleanu and Pedersen (2018) that separate account investors, being larger and more sophisticated, are better equipped to select managers than mutual fund investors.

In this study, we offer an alternative explanation for the outperformance of separate account investors over mutual fund investors: structural differences between the vehicles in terms of liquidity provision, customization, and reporting practices coupled with significant differences in investment size. These differences combine to create a wedge between the reported performance of even near-identical separate account and mutual fund portfolios and fully explain the aggregate performance differences between the two groups of investors. In aggregate, therefore, investors in separate accounts seem no more skilled at selecting managers than investors in mutual funds.

The open-ended structure of mutual funds exposes them to unscheduled investments and redemptions, forcing them to provide liquidity to their investors and eroding performance.[2]

[1] Evidence about mutual funds' ability to beat benchmarks or generate alpha is less straightforward. While the early literature on the topic tends to find no evidence of mutual fund outperformance (see Jensen (1968) and Carhart (1997)), a more recent study by Berk and Binsbergen (2015) provides evidence to the contrary, but returns do not seem as big as those of separate accounts and, after fees, are not higher than benchmarks.

[2] Redemptions in kind help alleviate, but do not completely eradicate, this problem in mutual funds (see Agarwal et al. (2022)).

Separate accounts are largely spared this problem because they can exclude at least some of the costs of investment and divestment under the reporting rules for composites and because many asset owners in any case use transition managers to switch between portfolios. Furthermore, mutual fund fees typically have a broader coverage, including custody and set-up costs, which separate account investors pay independently. This broader coverage, coupled with generally smaller size of individual investments, tends to result in larger mutual fund fees and lower (reported) net-of-fees performance. Partially offsetting these differences, separate accounts face a potential drag of their own if they are customized to meet client demands, as this places constraints on the asset manager.

To isolate the effects of structural differences between separate accounts and mutual funds we exploit the fact that investment management companies frequently offer "twins", that is, near-identical separate account and mutual fund portfolios with the same manager and investment strategy. Our analysis points to a significant performance gap between these twins. Separate accounts have annual gross reported excess returns and alphas on average between 16 bps and 23 bps per year higher than the gross excess returns and alphas reported by their mutual fund twins. This gap increases with the illiquidity of the investment category, consistent with the cost for funds of facing investor subscriptions and redemptions (or providing liquidity for them) being higher in more illiquid categories. The performance gap widens when fees are included. Headline fees for separate accounts are lower than reported fees for their mutual fund twins – by about 59 bps for a medium-size mandate. Higher mutual fund fees reflect the smaller investments in mutual funds than in separate accounts, the more significant regulatory requirements of mutual funds, and the fact that mutual fund fees cover other costs, such as marketing, custody, and audit costs, which separate account fees generally do not.

This performance gap in our subsample of separate account/mutual fund twins matches the overall asset-weighted performance difference between separate account and mutual fund investments in our full sample. Separate account investors outperform category-matched mutual fund investors by between 14 bps and 24 bps per year, gross of fees, and by between 50 bps and 76 bps per year, net of fees.[3] Controlling for the average outperformance of separate accounts over their mutual fund twins, separate account investors therefore perform at the level of mutual fund investors, gross of fees, and slightly below them, net. Accordingly, the outperformance of separate accounts investors can be attributed entirely to structural and reporting differences between these vehicles and the greater size of investors in separate accounts and consequently lower fees, with no evidence that separate account investors choose better managers.

More refined calculations of the gap (by investment category or liquidity-based) do not alter this basic result. Neither does restricting the analysis to the asset-weighted subsample of separate account/mutual funds with twins. Separate account investors choose products that, once adjusted for structural differences, offer about the same underlying performance as those chosen by mutual fund investors. Their fixed income choices are better while their equity choices are marginally worse. Structural differences aside, their chosen products are, if anything, more expensive, so that in net terms their choices seem worse than those of mutual fund investors, especially in equities.

The failure of separate account investors to outperform mutual fund investors may come as a surprise. After all, separate account investors (being mostly institutional) are typically larger and more sophisticated than mutual fund investors and, as pointed out by Gârleanu

[3]Our estimates are smaller than those obtained by Gerakos, Linnainmaa, and Morse (2021) but equally significant. If we restrict our sample to match the sample period in Gerakos, Linnainmaa, and Morse (2021) the difference goes up, but so does the gap between twins.

and Pedersen (2018), we should expect such investors to have an advantage in manager search and selection. A possible explanation for this result may relate to a problem highlighted by Lakonishok, Shleifer, and Vishny (1992), that pension funds (which, by their sheer size, dominate the group of separate account investors) are characterized by multiple layers of agents, some of whom provide services which have more to do with justifying decisions than with enhancing performance (see also Jones and Martinez (2017), Hochberg and Rauh (2013), and Andonov, Hochberg, and Rauh (2018)).

Our paper is related to a growing number of studies looking at, or using, separate account composites. Most notable among them are Busse, Goyal, and Wahal (2010), the first large-scale study of performance persistence in separate accounts, Elton, Gruber, and Blake (2014), a comparison of separate accounts and mutual funds as investment vehicles, Gerakos, Linnainmaa, and Morse (2021), the most comprehensive performance study to date, or Jenkinson, Jones, and Martinez (2016) another recent study using separate account composites, this time to investigate investment consultants. Since our identification strategy involves separate-account/mutual-fund twins, our paper is related to other work on twinned portfolios, particularly Evans and Fahlenbrach (2012) on retail/institutional twins and subsequent studies by Chen, Chen, et al. (2017) and Rohleder, Tentesch, et al. (2020) on mutual fund/separate account twins.

More indirectly, our paper relates to the work of Edelen (1999) (as well as to the literature it spawned), which argues that fund managers provide a great deal of liquidity to investors and thus engage in a material volume of uninformed, liquidity-motivated trading, which likely harms fund returns. Owing to the commingling of assets and the net asset value rule, investors who redeem their mutual fund shares impose externalities on those who do not. Chen, Goldstein, and Jiang (2010) and Goldstein, Jiang, and Ng (2017) show that these

externalities increase the incentive for each individual investor to withdraw and amplifies the damage to the fund, particularly in illiquid funds.

The rest of the article is organized as follows. Section 4.2 provides institutional details about separate accounts and mutual funds. Section 4.3 explains the sample construction and shows descriptive statistics. Section 4.4 compares separate account composites and mutual funds aggregate performance. Section 4.5 explores the baseline differences between these two vehicles. Section 4.6 looks at the selection performance of separate account and mutual fund investors, and Section 4.7 concludes.

4.2 Separate accounts and mutual funds

Mutual funds pool assets for multiple investors, who each own shares (or "units") in the fund rather than having a direct holding in the fund's underlying assets, and they are open-ended, meaning that the number of shares in the fund can increase (decrease) as investors purchase (redeem) them. In the US, purchases and redemptions generally take place at a single price per share set at the end of each day at the net asset value per share of the fund (the "NAV rule").[4] Separate accounts, by contrast, are each managed for a single investor, who owns the underlying assets directly, typically through a custodian. Among practitioners, separate accounts are also called "segregated accounts". In the academic literature, although some studies include separate accounts in their analysis (e.g., Evans and Fahlenbrach (2012)), most tend to combine institutional portfolios that are not mutual funds under blanket names such as "funds" (Lakonishok, Shleifer, and Vishny (1992)), "products" (Busse, Goyal, and Wahal (2010)), or "asset manager funds" (Gerakos, Linnainmaa, and Morse (2021)).

[4]Since November 2018, "swing pricing", whereby a fund can adjust its net asset value per share for subscriptions and redemptions to reflect the costs to the fund of accommodating them (see Jin et al. (2022)), has been permitted in the US, but the practice is extremely rare.

Both mutual funds and separate accounts typically charge investors a management fee as a percentage of the value of the investment. In mutual funds this fee covers marketing costs, which separate accounts do not incur, as well as costs which are common to both types of vehicle but generally not included in separate account fees – notably custody costs.[5] Mutual funds charge the same fees to all investors in the same share class, while separate account fees are negotiable.[6] In both mutual funds and separate accounts, brokerage and other transaction costs incurred by the portfolio are passed onto investors through the performance of the portfolio rather than directly. When investors in mutual funds purchase or redeem shares, they usually do so in cash at the net asset value (under the NAV rule), although mutual funds may reserve the right to satisfy large redemptions in kind (or in specie), that is, by transferring a basket of the underlying assets to investors. Since the threshold to do so in the US is \$250,000 or 1% of the net asset value of the fund (see Agarwal et al. (2022)), redemptions in kind typically apply only to institutional investors.

In their reporting, managers of separate accounts adhere to the Global Investment Performance Standards (GIPS; for the latest edition, see CFA Institute (2020)). These require managers of several portfolios with a similar investment strategy to represent their performance in a single composite index, which gives the weighted average of the performance of its constituents. Investment managers are permitted temporarily to exclude an account from a composite index if that account experiences significant cash-flows in or out. This would occur if, for example, an account had received a cash subscription so large that the fund man-

[5]Management and custody fees are ongoing fees and do not include initial costs. Some mutual funds charge a "front-end load" on the initial subscription (and sometimes a "back-end load" on redemption). The costs of setting up a separate account typically include the fees of lawyers, auditors and, for foreign investments, tax consultants.

[6]Many mutual funds have only one single share class. When an asset manager offers retail and institutional twins, the creation of more than one share class allows them to charge different fees to each (see Evans and Fahlenbrach (2012)).

ager would need considerable time before investing the cash according to the fund's strategy. Practitioners report that such exclusions are not common because most inflows large enough to trigger an exclusion tend to come from institutional investors who use transition managers to ensure that inflows are already in the form stipulated by the fund manager (e.g., a portfolio of equities exactly matching the model strategy of the new manager) rather than cash.[7] Mutual fund performance data, on the other hand, are available at a more granular level (fund and share class) and at that level no exclusions are possible.[8]

Given their ability to scale, mutual funds allow small investors to achieve lower transaction costs and greater diversification than separate portfolios, while also enabling them to share liquidity risk (see Chordia (1996)). On the other hand, the commingling of assets and the NAV rule mean that mutual fund investors who redeem shares impose negative externalities on those who do not (see Edelen (1999)). There are various reasons for these externalities. First, to the extent that investors going into or out of mutual funds are guaranteed a price equivalent to the net asset value of their shares under the NAV rule, they do not bear the transaction costs incurred by the fund in adjusting the underlying portfolio, but bequeath them to continuing investors in the fund.[9] Secondly, to accommodate in- and outflows at short notice, the composition of a mutual fund portfolio is likely to deviate from that of the model portfolio, at least temporarily. Finally, to cater for unpredictable outflows,

[7]When institutional investors use a transition manager to switch portfolios, the transition manager transfers in kind the assets common to both portfolios (this part of the transition is called "retention") and liquidates the balance, investing the proceeds to create the target portfolio requested by the new manager. The costs of the transition are covered by the asset owner.

[8]Mutual fund performance data are available from various sources, with the Center for Research in Security Prices (CRSP) and Morningstar databases among the most widely used in the academic literature. On separate account composites, in addition to Morningstar, databases compiled by eVestment, Mercer, and Informa Financial Intelligence have been used for academic research.

[9]Mutual funds can pass these transaction costs onto those subscribing or redeeming shares in the fund by swing pricing (Jin et al. 2022), and they can discourage redemptions by temporarily prohibiting them ("gating") or by charging redemption fees (Cipriani et al. 2014).

mutual funds may hold a high level of cash, which can act as a drag on performance (for details, see Alexander, Cici, and Gibson (2007), Rakowski (2010), and Rohleder, Schulte, et al. (2018) as well as further literature cited in the last). These externalities can increase the incentive for each investor to redeem their shares in mutual funds (see Chen, Goldstein, and Jiang (2010)). This incentive is larger, and the costs associated with redemptions greater, in illiquid funds (Goldstein, Jiang, and Ng 2017). All these effects are likely to harm the performance of mutual funds.

Separate accounts do not offer small investors the scale benefits of mutual funds. On the other hand, being neither commingled nor subject to the NAV rule, they do not suffer the negative externalities mentioned above. Moreover, being separately managed, they can be customized along various dimensions, notably asset mix, style, tax structure, or (in the case of fixed income portfolios) duration. Separate accounts can also be structured to reflect an asset owner's individual environmental, social, and governance (ESG) preferences.[10] Reflecting the relative advantages of mutual funds and separate accounts, the former are predominantly retail products: at the end of 2020, 89% of the US mutual fund assets were held by households, with the remainder owned by institutional investors (IC 2021). By contrast, separate accounts are largely, if not exclusively, aimed at institutional investors.[11] There are, however, occasions when institutional investors opt for mutual funds rather than separate accounts, notably when the convenience of a mutual fund outweighs the benefits of customization. Mutual funds spare investors the frictional costs of setting up an account, e.g. dealing with custodians,

[10]When a particular customization results in a significantly different product or when that customization becomes common (e.g., to accommodate ESG preferences) it usually results in the creation of a separate composite.

[11]The retail/institutional distinction is based on the size of investment. Morningstar defines institutional mutual funds as those with minimum initial investment requirements of at least $100,000 or funds that designate themselves as institutional. As for separate accounts, even though some of them are owned by wealthy individuals, they are usually considered institutional products by virtue of their size.

lawyers, auditors, and, for foreign investments, market authorities, tax consultants, and regulators; a small institutional investor may find these frictional costs too great and invest only in mutual funds. But institutions of any size seeking to invest in a complex mix of assets and markets, especially if they wish to do so quickly, are likely to find mutual funds attractive because here the costs, delays, and risks of setting up a separate account themselves are often prohibitive. This is especially the case in emerging markets where local knowledge is paramount.

In the present paper we are interested in the impact of structural differences, whether in terms of liquidity provision, customization, or size, on the relative performance of mutual funds and separate accounts, and we use "twin" products to measure it. According to asset managers, a twin product is typically created when a mutual fund or separate account has performed well and the manager creates a near-replica to appeal to a different clientele; for example, a mutual fund might be replicated from a separate account that has consistently outperformed.[12] Not all twins comprise one mutual fund and one separate account: there are also mutual fund twins targeted at distinct retail and institutional clienteles. According to practitioners, deviations in performance between twins are small, reflecting the fact that they have the same portfolio manager and strategy and that there is a potential legal liability for performance differences (see Evans and Fahlenbrach (2012)). At the same time, practitioners report that identical performance is in practice impossible. Some portfolio managers are prepared to accept short-term differences in portfolio composition between twins if this will improve the performance of one of the twins without harming that of the other. For example, a manager may refrain from acting immediately on every small flow into or out of

[12]The fractions of separate accounts and mutual funds that are set up first in our twins sample are of similar magnitude, with 43% for separate accounts and 34% for mutual funds. For the other 23% of twins, both vehicles are set up at the same time.

a mutual fund but wait until cumulative net flows make it economical to trade in the fund's underlying securities. And even if some portfolio managers delegate to a dedicated implementation team the task of achieving maximum replication between twin products, the different flows experienced by one twin compared with the other make short-term performance gaps unavoidable.

4.3 Data description

We draw our data on mutual funds and separate accounts for the period 2000–2019 from Morningstar. For mutual funds, Morningstar collects general information from public sources such as regulatory filings and fund company documents. For performance-related information (including total returns, net asset values, dividends, and capital gains) and for details on underlying portfolio holdings, Morningstar receives daily updates from individual fund companies, transfer agents, and custodians.

Morningstar's separate account database requires more specialized information, which is gathered by surveys of fund management companies. The reporting unit for performance data is the "composite" of similarly managed separate portfolios. Investors in the same separate account composite may have slightly different portfolio holdings if different investors have customized account needs, tax considerations, and security preferences. Separate account managers calculate and report composite returns for each investment strategy they offer. Although separate accounts are not regulated and there is some discretion about when and how their data are reported, 90% of the separate accounts in Morningstar's database come from firms that are compliant with the Association for Investment Management and Research (AIMR), which requires consistent and standardized reporting.

Like other separate account data providers, Morningstar presents performance information gross of fees. To calculate net returns we merge Morningstar gross return data with data on separate account fees from eVestment, another data provider. The eVestment fees data contain a sliding fee schedule for each separate account composite, with fees in basis points for different mandate sizes from $10 million to $500 million; this allows us to calculate fees and net returns for mandates of different sizes.[13] We match separate accounts in Morningstar and eVestment using a hierarchical algorithm. First, we require asset management company names to match (supervised fuzzy matching). Secondly, conditional on this match, we use an ad hoc loss function algorithm that matches products based on historical returns, asset class, and (fuzzily matched) product name. We match 64% of the separate accounts in Morningstar with eVestment, which corresponds to a match of 76% of the (separate account–quarter) observations in our panel dataset.[14] For unmatched observations, we use asset-weighted average fees from the same Morningstar category–quarter. In contrast to mutual funds, in which all investors in a given fund pay the same fee, separate account fees are negotiated between asset manager and investor (sometimes mediated by a separate account program sponsor and/or advisor), so they may vary from one investor to another.

In this study we compare separate accounts and mutual funds on two Morningstar levels, the "strategy" and "category" levels. With rare exceptions, separate account strategies are coterminous with separate account composites, as required by GIPS reporting standards.[15]

[13]One advantage of using Morningstar, rather than eVestment, data for returns and assets under management is that Morningstar has broader mutual fund coverage, particularly for retail funds. Moreover, Morningstar assigns strategy IDs to separate accounts and mutual funds, which allows us to track separate account-mutual fund pairs (twins) following the same strategy.

[14]As a sanity check we compare eVestment's fees with implied fees (the difference between gross and net returns) in the Morningstar data. For matched observations, the median implied annualized Morningstar fee of 68 bps is within the eVestment fee schedule that ranges from 49 bps for a $500 million mandate size to 70 bps for a $10 million mandate size.

[15]See sections 3.A.1 to 3.A.5 in CFA Institute (2020). The few exceptions involve asset managers who do not follow GIPS. In the literature, separate account composites have frequently been referred to as funds,

Among mutual funds, a Morningstar strategy comprises one or more funds offering substantially identical pools of assets (often branded differently) sub-advised by the same manager.[16] Morningstar identifies strategies by surveying asset management companies, as well as by performing quantitative and qualitative analysis. To identify the strategies followed by separate accounts and mutual funds, we use Morningstar Strategy IDs. The Strategy ID is a Morningstar identifier that links investments that follow the same investment process and allows us to identify separate account-mutual fund twins.[17] Reflecting the precision of Morningstar Strategy IDs, the mean (median) return correlation between the separate account and mutual fund twins in our sample is 98.68% (99.88%).[18]

At a broader level, Morningstar classifies separate accounts and mutual funds by investment category based on their underlying portfolio holdings and other statistics for the previous three years. Category names are not specific to asset management companies whereas strategy names generally are. For example, the category "US Muni National Long" includes 98 different strategies in our dataset, each branded with the name of an asset management company. Following Gerakos, Linnainmaa, and Morse (2021), we restrict the sample to equity and fixed income composites/mutual funds that are offered in the US, and we exclude passive products.

We use Morningstar returns (gross and, after deducting eVestment fees, net) as the basis

products, or even strategies.

[16]If there is more than one share class within a mutual fund (e.g., one for retail and one for institutional investors), we aggregate share class information by averaging share class performance variables within each fund.

[17]When assigning strategy descriptors, Morningstar consider a wide range of factors, notably investment objective, investment decision-making process, portfolio management team, primary benchmark, portfolio characteristics, management approach, investment analysis process, security allocation approach. These are in addition to asset-class-specific factors, such as, for equity strategies, size, style, sector, and region.

[18]1,775 (94%) of the twins have a return correlation of greater than 95%, the lower bound for twin status in Evans and Fahlenbrach (2012). Our results are virtually unchanged if we exclude twins with return correlations lower than 95% from our sample.

for the computation of three different performance measures: excess returns over Morningstar category benchmarks, alphas with respect to Morningstar category benchmarks, and alphas with respect to a set of Vanguard index funds. For each category, we use the S&P Dow Jones benchmark listed in Morningstar for that category. If Morningstar does not list an S&P Dow Jones benchmark for a category, we use the most common prospectus benchmark among the mutual funds belonging to that category. Table 4.11 lists all Morningstar categories in our sample, and, for each category, the number of mutual funds and separate account composites as well as the benchmark we use. Table 4.12 lists the set of Vanguard index funds that we use as Vanguard benchmarks – two sets of benchmarks, one for equity funds/composites and one for fixed income funds/composites. Benchmark return data are from Eikon and Bloomberg. Performance and benchmark data are at the quarterly frequency (until recently the standard reporting frequency for separate accounts).

The overall sample comprises 11,153 separate account composites and 10,786 mutual funds. Of these, 97% of separate account composites and 99% of mutual funds have AUM information. Separate account composites represent 10,953 strategies in 70 different Morningstar categories, while mutual funds represent 5,706 strategies in 79 different Morningstar categories. There are 1,861 asset managers operating in the separate account segment and 1,139 asset managers operating in the mutual fund segment, many of these operating in both. These numbers illustrate the structure of the data. At the product level (the basic unit of analysis) we have separate account composites and mutual funds, the latter sometimes with multiple share classes. Among separate accounts, composites and strategies tend to match one to one (as required by GIPS standards), but asset management companies may offer more than one mutual fund following a given strategy (sometimes branded differently). Reflecting the fact that many companies manage multiple strategies in a given Morningstar

category, we have an average of 156 separate account strategies per category and of 72 mutual fund strategies per category.

In Table 4.1 we present descriptive statistics for the overall sample of separate accounts and mutual funds by year. Mean annual average and aggregate assets under management (AUM) are, respectively, 13% and 29% higher for separate accounts than for mutual funds. Over the sample period, mutual funds experienced a larger relative increase in the number of strategies represented and in mean annual average AUM. By the end of our sample period, assets under management in actively managed separate accounts offered in the US totaled $11 trillion and in mutual funds $10 trillion. Table 4.2 shows descriptive statistics for the overall sample by asset class. For both separate accounts and mutual funds, the split between equity and fixed income is roughly two-to-one both in the average number of composites/funds per year and in the average total AUM per year. Whilst average annual AUM per composite/fund are similar for equity vehicles, fixed income separate account composites tend to be larger than mutual funds.

4.4 Aggregate performance of separate account and mutual fund investors

We compare the aggregate performance of separate account investors with that of category-matched mutual fund investors on three measures: excess returns over Morningstar category benchmarks, one-factor alphas with respect to those benchmarks, and alphas with respect to a set of Vanguard index funds as in Berk and Binsbergen (2015). We report gross-of-fee and net-of-fee aggregate performance differences separately. For the net-of fee excess returns, our calculation of excess returns and alphas is based on three investor sizes: small investors

($10 million mandate), medium investors ($75 million mandate), and large investors ($500 million mandate).

To calculate excess returns over benchmarks, Morningstar category benchmark returns are subtracted from separate account composite or mutual fund returns. Table 4.11 lists all Morningstar categories and their benchmarks. We calculate both alpha variables by following the same estimation procedure but using different benchmark sets. We regress composite/fund excess returns (over the risk-free rate) on benchmark excess returns (over the risk-free rate), running a separate regression for each composite/fund. We collect the intercepts and residuals from these regressions and calculate quarterly alphas by adding the residual to the intercept for each composite/fund in each quarter. We use Morningstar category benchmark returns to calculate category benchmark alphas. We follow Berk and Binsbergen (2015) and estimate Vanguard benchmark alphas by using two sets of seven benchmarks, one set for equity and the other for fixed income composites/funds.[19] Table 4.12 lists the set of Vanguard index funds used for Vanguard alpha computations.

We aggregate excess returns and alphas of separate accounts and mutual funds in the following way. First, we compute asset-weighted excess returns and alphas at the Morningstar category-quarter level. We do this separately for separate accounts and mutual funds, using gross-of-fee and net-of-fee versions of the three performance measures mentioned above and assets invested in each vehicle type. For each investment category and quarter, we thus compute asset-weighted quarterly excess returns and alpha differences between separate accounts

[19]We follow the procedure described in the appendix of Berk and Binsbergen (2015) to account for the fact that some of the fixed income benchmarks do not go all the way back to the beginning of our sample period. We use a representative but smaller set of benchmarks because our time series is shorter and returns are measured at the quarterly frequency.

and mutual funds as follows:

$$\sum_{i=1}^{N} w_i^S \alpha_i^S - \sum_{i=1}^{N} w_i^M \alpha_i^M \tag{4.1}$$

where w_i^S is the percentage of separate account assets in the investment category invested in strategy i, α_i^S is the separate account excess return or alpha (gross or net) of strategy i, w_i^M is the percentage of mutual fund assets in the investment category invested in strategy i, and α_i^M is the mutual fund excess return or alpha (gross or net) of strategy i.[20] Next, we calculate quarterly asset-weighted excess returns and alphas by using investment category separate account assets under management as category weights, for both separate accounts and mutual funds. This results in a time series of quarterly separate account excess returns and alphas and a category-matched time series of quarterly mutual fund excess returns and alphas. As in Gerakos, Linnainmaa, and Morse (2021), this ensures that we are not comparing investments in different categories.

Table 4.3 shows differences in aggregate performance of separate account investments and category-matched mutual fund investments. We find some evidence of separate account investors obtaining higher gross-of-fees risk-adjusted returns than mutual fund investors, with annualized differences ranging from 14 to 24.4 bps. However, only the difference in gross alphas with respect to Vanguard benchmarks is statistically significant. When using net-of-fees risk-adjusted returns, we find strong evidence of separate account investors obtaining higher risk-adjusted returns than mutual fund investors. In this case, all differences are statistically significant, and annualized estimates range from 50.4 to 76.4 bps per year. Our risk-adjusted return differences are of comparable, albeit smaller, magnitudes to those reported by Gerakos, Linnainmaa, and Morse (2021) for their sample. Differences are higher

[20] We describe the process using strategy notation, but we could equivalently do it using composite-fund notation (as all composites/funds within a strategy are asset weighted).

for larger separate account investors, who typically pay lower fees (the difference between the net performance of large and small investors is in the order of 16 bps per year).[21]

4.5 Baseline differences between vehicles

To explore the impact on reported performance of structural differences between separate accounts and mutual funds we next compare the excess returns and alphas of separate account and mutual fund twins. We exploit the fact that investment management companies often subadvise more than one mutual fund and offer equivalent investment pools in other vehicles as well, notably separate accounts. These variants on one product have the same target portfolio but experience short-term deviations to accommodate different levels of customer flows or small differences reflecting the customization requests of separate account investors (see Section 4.2). By directly comparing separate account and mutual fund versions of the same product (twins), we can estimate the net impact on performance of the greater liquidity demands faced by mutual fund structures and the customization demands affecting separate accounts.

We can then decompose asset-weighted quarterly differences in excess returns and alphas between separate accounts and mutual funds into two parts: (i) the average structural outperformance or underperformance of separate accounts and (ii) a selection component. That is, within each investment category and quarter we decompose Equation 4.1 as follows:

$$\underbrace{\sum_{i=1}^{N}\frac{1}{N}\alpha_i^S-\sum_{i=1}^{N}\frac{1}{N}\alpha_i^M}_{Structural\ \ component}+\underbrace{\sum_{i=1}^{N}(w_i^S-\frac{1}{N})\alpha_i^S-\sum_{i=1}^{N}(w_i^M-\frac{1}{N})\alpha_i^M}_{Selection\ \ component} \tag{4.2}$$

[21] Because of composite reporting practices, separate account composites may also include some mutual fund investments. To the extent that this is the case, the differences reported here would be a lower bound for the difference between pure separate account investments and mutual fund investments.

where variables are defined as in Equation 4.1.

The equal-weighted difference among twins measures the structural gap in performance between vehicles, independently of whether investors take advantage of this gap. The fund selection component indicates the extent to which differences in Equation 4.1 reflect superior (or inferior) selection by the users of separate accounts, who are for the most part large institutional investors.

To analyze the first component of this decomposition we construct a sample of separate account-mutual fund twins comprising separate accounts and mutual funds that follow the same investment strategy. We use Morningstar Strategy IDs to identify these substantially identical pools of assets. Within each strategy and vehicle type, we average performance variables, if necessary. This results in quarterly performance time series for separate accounts and mutual funds for each strategy ID. We restrict the sample to those strategies and quarters that have both separate accounts and mutual fund versions (twins), and compute equal-weighted excess returns and alphas at the quarter level for each vehicle. By abstracting from investors' choices and keeping the underlying portfolio holdings of separate accounts and mutual funds constant (except for the small deviations to satisfy client triggered flows and customization requests), we isolate structural differences between these vehicles.

Table 4.4 presents descriptive statistics for the sample of twins. This sample shows patterns similar to those in the full sample: a higher fraction of strategies and average total assets in equities than in fixed income, and a larger difference in average annual AUM between separate accounts and mutual funds in fixed income than in equities. The twins sample includes 1,893 distinct strategies in 63 different Morningstar categories. These represent 17% (33%) of strategies and 90% (80%) of Morningstar categories for separate accounts (mutual funds) in the full sample. Average annual total AUM in the twins sample are 49% and 41%,

respectively, of the full sample totals for separate accounts and mutual funds, which means that some 45% of assets are invested in products that have a twin. Overall, the twins sample is therefore a sizeable subsample of the whole.

From this sample we obtain average performance gap estimates between separate accounts and their mutual funds twins, which we report in Table 4.5, using the same performance measures as in Table 4.3. When looking at gross excess returns and alphas, we find a statistically significant performance gap for all three performance measures, with annualized estimates ranging from 16.4 to 22.8 bps. These gaps are similar in magnitude to those in Table 4.3 and consistent with those reported by Chen, Chen, et al. (2017) for their sample. All net-of-fees performance gaps are also statistically significant, and annualized gaps range from 73.6 to 93.2 bps. The net performance gaps in the twins sample are similar to (or even larger than) those in Table 4.3. These results provide evidence of separate accounts outperforming their mutual fund twins. This structural outperformance may be the result of the different levels of customer flows experienced by separate accounts and mutual funds (or the way they deal with them), fee differences (for reasons of scale and range of services covered), or other reasons.[22]

4.5.1 Differences in gross performance

If the performance gap between separate account composites and mutual funds reflects client flows and the different ways in which these two vehicles deal with them, the liquidity of the underlying asset class would be expected to affect the magnitude of the gap. In particular, if

[22] Another potential factor contributing to differences in performance between separate accounts and their mutual fund twins is favoritism. Favoritism, if any, would also be captured by the structural component of the decomposition. However, the evidence on favoritism in the context of separate accounts and mutual funds is scarce (Chen, Chen, et al. (2017) find some evidence of favoritism while Del Guercio, Genç, and Tran (2018) do not) and the dearth of performance fees in separate accounts makes it less likely than in other settings (e.g., hedge funds).

mutual funds are subject to larger and more volatile customer flows than separate accounts – notably because in the latter, customer flows are usually handled by transition managers – this may partly explain their relative underperformance. Moreover, we might expect that underperformance by mutual funds to be larger in more illiquid asset classes.[23]

We explore this possibility by relating the gross performance gap between separate accounts and mutual funds to the liquidity of the underlying investment category. We proxy for the liquidity of the underlying investment category by using the lagged average turnover of the Morningstar investment category of the separate account-mutual fund twins. This measure, called latent liquidity, is advocated by Mahanti et al. (2008) for situations where data of the underlying holdings are scarce, as is the case with separate accounts.

Table 4.6 shows the average excess return and alpha gap between separate account and mutual fund twins as a function of the liquidity of the underlying assets. The results show that the performance gap between separate accounts and their mutual funds twins, on any of our three measures, increases significantly as the liquidity of the investment category decreases.

4.5.2 Fee differences

The previous analysis is on a gross-of-fees basis, which is the right metric to compare underlying portfolios. Including fees magnifies the performance differences. This is because, as shown in Table 4.7, mutual funds usually charge higher fees than separate accounts. Average

[23]The typical costs of transition between separate accounts vary by asset class, reflecting, first, different levels of market impact and, secondly, different levels of "retention" (the extent to which securities can be transferred in kind). According to a leading transition manager, for a $1 billion transition between two separate US large cap growth accounts, the expected round-trip cost of liquidating one entire portfolio and investing in another would be some 50 bps and retention would be around 50%, making the cost of transition 25 bps; for a similar-sized transition between two diversified emerging market accounts, the expected round-trip cost for total liquidation and reinvestment would be 100 bps and the retention rate 25%, making the cost of transition 75 bps.

headline fee differences between separate accounts and mutual funds range from 52 to 68 bps per year, with the fee difference increasing in separate account mandate size.

Mutual fund fees are higher for several reasons: their more significant regulatory requirements, the larger amounts usually invested through separate accounts (economies of scale and market power), and the different coverage of fees in each segment (what investors are paying for). For instance, custody fees are typically not included in separate account fees (as assets remain with the asset owner's custodian) but are included in mutual fund fees.[24]

Separate account fees are also usually negotiable. Approximately 80% of separate account fees in our sample are labelled as negotiable, so what we have is likely an upper bound for those fees. If actual fees are lower, the fee/expense difference between separate accounts and mutual funds would be higher than our estimates.

4.6 Selection performance of separate account investors

Results in the previous two sections (reported in Tables 4.3 and 4.5) suggest that the apparent outperformance of separate account investors over mutual fund investors is not so much the result of separate account investors' ability to select better products (or better asset managers), but a consequence of structural differences between these two investment vehicles. To explore this question in more detail, we compare the performance separate account investors would have achieved if they had invested, not in separate accounts, but in their hypothetical mutual fund twins with the performance of mutual fund investors. We also explore whether these results vary across the two main asset classes: equities and fixed income.

Not every separate account has a mutual fund twin, so we compute hypothetical mutual

[24]In our sample, approximately 90% of separate account fees do not include custody fees.

fund twin excess returns and alphas, α_i^{M*}, by subtracting performance gap estimates (from the twins sample), α_i^{Gap}, from separate account excess returns and alphas in the full sample.[25] Within each investment category, we then compute asset-weighted quarterly performance differences between the hypothetical mutual fund choices of separate account investors and the actual mutual fund choices of mutual fund investors as follows:

$$. \sum_{i=1}^{N} w_i^S \alpha_i^{M*} - \sum_{i=1}^{N} w_i^M \alpha_i^M \tag{4.3}$$

where $\alpha_i^{M*} = \alpha_i^S - \alpha_i^{Gap}$.[26]

In computing hypothetical mutual fund excess returns and alphas we make three alternative assumptions about the performance gap: i) the performance gap is constant across investment categories, ii) the performance gap is a linear function of investment category lagged liquidity, and iii) the performance gap is specific to the investment category. For the constant gap calculations, we subtract the performance gap estimates in Table 4.5 from separate account excess returns and alphas in the full sample to compute counterfactual excess returns and alphas. Under this assumption, estimates of Equation 4.3 must equal the difference between the overall performance difference between separate account and mutual fund investors in Table 4.3 and the baseline performance difference between separate account and mutual fund vehicles in Table 4.5. For the liquidity gap calculation, we use the performance gap and liquidity estimates from Table 4.6 to adjust separate account excess returns and alphas. We do so by subtracting from separate account excess returns or alphas, $\alpha_{i,q}^S$, the sum $a + b * \textit{Lagged Latent Liquidity}_{i,q}$, where a and b are the constant and slope coefficients,

[25]Thus, we assume that any mutual fund product would be available in separate account form, and vice versa, if there were demand for it.

[26]When $\alpha_i^{Gap} = \bar{\alpha}_i^S - \bar{\alpha}_i^M$, with $\bar{\alpha}_i^S = \sum_{i=1}^{N} \frac{1}{N} \alpha_i^S$ and $\bar{\alpha}_i^M = \sum_{i=1}^{N} \frac{1}{N} \alpha_i^M$, this is effectively the selection component of Equation 4.2.

respectively, estimated in Table 4.6 and q is the quarter in question.[27] For the category gap calculations, we re-run the average performance gap analysis in the twins sample for each Morningstar category separately and store the performance gap estimates. We then use these category specific gaps to adjust separate account excess returns and alphas.

Finally, we aggregate adjusted separate account and non-adjusted mutual fund returns following the same steps described in Section IV when computing aggregate performance differences. We do this for gross and net versions of all three performance measures.

The results from this counterfactual performance analysis, collected in Table 4.8, indicate that if we remove the average or expected outperformance of separate accounts over their mutual fund twins, separate account investors perform at the level of mutual fund investors gross of fees and slightly below them net of fees. These results hold under any of the three adjustment approaches and imply that, on average, separate account investors choose products that, once adjusted, are slightly more expensive than those chosen by mutual fund investors, for the same underlying gross performance.[28] These results also hold if we restrict the analysis to the set of strategies (and quarters) that have both separate accounts and mutual fund versions (the twins subsample). In this subsample, which comprises some 45% of the assets of the full sample and that should be free of potential concerns that separate accounts and mutual funds without a twin are fundamentally different from those with twins, the counterfactual performance of separate accounts investors is not higher, and if anything is lower, than that of mutual fund investors (see Table 4.13).

We next investigate whether results differ across equity and fixed income asset classes. We

[27]For products with missing values of lagged latent liquidity, we use the constant performance gap instead.

[28]This conclusion holds even if separate account composites include some mutual fund investments (i.e., even if they are a weighted average of pure separate account and mutual fund investments). In that case, the actual difference between pure separate account investments and mutual fund would be larger than reported before, but so would the structural performance gap between both vehicles.

therefore repeat the above analysis for equity and fixed income separate accounts and mutual funds separately. Table 4.9 shows actual (as in Table 4.3) and counterfactual (as in Table 4.8) differences in aggregate performance of separate account investors and mutual fund investors in these two asset classes. Consistent with the findings of Gerakos, Linnainmaa, and Morse (2021), the actual outperformance of separate account investors is higher in fixed income products. In their fixed income allocations separate account investors outperform mutual fund investors both gross and net of fees whereas in their equity allocations separate account investors significantly outperform mutual fund investors only on a net-of-fees basis. When removing average performance gaps, equity separate account investments show no significant difference from mutual fund investments gross of fees and significantly underperform net of fees. That is, in equities, separate account investors choose products that perform in line with those chosen by mutual fund investors before fees, but which on average carry larger fees than mutual fund investors' choices. In fixed income, separate account investments perform significantly better than mutual fund investments gross of fees but show no significant difference net of fees. In other words, when it comes to fixed income investments, separate account investors seem to choose better performing products than mutual fund investors, but the greater fees of these products wipe out the outperformance.

To better understand the differences between gross and net performance in equity and fixed income investments, we compare the differences between asset-weighted fees and equal-weighted fees for separate accounts and mutual funds in each investment category and asset class. This shows whether, on aggregate, separate account and mutual fund investors allocate capital to more or less expensive products relative to the average-fee products that are available to them in the same investment category. We compute this fee difference for each quarter and Morningstar category and pool the data. We then weight each observation

(category-quarter) based on the share of separate account AUMs in that quarter to ensure that the results are consistent with the time series procedure that we use in the rest of the paper. We do this for separate accounts and mutual funds separately, and for the difference between both vehicle types. The results of this estimation, collected in Table 4.10, show that separate account investors choose more expensive products (relative to the average-fee products that are available to them) compared to mutual fund investors, and that this difference is larger for equity products.

4.7 Conclusion

Separate accounts are an important means by which large investors access actively managed strategies. Mutual funds, by contrast, are largely aimed at small investors. A comparison between the performance of separate accounts and mutual funds is difficult because of differences in coverage, scale, and reporting practices between them. However, by studying mutual fund and separate account twins, that is, pairs of products with the same portfolio manager and the same investment strategy, we isolate the effect on performance of structural differences between these vehicles. We then control for these structural differences to see if there is any evidence of separate account investors outperforming mutual fund investors.

We document a significant performance gap between separate account and their mutual fund twins, with the gross reported excess returns and alphas of separate accounts on average 16 bps to 23 bps per year higher than the gross reported excess returns and alphas of their mutual fund twins. These numbers are likely to represent a close lower bound to the performance gap, since separate account composites sometimes include mutual funds. Importantly, not all this performance gap is real, as separate account reporting excludes some costs that

investors in them pay separately (like custody fees and, to some extent, transition costs).

Controlling for this structural gap in (reported) performance, we find that separate account investments perform at the same level as mutual fund investments, gross of fees, and slightly below them, net of fees. In other words, separate account investors choose products that, once adjusted for structural differences, have the same underlying performance as those chosen by mutual fund investors but are marginally more expensive. This lack of underlying outperformance may seem surprising, given that separate account investors are for the most part institutional and typically larger and more sophisticated than mutual fund investors, who are for the most part individuals. However, separate account investors are also a heterogeneous group. Their failure to outperform mutual fund investors at manager selection may reflect the extra layers of agency problems in some of the largest and most important among them, as noted by Lakonishok, Shleifer, and Vishny (1992). Those agency problems may neutralize the size and sophistication advantage in manager search and selection highlighted by Gârleanu and Pedersen (2018).

4.8 References

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4.9 Tables

Table 4.1

Separate Accounts and Mutual Funds - Descriptive Statistics by Year

This table presents descriptive statistics on the sample of separate accounts and mutual funds used in this study. It shows the number of separate account composites and mutual funds available each year (in the Morningstar database) between January 2000 and December 2019, the number of strategies these composites or funds represent, and the number of management companies running these strategies in each of these two universes. It also shows, for each of those years and universes, the number of composites/funds with assets under management information, the average assets under management for those composites/funds (in millions of US dollars) and the total assets invested in using either vehicle (in millions of US dollars).

	Separate Accounts						Mutual Funds					
	Number of Composites	Number of Strategies	Number of Asset Managers	Number of Composites with Assets Under Management Information	Average Assets Under Management per Composite (in $ millions)	Total Reported Assets Under Management (in $ millions)	Number of Funds	Number of Strategies	Number of Asset Managers	Number of Funds with Assets Under Management Information	Average Assets Under Management per Fund (in $ millions)	Total Reported Assets Under Management (in $ millions)
2000	4,463	4,379	1,104	3,464	1,021	3,538,415	5,456	2,436	567	5,222	739	3,861,481
2001	4,853	4,762	1,169	3,792	906	3,435,732	5,363	2,582	576	5,150	640	3,297,938
2002	5,265	5,167	1,221	4,153	852	3,538,922	5,241	2,681	575	5,079	614	3,118,519
2003	5,692	5,588	1,280	4,524	961	4,345,360	5,274	2,787	568	5,153	664	3,419,706
2004	6,166	6,050	1,336	5,045	1,117	5,632,781	5,260	2,882	569	5,164	799	4,127,948
2005	6,610	6,485	1,370	5,554	1,215	6,747,934	5,334	3,025	571	5,256	882	4,636,843
2006	6,829	6,689	1,373	5,930	1,372	8,135,335	5,553	3,197	579	5,502	980	5,393,958
2007	7,000	6,852	1,355	6,414	1,465	9,399,478	5,679	3,357	592	5,625	1,115	6,274,399
2008	7,092	6,945	1,321	6,606	1,198	7,915,377	5,760	3,541	607	5,714	916	5,235,392
2009	7,068	6,919	1,326	6,614	1,069	7,069,795	5,592	3,661	590	5,552	857	4,758,535
2010	7,180	7,028	1,322	6,743	1,228	8,279,139	5,327	3,802	597	5,290	1,111	5,878,719
2011	7,289	7,133	1,324	6,924	1,297	8,980,085	5,421	4,014	622	5,390	1,177	6,346,495
2012	7,373	7,215	1,313	7,079	1,356	9,595,945	5,441	4,250	639	5,405	1,274	6,885,417
2013	7,382	7,221	1,307	7,098	1,492	10,592,818	5,455	4,449	643	5,419	1,447	7,843,701
2014	7,351	7,182	1,287	7,059	1,609	11,355,531	5,574	4,645	663	5,542	1,570	8,700,533
2015	7,365	7,193	1,273	7,067	1,532	10,824,650	5,710	4,846	688	5,690	1,522	8,662,104
2016	7,292	7,115	1,242	6,934	1,553	10,766,046	5,684	4,966	675	5,666	1,520	8,611,369
2017	7,190	7,006	1,197	6,864	1,640	11,255,161	5,618	5,017	660	5,609	1,710	9,589,541
2018	6,943	6,756	1,115	6,620	1,709	11,311,393	5,526	5,008	648	5,522	1,801	9,946,715
2019	6,650	6,474	1,063	6,229	1,780	11,085,176	5,437	4,933	644	5,430	1,919	10,418,852
Mean	6,653	6,508	1,265	6,036	1,318	8,190,254	5,485	3,804	614	5,419	1,163	6,350,408

Table 4.2

Separate Accounts and Mutual Funds - Descriptive Statistics by Asset Class

This table shows the asset class distribution of the sample of separate accounts and mutual funds used in this study. For each of the two asset classes and vehicle types covered in our study it shows: the average number of composites/funds offered per year, the average number of Morningstar categories covered by those composites/funds, the average number of composites/funds with assets under management information per year, the average assets under management for those composites/funds (in millions of US dollars) per year, and the average total assets invested in the composites/funds (in millions of US dollars) per year.

	Average Number of Composites/Funds per Year		Average Number of Morningstar Categories Covered per Year		Average Number of Composites/Funds with Assets Under Management Information per Year		Average Assets Under Management per Composite/Fund and Year (in $ millions)		Average Total Reported Assets Under Management per Year (in $ millions)	
	Separate Accounts	Mutual Funds	Separate Accounts	Mutual Funds	Separate Accounts	Mutual Funds	Separate Accounts	Mutual Funds	Separate Accounts	Mutual Funds
Equity	4731	3617	39	41	4,296	3,566	1,231	1,206	5,402,915	4,326,020
Fixed Income	1922	1868	27	35	1,740	1,853	1,533	1,085	2,787,339	2,024,388

Table 4.3

Separate Accounts and Category Matched Mutual Funds – Asset-Weighted Excess Returns and Alphas

This table compares the performance of separate account investors with the performance of mutual fund investors. Performance is measured using excess returns over category benchmarks, one-factor alphas with respect to those same benchmarks, and alphas with respect to a set of Vanguard index funds as in Berk and van Binsbergen (2015). We compute asset-weighted separate account excess returns and alphas and compare them to asset-weighted mutual fund excess returns and alphas for the same Morningstar investment category. Investment category excess returns and alphas for these two vehicle types are then weighted by separate account assets under management in the category to obtain time series of quarterly separate account excess returns and alphas and a category-matched time series of quarterly mutual fund excess returns and alphas. Panel A reports gross of fee results and Panel B reports net of fee results. We compute three net returns that apply to investors of different sizes: small investors ($10 million mandate), medium investors ($75 million mandate), and large investors ($500 million mandate). The data cover the period from January 2000 through December 2019. *t*-statistics based on standard errors, robust to conditional heteroscedasticity and serial correlation as in Newey and West (1987), are reported in parentheses. Average quarterly differences are annualized by multiplying the quarterly figures times four and reported as basis points. ***, **, * denote statistical significance at 1%, 5%, and 10% levels, respectively.

	Panel A: Gross Performance		
	Gross Excess Returns	Gross Alphas (Category Benchmark)	Gross Alphas (Vanguard Benchmarks)
Separate Accounts	0.251***	0.358***	0.208***
	(2.65)	(4.40)	(4.53)
Matched Mutual Funds	0.215***	0.323***	0.147***
	(2.78)	(4.41)	(3.86)
SA-MF Difference	0.036	0.035	0.061**
	(0.91)	(1.19)	(2.30)
Annualized Difference (bps per year)	14.40	14.00	24.40

	Panel B: Net Performance								
	Net Excess Neturns			Net Alphas (Category Benchmark)			Net Alphas (Vanguard Benchmarks)		
	Small Investor	Medium Investor	Large Investor	Small Investor	Medium Investor	Large Investor	Small Investor	Medium Investor	Large Investor
Separate Accounts	0.102	0.118	0.142	0.210**	0.225***	0.249***	0.059	0.075	0.098**
	(1.08)	(1.24)	(1.49)	(2.58)	(2.76)	(3.05)	(1.29)	(1.63)	(2.14)
Matched Mutual Funds	-0.028	-0.028	-0.028	0.083	0.083	0.083	-0.093**	-0.093**	-0.093**
	(-0.38)	(-0.38)	(-0.38)	(1.15)	(1.15)	(1.15)	(-2.36)	(-2.36)	(-2.36)
SA-MF Difference	0.131***	0.147***	0.170***	0.126***	0.142***	0.166***	0.152***	0.167***	0.191***
	(3.27)	(3.63)	(4.21)	(4.01)	(4.46)	(5.18)	(5.32)	(5.80)	(6.59)
Annualized Difference (bps per year)	52.40	58.80	68.00	50.40	56.80	66.40	60.80	66.80	76.40

Table 4.4

Separate Account-Mutual Fund Twins Sample - Descriptive Statistics by Asset Class

This table shows the asset class distribution of the sample of separate account and mutual funds twins. For each of the two asset classes covered in our study it shows: the average number of strategies simultaneously offered in separate account and mutual fund form per year, the average number of Morningstar categories covered by those strategies, the average number of strategies with assets under management information for both investment vehicles per year, the average assets under management for those strategies (in millions of US dollars) in each vehicle per year, and the average total assets invested in the strategies (in millions of US dollars) per year using each vehicle.

	Average Number of Strategies per Year	Average Number of Morningstar Categories Covered per Year	Average Number of Strategies with Assets Under Management Information for Both Vehicles per Year	Average Assets Under Management per Strategy and Vehicle (in $ millions)		Average Total Reported Assets Under Management per Vehicle Type and Year (in $ millions)	
				Separate Accounts	Mutual Funds	Separate Accounts	Mutual Funds
Equity	1029	30	997	2,747	1,907	2,857,249	2,004,260
Fixed Income	307	23	298	3,874	2,191	1,248,165	741,003

Table 4.5

Separate Account-Mutual Fund Twins - Baseline Performance Differences

This table shows the average performance difference between separate accounts and mutual funds following the same strategy (twins). These twins are substantially identical pools of assets that follow the same investment process. Performance differences are equal-weighted and measured using excess returns over category benchmarks, one-factor alphas with respect to those same benchmarks, and alphas with respect to a set of Vanguard index funds as in Berk and van Binsbergen (2015). Panel A reports gross of fee differences and Panel B reports net of fee differences. We compute three net returns that apply to investors of different sizes: small investors ($10 million mandate), medium investors ($75 million mandate), and large investors ($500 million mandate). The data cover the period from January 2000 through December 2019. *t*-statistics based on standard errors, robust to conditional heteroscedasticity and serial correlation as in Newey and West (1987), are reported in parentheses. Average quarterly differences are annualized by multiplying the quarterly figures times four and reported as basis points. ***, **, * denote statistical significance at 1%, 5%, and 10% levels, respectively.

	Panel A: Gross Performance Difference		
	Gross Excess Returns	Gross Alphas (Category Benchmark)	Gross Alphas (Vanguard Benchmarks)
SA-MF Difference	0.041***	0.056***	0.057***
	(2.82)	(4.80)	(5.65)
Annualized Difference (bps per year)	16.40	22.40	22.80

	Panel B: Net Performance Difference								
	Net Excess Neturns			Net Alphas (Category Benchmark)			Net Alphas (Vanguard Benchmarks)		
	Small Investor	Medium Investor	Large Investor	Small Investor	Medium Investor	Large Investor	Small Investor	Medium Investor	Large Investor
SA-MF Difference	0.184***	0.201***	0.224***	0.191***	0.208***	0.231***	0.193***	0.210***	0.233***
	(10.91)	(11.94)	(13.34)	(12.88)	(14.05)	(15.64)	(18.14)	(19.76)	(21.95)
Annualized Difference (bps per year)	73.60	80.40	89.60	76.40	83.20	92.40	77.20	84.00	93.20

Table 4.6

Separate Account-Mutual Fund Twins Performance Differences as a Function of Liquidity

This table shows the average performance difference between separate account and mutual fund twins as a function of the liquidity of underlying assets. The dependent variable is the difference in quarterly gross performance between the separate account and mutual fund vehicles. Quarterly performance differences are measured using excess returns over category benchmarks, one-factor alphas with respect to those same benchmarks, and alphas with respect to a set of Vanguard index funds as in Berk and van Binsbergen (2015). We regress these performance differences on Mahanti, Nashikkar, Subrahmanyam, Chacko, and Mallik's (2008) lagged latent liquidity measure (lagged average turnover of the Morningstar category the fund/product belongs to). The unit of analysis is the pair-quarter. The data cover the period from January 2000 through December 2019. *t*-statistics based on standard errors, robust to conditional heteroscedasticity and cross-sectional and temporal correlation as in Driscoll and Kraay (1998), are reported in parentheses. ***, **, * denote statistical significance at 1%, 5%, and 10% levels, respectively.

	Gross Returns	Gross Alphas (Strategy Benchmark)	Gross Alphas (Vanguard Benchmarks)
Lagged Latent Liquidity	-0.023***	-0.032***	-0.042***
	(-3.40)	(-4.40)	(-5.40)
Constant	0.049***	0.073***	0.087***
	(3.16)	(4.96)	(5.82)

Table 4.7

Separate Account-Mutual Fund Twins Headline Fees Difference

This table shows the mean and median fee difference for separate accounts and their twin mutual funds. Mean and median headline fees, in basis points, are shown for different investment mandate sizes. *t*-statistics from paired *t*-tests for the differences in mean headline fees between the two vehicle types for each investment mandate size are reported in parenthesis. ***, **, * denote statistical significance at 1%, 5%, and 10% levels, respectively.

	Separate Accounts		Mutual Funds		
Investment Mandate Size (in USD million)	Mean	Median	Mean	Median	Difference of Means
10 USD Million (Small Investor)	69	73	121	121	-52 (-71.65)
25 USD Million	68	70	121	121	-53 (-74.49)
50 USD Million	65	66	121	121	-56 (-78.34)
75 USD Million (Medium Investor)	62	63	121	121	-59 (-81.73)
100 USD Million	61	61	121	121	-60 (-82.98)
200 USD Million	57	56	121	121	-64 (-87.54)
500 USD Million (Large Investor)	53	52	121	121	-68 (-90.32)
N	1,446	1,446	1,446	1,446	1,446

Table 4.8

Separate Accounts and Category Matched Mutual Funds - Counterfactual Performance Differences

This table compares the performance separate account investors would have achieved had they invested in hypothetical mutual fund twins with the performance of mutual fund investors. Performance is measured using excess returns over category benchmarks, one-factor alphas with respect to those same benchmarks, and alphas with respect to a set of Vanguard index funds as in Berk and van Binsbergen (2015). Hypothetical mutual fund twins are built by subtracting from separate accounts the average return or alpha difference between separate accounts and their twin mutual funds (in the twin sample), a difference that is a linear function of latent liquidity, or a category-specific average difference. Panel A reports gross of fee results and Panel B reports net of fee results. We compute three net returns that apply to investors of different sizes: small investors ($10 million mandate), medium investors ($75 million mandate), and large investors ($500 million mandate). The data cover the period from January 2000 through December 2019. *t*-statistics based on standard errors, robust to conditional heteroscedasticity and serial correlation as in Newey and West (1987), are reported in parentheses. Average quarterly differences are annualized by multiplying the quarterly figures times four and reported as basis points. ***, **, * denote statistical significance at 1%, 5%, and 10% levels, respectively.

	Panel A: Gross Counterfactual Performance Differences		
	Gross Excess Returns	Gross Alphas (Category Benchmark)	Gross Alphas (Vanguard Benchmarks)
CSA-MF Difference (Constant Gap)	-0.006	-0.020	0.004
	(-0.15)	(-0.68)	(0.15)
Annualized Difference (bps per year)	-2.40	-8.00	1.60
CSA-MF Difference (Liquidity-Based Gap)	0.003	-0.013	0.007
	(0.09)	(-0.43)	(0.26)
Annualized Difference (bps per year)	1.20	-5.20	2.80
CSA-MF Difference (Category-Specific Gap)	-0.021	-0.033	-0.007
	(-0.55)	(-1.13)	(-0.25)
Annualized Difference (bps per year)	-8.40	-13.20	-2.80

	Panel B: Net Counterfatual Performance Differences								
	Net Excess Neturns			Net Alphas (Category Benchmark)			Net Alphas (Vanguard Benchmarks)		
	Small Investor	Medium Investor	Large Investor	Small Investor	Medium Investor	Large Investor	Small Investor	Medium Investor	Large Investor
CSA-MF Difference (Constant Gap)	-0.053	-0.054	-0.054	-0.065**	-0.066**	-0.066**	-0.041	-0.043	-0.042
	(-1.32)	(-1.34)	(-1.33)	(-2.06)	(-2.08)	(-2.06)	(-1.45)	(-1.48)	(-1.46)
Annualized Difference (bps per year)	-21.20	-21.60	-21.60	-26.00	-26.40	-26.40	-16.40	-17.20	-16.80
CSA-MF Difference (Liquidity-Based Gap)	-0.044	-0.045	-0.045	-0.058*	-0.059*	-0.058*	-0.039	-0.040	-0.040
	(-1.11)	(-1.13)	(-1.11)	(-1.82)	(-1.84)	(-1.82)	(-1.35)	(-1.38)	(-1.35)
Annualized Difference (bps per year)	-17.60	-18.00	-18.00	-23.20	-23.60	-23.20	-15.60	-16.00	-16.00
CSA-MF Difference (Category-Specific Gap)	-0.070*	-0.071*	-0.071*	-0.081**	-0.082**	-0.081**	-0.055*	-0.056*	-0.056*
	(-1.77)	(-1.77)	(-1.76)	(-2.60)	(-2.59)	(-2.58)	(-1.97)	(-1.97)	(-1.96)
Annualized Difference (bps per year)	-28.00	-28.40	-28.40	-32.40	-32.80	-32.40	-22.00	-22.40	-22.40

Table 4.9

Separate Accounts and Category Matched Mutual Funds - Actual and Counterfactual Performance Differences in Equity and Fixed Income

This table compares the actual performance of separate account investors, and the performance separate account investors would have achieved had they invested in hypothetical mutual fund twins, with the performance of mutual fund investors. Performance is measured using excess returns over category benchmarks, one-factor alphas with respect to those same benchmarks, and alphas with respect to a set of Vanguard index funds as in Berk and van Binsbergen (2015). Hypothetical mutual fund twins are built by subtracting from separate accounts the average return or alpha difference between separate accounts and their twin mutual funds (in the twin sample), a difference that is a linear function of latent liquidity, or a category-specific average difference. Results are shown separately for equity and fixed income products. Net of fee results assume a $75 million mandate (medium investors). The data cover the period from January 2000 through December 2019. *t*-statistics based on standard errors, robust to conditional heteroscedasticity and serial correlation as in Newey and West (1987), are reported in parentheses. Average quarterly differences are annualized by multiplying the quarterly figures times four and reported as basis points. ***, **, * denote statistical significance at 1%, 5%, and 10% levels, respectively.

	Panel A: Equity					
	Gross Excess Returns	Gross Alphas (Category Benchmark)	Gross Alphas (Vanguard Benchmarks)	Net Excess Neturns	Net Alphas (Category Benchmark)	Net Alphas (Vanguard Benchmarks)
SA-MF Difference	0.026	0.025	0.053	0.134***	0.128***	0.155***
	(0.57)	(0.72)	(1.55)	(2.80)	(3.37)	(4.19)
Annualized Difference (bps per year)	10.40	10.00	21.20	53.60	51.20	62.00
CSA-MF Difference (Constant Gap)	-0.037	-0.056	-0.027	-0.093*	-0.109***	-0.081**
	(-0.81)	(-1.59)	(-0.79)	(-1.94)	(-2.87)	(-2.18)
Annualized Difference (bps per year)	-14.80	-22.40	-10.80	-37.20	-43.60	-32.40
CSA-MF Difference (Liquidity-Based Gap)	-0.022	-0.044	-0.024	-0.077*	-0.095**	-0.077**
	(-0.50)	(-1.27)	(-0.71)	(-1.68)	(-2.60)	(-2.11)
Annualized Difference (bps per year)	-8.80	-17.60	-9.60	-30.80	-38.00	-30.80
CSA-MF Difference (Category-Specific Gap)	-0.067	-0.084**	-0.050	-0.126**	-0.141***	-0.109***
	(-1.44)	(-2.38)	(-1.49)	(-2.61)	(-3.69)	(-2.95)
Annualized Difference (bps per year)	-26.80	-33.60	-20.00	-50.40	-56.40	-43.60
	Panel B: Fixed Income					
	Gross Excess Returns	Gross Alphas (Category Benchmark)	Gross Alphas (Vanguard Benchmarks)	Net Excess Neturns	Net Alphas (Category Benchmark)	Net Alphas (Vanguard Benchmarks)
SA-MF Difference	0.061	0.063*	0.076**	0.178***	0.177***	0.190***
	(1.40)	(1.71)	(2.00)	(4.07)	(4.83)	(5.10)
Annualized Difference (bps per year)	24.40	25.20	30.40	71.20	70.80	76.00
CSA-MF Difference (Constant Gap)	0.077*	0.076**	0.082**	0.047	0.045	0.053
	(1.76)	(2.07)	(2.15)	(1.07)	(1.23)	(1.42)
Annualized Difference (bps per year)	30.80	30.40	32.80	18.80	18.00	21.20
CSA-MF Difference (Liquidity-Based Gap)	0.078*	0.076**	0.080**	0.049	0.046	0.052
	(1.79)	(2.08)	(2.12)	(1.11)	(1.26)	(1.40)
Annualized Difference (bps per year)	31.20	30.40	32.00	19.60	18.40	20.80
CSA-MF Difference (Category-Specific Gap)	0.085*	0.086**	0.089**	0.057	0.057	0.062*
	(1.92)	(2.28)	(2.32)	(1.30)	(1.54)	(1.67)
Annualized Difference (bps per year)	34.00	34.40	35.60	22.80	22.80	24.80

Table 4.10

Differences between Asset-Weighted and Equal-Weighted Fees for Separate Account and Mutual Fund Investors

This table shows the average difference between asset-weighted fees and equal weighted fees at the investment category level for separate account and mutual fund investors. We compute the difference between asset-weighted fees and the equal-weighted fees for each quarter and investment category and run a pooled time series-cross section regression with these observations. In these regressions each observation is weighted based on the separate account asset share that quarter so as to replicate the time series procedure used in the rest of the paper. We do this for separate accounts and mutual funds separately as well as for the difference between the two. We compute fees that apply to investors of different sizes: small investors ($10 million mandate), medium investors ($75 million mandate), and large investors ($500 million mandate). Results are separately shown for the full sample as well as for the sample of separate account-mutual fund twins. The data cover the period from January 2000 through December 2019. *t*-statistics based on standard errors clustered at the investment category level are reported in parentheses. ***, **, * denote statistical significance at 1%, 5%, and 10% levels, respectively.

	Full Sample			Twins Sample		
	Small Investor	Medium Investor	Large Investor	Small Investor	Medium Investor	Large Investor
<u>All Asset Classes</u>						
Separate Accounts	-2.224***	-1.302***	-1.968***	-0.425	-0.216	-0.567
	(-4.69)	(-3.30)	(-4.74)	(-0.95)	(-0.58)	(-1.29)
Mutual Funds	-19.560***	-19.560***	-19.560***	-8.376***	-8.376***	-8.376***
	(-9.54)	(-9.54)	(-9.54)	(-4.00)	(-4.00)	(-4.00)
SA-MF Difference	17.335***	18.258***	17.592***	7.951***	8.160***	7.809***
	(9.22)	(9.84)	(9.76)	(4.05)	(3.68)	(3.52)
<u>Equity</u>						
Separate Accounts	-2.540***	-1.615***	-2.486***	-0.149	-0.052	-0.243
	(-4.14)	(-3.24)	(-5.49)	(-0.27)	(-0.11)	(-0.47)
Mutual Funds	-24.239***	-24.239***	-24.239***	-9.685***	-9.685***	-9.685***
	(-22.89)	(-22.89)	(-22.89)	(-3.25)	(-3.25)	(-3.25)
SA-MF Difference	21.699***	22.624***	21.754***	9.536***	9.633***	9.442***
	(20.49)	(23.83)	(23.05)	(3.36)	(2.96)	(2.88)
<u>Fixed Income</u>						
Separate Accounts	-1.418***	-0.461**	-0.703**	-0.969**	-0.575	-1.223**
	(-4.54)	(-2.43)	(-2.47)	(-2.34)	(-1.49)	(-2.54)
Mutual Funds	-8.901***	-8.901***	-8.901***	-6.054**	-6.054**	-6.054**
	(-4.05)	(-4.05)	(-4.05)	(-2.07)	(-2.07)	(-2.07)
SA-MF Difference	7.483***	8.440***	8.198***	5.086*	5.479**	4.832*
	(3.50)	(3.83)	(3.56)	(1.95)	(2.10)	(1.91)

4.10 Appendix

Table 4.11

Morningstar Categories and Benchmarks

This table lists all Morningstar categories in our sample. For each category, it reports the number of mutual funds and separate account composites as well as the benchmark chosen for that category.

Morningstar Category	Number of Mutual Funds	Number of Separate Account Composites	Benchmark Name
Equity			
US Fund China Region	36	8	S&P China BMI Total Return
US Fund Communications	21	0	S&P Composite 1500 Telecommunication Services (Sector) TR
US Fund Consumer Cyclical	12	1	S&P 1500 Cons Discretionary TR
US Fund Consumer Defensive	4	1	S&P 1500 Cons Staples TR
US Fund Diversified Emerging Mkts	364	334	S&P Emerging BMI (US Dollar) Total Return
US Fund Diversified Pacific/Asia	25	20	S&P Asia Pacific BMI Total Return
US Fund Energy Limited Partnership	36	63	Dow Jones US Pipelines TSM
US Fund Equity Energy	29	24	S&P 1500 ES Energy Total Return
US Fund Equity Precious Metals	29	4	FTSE Goldmines Total Return
US Fund Europe Stock	71	93	MSCI Europe Net Total Return USD
US Fund Financial	54	17	S&P 1500 ES Financials Total Return
US Fund Foreign Large Blend	357	338	MSCI ACWI ex USA Large Cap Gross Total Return USD
US Fund Foreign Large Growth	201	206	S&P Developed Ex US BMI Growth TR USD
US Fund Foreign Large Value	152	205	S&P Developed Ex US Small Value
US Fund Foreign Small/Mid Blend	45	28	S&P Developed Ex US BMI Mid Cap Total Return
US Fund Foreign Small/Mid Growth	59	68	S&P Developed Ex US BMI Mid Cap Total Return
US Fund Foreign Small/Mid Value	41	48	S&P Developed Ex US SmallCap (US Dollar) Total Return
US Fund Global Real Estate	88	81	S&P Global REIT Total Return
US Fund Health	79	16	S&P 1500 Health Care TR
US Fund India Equity	14	2	FTSE India
US Fund Industrials	10	2	S&P 1500 Industrials TR
US Fund Infrastructure	32	17	Dow Jones Brookfield Global Infrastructure Total Return
US Fund Japan Stock	34	48	S&P Japan BMI Total Return
US Fund Large Blend	906	1,146	S&P 500 Total Return
US Fund Large Growth	926	1,051	Russell 1000 EOD Growth Total Return
US Fund Large Value	721	897	Russell 1000 EOD Value Total Return
US Fund Latin America Stock	22	11	S&P Latin America BMI Total Return
US Fund Mid-Cap Blend	234	329	S&P 400 Total Return
US Fund Mid-Cap Growth	442	528	Russell MidCap Growth EOD Total Return
US Fund Mid-Cap Value	202	260	Russell MidCap Value EOD Total Return
US Fund Miscellaneous Region	18	13	S&P Global BMI TR USD
US Fund Miscellaneous Sector	6	17	S&P 500 TR USD
US Fund Natural Resources	60	24	FTSE All World Basic Materials Total Return USD
US Fund Pacific/Asia ex-Japan Stk	80	44	S&P Asia Pacific Ex Japan BMI Total Return USD
US Fund Real Estate	119	91	FTSE Nareit Equity REIT Total Return
US Fund Small Blend	346	418	Dow Jones US SmallCap Total Stock Market
US Fund Small Growth	440	534	S&P SmallCap 600 Growth Total Return
US Fund Small Value	219	279	MSCI North America Small Cap Cap Gross Total Return USD
US Fund Technology	175	25	Dow Jones US Technology Total Return
US Fund Utilities	26	9	S&P 1500 Utilities Total Return
US Fund World Large Stock	496	661	FTSE All World Total Return

Morningstar Category	Number of Mutual Funds	Number of Separate Account Composites	Benchmark Name
Fixed Income			
US Fund Bank Loan	73	45	S&P LSTA Leveraged Loan Total Return
US Fund Corporate Bond	57	132	S&P 500 Investment Grade Corporate Bond Total Return
US Fund Emerging Markets Bond	113	112	Bloomberg Barclays Emerging Market USD Aggregate Total Return
US Fund High Yield Bond	320	280	S&P 500 High Yield Corporate Bond
US Fund High Yield Muni	58	10	S&P Municipal Bond High Yield
US Fund Inflation-Protected Bond	65	42	Bloomberg Barclays Global Inflation-Linked: U.S. TIPS TR Unhedged
US Fund Intermediate Core Bond	426	755	Bloomberg Barclays US Aggregate Total Return Value Unhedged USD
US Fund Intermediate Core-Plus Bond	162	76	Bloomberg Barclays US Aggregate Total Return Value Unhedged USD
US Fund Intermediate Government	148	64	Bloomberg Barclays US MBS Total Return Value Unhedged USD
US Fund Long Government	21	27	S&P/BGCantor US Treasury Bond Total Return USD
US Fund Long-Term Bond	34	122	Bloomberg Barclays US Government Credit Long Total Return
US Fund Multisector Bond	155	159	Bloomberg Barclays Multiverse Total Return USD
US Fund Muni California Intermediate	41	9	S&P Municipal Bond California
US Fund Muni California Long	57	0	S&P Municipal Bond California
US Fund Muni Massachusetts	24	0	S&P Municipal Bond Massachusetts TR
US Fund Muni Minnesota	24	0	S&P Municipal Bond Minnesota TR
US Fund Muni National Interm	161	235	S&P Municipal Bond Total Return
US Fund Muni National Long	126	54	S&P Municipal Bond Total Return
US Fund Muni National Short	104	147	S&P Municipal Bond Short
US Fund Muni New Jersey	25	0	S&P Municipal Bond New Jersey TR
US Fund Muni New York Intermediate	26	3	S&P Municipal Bond New York TR
US Fund Muni New York Long	45	0	S&P Municipal Bond New York TR
US Fund Muni Ohio	25	0	S&P Municipal Bond Ohio TR
US Fund Muni Pennsylvania	30	0	S&P Municipal Bond Pennsylvania TR
US Fund Muni Single State Interm	159	5	S&P Municipal Bond TR
US Fund Muni Single State Long	180	0	S&P Municipal Bond TR
US Fund Muni Single State Short	23	3	S&P Municipal Bond Short TR
US Fund Muni Target Maturity	4	0	S&P Municipal Bond TR
US Fund Nontraditional Bond	127	48	Bloomberg Barclays Multiverse Total Return USD
US Fund Preferred Stock	16	29	S&P Preferred Stock Total Return
US Fund Short Government	103	67	Bloomberg Barclays 1-3 Yr Gov Total Return Value Unhedged USD
US Fund Short-Term Bond	243	364	Bloomberg Barclays 1-3 Yr Credit Total Return Value Unhedged US
US Fund Ultrashort Bond	117	109	Bloomberg Barclays US Treasury Bellwethers 6 Months TR Unhedged
US Fund World Bond	159	170	S&P Global Developed Sovereign Bond
US Fund World Bond-USD Hedged	28	4	Bloomberg Barclays Global Aggregate Total Return Hedged

Table 4.12

Benchmark Vanguard Index Funds

This table lists the set of Vanguard index funds that we use for alpha computations. For each fund, it reports the first and last quarters for which we have returns.

Vanguard Index Fund	Start Date	End Date
Equity		
Emerging Mkts Stock Index Investor	2000q1	2019q4
Small Cap Index Investor	2000q1	2019q4
Value Index Investor	2000q1	2019q4
European Stock Index Investor	2000q1	2019q4
Pacific Stock Index Investor	2000q1	2019q4
500 Index Investor	2000q1	2019q4
Mid Cap Index Investor	2000q1	2019q4
Fixed Income		
Emerging Mkts Govt Bd Index Admiral	2016q1	2019q4
Total Intl Bd Index Investor	2016q1	2019q4
Short-Term Bond Index Investor	2000q1	2019q4
Long-Term Investment-Grade Investor	2000q1	2019q4
High-Yield Corporate Investor	2000q1	2019q4
Interm-Term Tx-Ex Investor	2000q1	2019q4
Long-Term Treasury Investor	2000q1	2019q4

Table 4.13

Separate Accounts and Category Matched Mutual Funds - Counterfactual Performance Differences in the Twins Sample

This table compares the performance separate account investors would have achieved had they invested in hypothetical mutual fund twins with the performance of mutual fund investors. It does so using only those strategies and quarters that have both separate accounts and mutual fund versions (the twins sample). Hypothetical mutual fund twins are built by subtracting from separate accounts the average return or alpha difference between separate accounts and their twin mutual funds (in the twin sample), a difference that is a linear function of latent liquidity, or a category-specific average difference. Panel A reports gross of fee results and Panel B reports net of fee results. We compute three net returns that apply to investors of different sizes: small investors ($10 million mandate), medium investors ($75 million mandate), and large investors ($500 million mandate). The data cover the period from January 2000 through December 2019. *t*-statistics based on standard errors, robust to conditional heteroscedasticity and serial correlation as in Newey and West (1987), are reported in parentheses. Average quarterly differences are annualized by multiplying the quarterly figures times four and reported as basis points. ***, **, * denote statistical significance at 1%, 5%, and 10% levels, respectively.

	Panel A: Gross Counterfactual Performance Differences		
	Gross Excess Returns	Gross Alphas (Category Benchmark)	Gross Alphas (Vanguard Benchmarks)
CSA-MF Difference (Constant Gap)	-0.031*	-0.049***	-0.034*
	(-1.70)	(-2.65)	(-1.67)
Annualized Difference (bps per year)	-12.40	-19.60	-13.60
CSA-MF Difference (Liquidity-Based Gap)	-0.020	-0.039**	-0.028
	(-1.12)	(-2.14)	(-1.37)
Annualized Difference (bps per year)	-0.80	-15.60	-11.20
CSA-MF Difference (Category-Specific Gap)	-0.047**	-0.065***	-0.046**
	(-2.62)	(-3.56)	(-2.29)
Annualized Difference (bps per year)	-18.80	-26.00	-18.40

	Panel B: Net Counterfatual Performance Differences								
	Net Excess Neturns			Net Alphas (Category Benchmark)			Net Alphas (Vanguard Benchmarks)		
	Small Investor	Medium Investor	Large Investor	Small Investor	Medium Investor	Large Investor	Small Investor	Medium Investor	Large Investor
CSA-MF Difference (Constant Gap)	-0.059***	-0.060***	-0.058***	-0.075***	-0.076***	-0.074***	-0.061***	-0.062***	-0.061***
	(-3.10)	(-3.11)	(-3.00)	(-3.72)	(-3.72)	(-3.61)	(-2.88)	(-2.90)	(-2.80)
Annualized Difference (bps per year)	-23.60	-24.00	-23.20	-30.00	-30.40	-29.60	-24.40	-24.80	-24.40
CSA-MF Difference (Liquidity-Based Gap)	-0.049**	-0.050**	-0.048**	-0.066***	-0.066***	-0.064***	-0.056**	-0.057**	-0.055**
	(-2.62)	(-2.59)	(-2.46)	(-3.28)	(-3.25)	(-3.12)	(-2.64)	(-2.62)	(-2.50)
Annualized Difference (bps per year)	-19.60	-20.00	-19.20	-26.40	-26.40	-25.60	-22.40	-22.80	-22.00
CSA-MF Difference (Category-Specific Gap)	-0.076***	-0.077***	-0.076***	-0.093***	-0.094***	-0.092***	-0.076***	-0.076***	-0.075***
	(-4.02)	(-3.99)	(-3.89)	(-4.64)	(-4.61)	(-4.51)	(-3.64)	(-3.63)	(-3.54)
Annualized Difference (bps per year)	-30.40	-30.80	-30.40	-37.20	-37.60	-36.80	-30.40	-30.40	-30.00

Chapter 5

Conclusion

This thesis contributes to our understanding of private markets by investigating questions in entrepreneurial finance and asset management. Chapter 2 examines if US venture capitalists have a distinct investment style that is more tolerant of financial losses when investing abroad. Using Swedish data on all private firms for over two decades, it finds that USVCs already have a higher tolerance for losses at the investment stage and that they help their portfolio companies to raise more follow-on VC funding, which allows their portfolio companies to sustain a higher level of losses. USVC-backed companies are also more likely to exit successfully, which implies that their higher level of losses is not driven by a higher tolerance for risk of USVCs but rather by deeper pockets which allow USVCs to sustain losses for longer. Finally, companies backed by USVCs rely less on overdraft facilities and bank loans, consistent with the notion that equity is more suitable than debt for loss-making companies. Chapter 2 thus highlights a novel benefit of encouraging USVCs to invest locally, sheds light on why most unicorn start-ups tends to be USVC backed and offers a potential explanation for why entrepreneurial ecosystems outside of the US has so far generated so few unicorns.

Chapter 3 examines whether outside expertise of directors matters for start-up company

performance and growth. It uses shocks to the attention of directors who sit on multiple boards simultaneously for identification. Chapter 3 finds that a company's fraction of directors who are distracted leads to declines in ROA and sales growth, and that companies suffer to a greater extent when more experienced directors are distracted. Effect sizes amount to 8% and 11% of the sample median of ROA and sales growth, which is larger than what prior literature has documented for public companies. Chapter 3 complements existing studies by highlighting directors as a different channel through which start-ups in general, not just those that attract VC investment, can access valuable advice that matters for company performance and growth.

Chapter 4 builds on the fact that separate accounts are an important means by which large investors access actively managed strategies. Mutual funds, by contrast, are largely aimed at small investors. A comparison between the performance of separate accounts and mutual funds is difficult because of differences in coverage, scale, and reporting practices between them. However, by studying mutual fund and separate account twins, that is, pairs of products with the same portfolio manager and the same investment strategy, Chapter 4 isolates the effect on performance of structural differences between these vehicles. Chapter 4 then controls for these structural differences to see if there is any evidence of separate account investors outperforming mutual fund investors. Chapter 4 documents a significant performance gap between separate account and their mutual fund twins, with the gross reported excess returns and alphas of separate accounts on average 16 bps to 23 bps per year higher than the gross reported excess returns and alphas of their mutual fund twins. These numbers are likely to represent a close lower bound to the performance gap, since separate account composites sometimes include mutual funds. Importantly, not all this performance gap is real, as separate account reporting excludes some costs that investors in them pay

separately (like custody fees and, to some extent, transition costs). Controlling for this structural gap in (reported) performance, Chapter 4 finds that separate account investments perform at the same level as mutual fund investments, gross of fees, and slightly below them, net of fees. In other words, separate account investors choose products that, once adjusted for structural differences, have the same underlying performance as those chosen by mutual fund investors but are marginally more expensive. This lack of underlying outperformance may seem surprising, given that separate account investors are for the most part institutional and typically larger and more sophisticated than mutual fund investors, who are for the most part individuals. However, separate account investors are also a heterogeneous group. Their failure to outperform mutual fund investors at manager selection may reflect the extra layers of agency problems in some of the largest and most important among them, as noted by Lakonishok, Shleifer, and Vishny (1992). Those agency problems may neutralize the size and sophistication advantage in manager search and selection highlighted by Gârleanu and Pedersen (2018).

Going forward, I plan to utilise the dataset with granular information on the population of Swedish companies that I assembled for Chapters 2 and 3 to study in how far other company characteristics impact entrepreneurial success. For example, running out of cash is one of the most cited reasons for why start-ups fail. I plan to explore how entrepreneurs manage cash by using the data available to me (here, income statements and balance sheets) to construct cash flow statements, which show a detailed breakdown of sources of cash inflows and outflows. In addition, I hope to extend the dataset by including more data at the individual level which would enable me to study the matching of individuals and companies. More specifically, I hope to build on the results in Chapter 3 by studying the determinants of director appointments at start-ups to contribute to a burgeoning literature

on boards in private companies. More broadly, I aspire to conduct impactful research that helps entrepreneurs and practitioners make more informed decisions.

References

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