Essays in Empirical Corporate Finance

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Contents

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Summary

This dissertation consists of three essays in empirical corporate finance. The first and second essays focus on different types of individual investors in startups, namely angel investors and individual investors with family ties to the entrepreneur, respectively. These studies are both based on Norwegian startups, for which equity transactions are observable, facilitating measurement of returns to investments in private startups. The third essay focuses on another type of corporate stakeholder that is fundamental to all firms, namely customers, and analyzes effects of strong reliance on a few major customers for suppliers' operating performance. Lacking information about customers for startups, this analysis is carried out in the context of publicly listed firms in the United States, which features detailed information about trade relationships between suppliers and their major customers.

Individual investors in startups

While acknowledged as an important source of entrepreneurial finance, there is relatively little empirical evidence on startup financing from individual investors, primarily due to data limitations. The first two essays of my thesis are facilitated by access to data sourced from the tax records of Norwegian companies and their shareholders, allowing us to observe equity transactions in private firms by individual investors. The data covers equity transactions by essentially all investors in all limited liability firms and includes detailed information about share transactions, enabling measurement of returns on investments in privately held firms. Both studies also focus on early-stage investments in growth-oriented startups, referred to as High-Innovation-Potential (HIP) startups. Facing the population of Norwegian startups, both studies employ a methodology to identify HIP startups. An important component of this methodology is a measure of firms' innovative potential that facilitates the identification of HIP firms based on characteristics observable at the time of firm foundation, potentially before their innovative potential is realized.

Essay 1: Are Some Angels Better than Others?

The first essay, titled “Are Some Angels Better than Others?”, co-authored with Katja Kisseleva, Aksel Mjøs and David T. Robinson studies the investment performance of individual angel investors. Angel investment represents a large and growing segment of entrepreneurial finance. While exact measurement of this market is hard to come by, due to its informal nature, estimates commonly point to strong growth over recent years and a market that features a larger number of firms, by several times, when compared to the number of firms receiving institutional venture capital (VC) investment. However, despite the importance of this part of the capital market, we know relatively little about it. Who are angel investors? What do their investments look like? Are some angels systematically better than others? What drives performance variation in this market?

These questions are important not only because they sharpen our understanding of early-stage finance, or because they connect household finance and entrepreneurship. Numerous policy initiatives around the world aim to encourage investments by individuals in startups. The emergence of online startup investment platforms also raises questions about the nature of the angel investment market. Understanding the performance of angel investments is essential for evaluating the efficacy and desirability of such policies and programs.

We identify all investors in a large sample of High-Innovation-Potential (HIP) startups founded in Norway between 2004 and 2017 and define angel investments as any equity investment in a HIP firm by an individual investors who is not part of that firm’s founding team. Our analyses can be grouped into three broad parts. First, we study the distribution of angel investment returns and show that most angel investments perform poorly. Approximately one-third of all investments are a total loss, and only one-quarter of them generate distributions in excess of the invested capital. Nevertheless, the returns are characterized by pronounced skewness: the top decile of investments yield more than three times the invested capital, and the top 1% of realized investments generate a 50-fold return. As a result, despite the massive losses incurred in most angel investments, the overall mean payback is twice the invested capital.

The second piece of our study explores determinants of the cross-sectional variation in investment performance. While observable characteristics collectively explain only a small percentage of the overall variation in investment returns, we find that individual investor fixed effects explain approximately one-third of the total variation. Next, while the decision to become a repeat investor is in itself endogenously linked to the realized return of the first angel investments, angel investors exhibit a form of performance persistence, as the success or failure of the last firm in which an angel invested predicts the success or failure of the angel's next firm of investment. Taken together, these results suggest that some angel investors perform systematically better than others and that persistent differences between individual angel investors, although unobserved, are important for understanding this market.

The third piece of our study asks why some angels perform better than others. To explore this, we first examine whether performance differences arise from better performing angels avoiding low-performing investments or instead from successfully seeking out high-performing investments. We show that top-performing angels are much more likely than other investors to achieve 90^{th} or 95^{th} percentile investment outcomes, but no more likely than less well-performing investors to earn returns just above the median. Similarly, top-performing angels are much more likely to invest in firms that also raise institutional venture capital (VC) funding. Thus, better angels do not earn higher returns by avoiding left-tail realizations so much as they do from achieving extreme right-tail outcomes.

We next focus on the role of angels' networks, which could potentially operate in a number of different ways. First, to measure the possibility that a small group of investors with privileged access to investment opportunities dominate the upper tail of the return distribution, we compute the concentration of each angel's set of co-investors. We find that top-performing angels are less likely than others to invest in tight-knit clusters, speaking against the idea that a small group of angels has privileged access to high-quality deals from which others are potentially excluded. To offer another perspective on access to deal flow, we measure angels' connections to other individuals through overlapping board memberships. We find that angels who go on to later become top-performing angel investors have more connections to other board members in and founders of HIP firms *before* they make their first angel investment. This is not simply a matter of knowing more people in the business world, as top-performing angels are not more likely than others to be connected to board members of non-HIP firms. This suggests that some of the better performance of top-performing angels derives from access to better investment opportunities as a result of being better networked.

Essay 2: With a Little Help from My Family: Informal Startup Financing

The second essay, titled "With a Little Help from My Family: Informal Startup Financing", co-authored with Katja Kisseleva and Brian K. Baik, studies startup financing from informal investors, which refers to investors in startups that are family of the entrepreneur. In addition to being economically important, these investors are associated with a set of interesting predictions for which the empirical evidence is rather scarce. For example, informal investors may require lower returns, due to having potential information advantages over other investors or because they invest based on altruistic motives. At the same time, informal financing may be less preferred, due to potential shadow costs in case of startup failure that may reduce the entrepreneur's risk-taking incentives. Motivated by these predictions, we study the returns to informal investments and the relationship between informal finance and startup performance.

We assemble a large data set containing investments by informal and external individual investors in a large sample of growth-oriented, potentially innovative startups (HIP firms). This data set facilitates comparison of the investment performance of informal investors versus that of external investors and the development of startups that receive informal finance versus that of externally funded startups. Our analysis of investment returns suggests that startup investments by informal investors earn lower returns than startup investments by investors without family ties to the entrepreneur. Our analysis of firm performance and startup outcomes yields results supportive of the idea that startups with informal investors take less risk. Informally financed startups are less likely to experience an exit event and, conditional on an exit event, informally financed startups take longer to get there. Informally financed startups are also less likely to raise financing from corporate, foreign or venture capital investors and we find that they experience lower growth rates.

One concern that we are facing is that entrepreneurs receiving informal finance may have substantially different growth aspirations. For example, it could be that entrepreneurs that resort to family and friends as investors are more oriented towards building a lifestyle business rather than pursuing growth, which implies a potential endogenous link between informal finance and firm outcomes. Thus, the analysis of the relationship between informal finance and firm outcomes is complicated by the possibility that resorting to informal finance is correlated with unobservable firm characteristics that potentially lie behind our results. To attenuate such concerns, we emphasize that we restrict our analysis to firms with likely high innovation potential, that are oriented towards growth and that are likely to seek other sources of early-stage financing, such as angel and VC investments. This is achieved by the methodology mentioned above for identifying High-Innovation-Potential (HIP) firms. Furthermore, we employ an identification strategy that seeks to utilize exogenous variation in informal finance through an instrumental variable for the presence of informal investors in startups. Arguably, we are capturing exogenous variation in informal finance using an instrument for having an informal investor that is based on the geographical distance between the startup and its individual investors. Our IV-estimations provide continued support for our baseline results on the relationship between informal finance and firm performance.

Customer concentration and firms' operating performance

Essay 3: The Consequences of Customer Concentration When Competition Hits

The third essay, titled "The Consequences of Customer Concentration When Competition Hits", studies the relationship between supplier firms' customer concentration and their operating performance, focusing on suppliers' product market competition as a determinant of this relationship. Customer concentration refers to suppliers' degree of concentration of sales to a few major customers and my study is facilitated by a regulatory setting in which publicly listed firms in the United States are required to disclose information about their trade relationships with major customers.

Focusing on product market competition as a determinant of the relationship between customer concentration and suppliers' operating performance is motivated by its influence on the key risk dimensions associated with having a concentrated customer base. I utilize large import tariff cuts in suppliers' industries to generate exogenous variation in the intensity of customer-supplier relationships. The idea is that tariff cuts intensify competition in suppliers' industries by making it less costly for customers to purchase from foreign suppliers. This improves the relative bargaining power of customers vis-à-vis their suppliers and leads to a higher likelihood of suppliers losing an existing customer. In addition, in this setting, the high degree of relationship-specific investments and product customization commonly associated with major customer relationships represents a risk for suppliers. Such investments may carry little value outside of the relationship setting and give rise to assets that are customer-specific and costly to re-deploy to alternative uses, in the event of experiencing reduced demand from existing customers following import tariff cuts.

I find that firms' ex-ante level of customer concentration is negatively related to asset turnover and operating profitability following tariff cuts. These effects persist when controlling for sales growth, facilitating the interpretation that increased customer bargaining power yield less profitable major customer relationships for suppliers. I also find that customer concentration is positively related to proxies for investments related to establishing new customer relationships and the speed at which firms convert their inventories into sales. This is consistent with customer concentration resulting in higher expenses related to establishing new customer relationships and with excess inventories, of specific goods and inputs, being more difficult to convert into sales. Taken together, my findings point to a specific setting where customer concentration represents an impediment to firm performance, namely when competition hits.

Chapter 1

Are Some Angels Better than Others?

Are Some Angels Better than Others?*

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Abstract

This paper studies the performance of angel investors. Returns are highly skewed: despite large losses in many investments, mean returns are twice invested capital. Unobserved investor characteristics explain far more of the total variation in angel performance than any collection of observable factors. Better angels do not earn higher returns by avoiding left-tail realizations so much as by achieving extreme right-tail outcomes. The best performing angels have larger networks of business connections in investment opportunities prior to their first angel investment and after an unsuccessful investment, suggesting that access to potential deal-flow is an important factor in driving performance.

Keywords: Angel investing, returns, performance persistence, investment behavior, entrepreneurship.
JEL codes: D14, G40, G50, G51, G53, L26.

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1 Introduction

Angel investments are a growing and important source of early-stage capital for startups. In 2016, there were approximately 64,000 angel-funded deals in the US, compared to 8,500 deals made by venture capital (VC) firms. The US angel capital market grew by approximately 19% from 2016 to 2020, when it reached a market size of 25.3 billion USD.[1] Despite the importance of this segment of the capital market, we know relatively little about it. Who are angel investors? What are the characteristics of their investment portfolios? Do some angels' persistently outperform others? If so, why?

These questions are important not simply because they sharpen our understanding of early-stage finance and because they connect household finance and entrepreneurship. Numerous policy initiatives around the world aim to encourage investments by individuals in startups. For example, several US states have implemented programs that provide accredited angel investors with investment tax credits.[2] Norway, the setting of our study, has begun to allow individuals to generate personal income tax deductions for investments in startup companies.[3] The emergence of online crowdfunding platforms also raises important questions about the nature of individual investors' exposure to startup firms. Understanding the performance of angel investments is essential for evaluating the efficacy and desirability of such policies and programs.

The primary challenge to studying this market is data availability. In this paper, we draw on detailed administrative and tax records from Norway. Our data include equity transactions between individuals and privately held or publicly traded firms. Detailed information on actual share transactions allows us to provide large-scale evidence on realized returns to angel investing and to observe angel investors' performance in other asset classes. The availability of information on multiple investments made by the same investors allows us to analyze performance persistence among angel investors and to uncover the importance of (unobserved) differences between them in explaining variation in investment performance.

Because we are focused on understanding early-stage investments in innovative startups, we define angel investments broadly to be any equity investment in a high-innovation-potential firm (HIP) made by a private individual who is not a part of that firm's founding team. In order to

[1]National Venture Capital Association, 2017 Yearbook, and University of New Hampshire's Center for Venture Research: https://paulcollege.unh.edu/sites/default/files/resource/files/2016-analysis-report-final.pdf and https://paulcollege.unh.edu/sites/default/files/resource/files/2020-analysis-report_.pdf.

[2]See Denes et al. (2023) for a detailed description of such programs.

[3]See https://www.skatteetaten.no/person/skatt/hjelp-til-riktig-skatt/aksjer-og-verdipapirer/om/skatteinsentivordningen/ for more information.

define an angel this way, it is critical to measure a firm's expected innovative potential based on characteristics observable at the time of firm founding, potentially before the firm has realized any of its innovative potential. To develop this measure, we use the strategy described in Kisseleva et al. (2024), which is inspired by the Startup Cartography Project in Andrews et al. (2022). In particular, we start by removing holding companies, subsidiaries, real estate firms, financial firms and firms in industries that are heavily regulated, that have high governmental involvement or that might be considered to have low innovation potential. We then define three indicators for high innovation propensity: one indicator for startups with an English-language name, one for startups located near the largest university cities, and one for startups with at least one geographically distant board member. We define a firm as potentially innovative if it satisfies at least one of these three criteria. Kisseleva et al. (2024) find that these flags are highly predictive of later-stage innovation outcomes, such as receipt of patents, later-stage venture funding, and growth.[4]

We identify all individual investors in such firms in Norway between 2004 and 2018. These investors account for approximately 1% of the Norwegian working-age population. To facilitate comparison with other empirical settings, we further differentiate between several angel investor types. First, we identify repeat investors, a group that aligns more closely with the sample of angel investors defined in Bach et al. (2022). Second, we flag angel investors who sit on other corporate boards as potentially sophisticated investors with management or corporate leadership experience. Finally, we flag angel investors in the top 10% of the wealth distribution, who more closely align with the minimum net worth criterion for being designated an "accredited investor" in US markets, such that we can connect our work to Lindsey and Stein (2020) and Denes et al. (2023).

Our results can be grouped into three broad sets of findings. First, we study the distribution of angel returns from investing in high-innovation-potential firms. Most angel investments perform poorly relative to alternative investments. Approximately one-third of all investments are a total loss, and only one-quarter of them generate positive undiscounted returns, i.e., distributions in excess of the invested capital.[5] Nevertheless, the returns are characterized by pronounced skewness: the top decile of investments yields more than three times the invested capital, and the top 1% of realized investments generate a 53-fold return. As a result, despite the massive losses incurred in most angel investments, the overall mean payback is twice the invested capital. The investment holding period increases in both tails of the return distribution, i.e. both for extremely positive

[4] We reproduce their findings in Appendix A.

[5] These results are in line with findings from surveys of UK angel investors in Mason and Harrison (2002) and the US in DeGennaro and Dwyer (2014).

outcomes and total losses. This speaks against the hypothesis of a consistently higher payoff for "patient" investors.

The second piece of our analysis explores the determinants of the cross-sectional variation in returns that we uncover. Observable characteristics such as investor age, board seat, investment amount and holding period are strong predictors of returns but collectively explain only a small percentage of the overall variation. Investor fixed effects explain approximately one-third of the total variation in angel investment performance—far more than any collection of observable factors. While the decision to become a repeat investor is in itself endogenously linked to the realized return of the first angel investments, angels exhibit a form of performance persistence. Namely, the success or failure of the last firm in which the angel invested predicts the success or failure of the current firm. Successes are especially persistent for wealthy angels and investments close in time and in the same industries. This result connects our findings to Braun et al. (2017); Kaplan and Schoar (2005); Korteweg and Sorensen (2017) and Nanda et al. (2020).

Why do some angels earn higher returns than others? To explore this question, we first examine whether the performance differential arises from angels avoiding low-performing investments or instead from their successfully seeking out high-performing investments. In other words, do their investing styles differ? High-performing angels are much more likely than other investors to achieve 90^{th} or 95^{th} percentile investment outcomes, but no more likely than less well-performing investors to earn returns just above median. Similarly, top-quintile angel investors are much likelier to invest in firms that raise VC funding. Thus, they do not earn higher returns by avoiding left-tail realizations so much as they do by achieving extreme right-tail outcomes. To use a baseball metaphor, it is not that high-performing angels hit singles and doubles instead of striking out more often than lesser performing investors; instead, they are more likely to hit home runs.

Our data do not allow us to analyze whether some angels are better than others because they are better at adding value to the firms in which they invest. However, the data do allow us to ask whether performance differences stem from better access to deal flow or instead, better selection ability. In other words, while we cannot separate selection from treatment, we can disentangle the source of differential selection and distinguish different selection opportunities from different selection abilities.

Network effects could potentially operate in a number of different ways. To measure the possibility that a small group of investors with privileged access to investment opportunities dominates the upper tail of the return distribution, we compute the concentration of each angel's set of co-investors. Top-performing angels are less likely than lesser-performing angels to invest in tight-knit clusters. This speaks against the idea that a small group of angels has privileged access to high-quality deals from which others are potentially excluded.

We can also measure the connections that angels investors have to potential startup founders or, more generally, board members, through overlapping board memberships, both before and after angel investments occur. This offers another perspective on access to deal flow. We find that angels who go on later to become top-performing angel investors in our sample angels who go on later to become top-performing angel investors in our sample are likelier to be connected to board members and founders of HIP firms *before* they make their first investment. In other words, they have business connections to founders of high-innovation potential firms before they themselves invest. This is not simply a matter of knowing more people in the business world: they are no likelier than lesser-performing angels to be connected to board members of non-HIP firms. Seen together, the wider co-investor base and board network of angel investors allows to interpret some of the unexplained better angel performance as deriving from larger professional networks in investment opportunities.

Our findings contribute to a burgeoning literature on angel investment, including Bach et al. (2022); DeGennaro and Dwyer (2014); Denes et al. (2023); Kerr et al. (2011); Lerner et al. (2018); Lindsey and Stein (2020); Mason and Harrison (2002); Wong (2002) and Xu (2023) as well as Hellmann and Thiele (2015) and Hellmann et al. (2021). This literature highlights the importance of exposure to angel investors for the subsequent success of the firms in question and points to connections between angel and later-stage institutional capital. By linking private investment performance to professional networks, our work helps illustrate the importance of selection access to investment opportunities as a source of returns in angel markets. This is especially important in light of the emphasis that earlier work has placed on the role of non-pecuniary motives in angel investing.

The paper is structured as follows. Section 2 describes our data and sample. Section 3 describes the returns to angel investing. Section 4 explores the cross-sectional variation in angel returns, while Section 5 disentangles possible explanations behind these differences. Section 6 concludes.

2 Data and Sample Construction

2.1 Data Source and Structure

Norwegian administrative data are recognized for their quality and detail and have been used prominently in research in labor economics, finance and innovation (for recent examples, see Fagereng et al., 2021; Hvide and Jones, 2018; Ring, 2023). Our main data come from the annual tax declarations of the population of Norwegian public and private limited liability companies and their shareholders. These declarations have been digitally collected and stored since 2004. We obtain data through December 2018. The data identify firms' shareholders and their shareholdings and all equity purchase, sale and liquidation transactions. Each record includes the date, monetary amount, and number of shares transacted. In addition, we observe whether the shares are purchased in primary financing rounds (88% of all purchases) or in secondary trades with existing investors.

At the most granular level of observation, an investment is a unique combination of an investor (name *aksjonaer_navn* and personal tax identification number *akt_lopenr*), purchase date (*erverv_dato*), firm identifier (*aksje_orgnr*), share class (*aksje_aksjeklasse*) and purchase type (*erverv_type*). By the end of our sample period, an investment may be fully or partially realized through sale or liquidation (*realisasjon_type*) of shares. Thus, in a case where a single initial purchase is liquidated across several distinct sales, we would observe more than one investment outcome. The outcome date is the date of the realization (*realisert_dato*) for realized returns or the last day of our sample period (December 31, 2018) for unrealized investments. Some examples to illustrate the data structure are as follows: (a) An investor j purchases 100 shares in firm i at time t. She sells 50 shares at time s and 50 shares at a later point in time k. This case is one investment with two distinct realized outcomes. (b) An investor j purchases 50 shares in firm i at time t and 50 shares in firm i at a later point in time z. She sells all 100 shares at time s. This case represents two investments, each of them having one realized outcome. (c) An investor j purchases 100 shares in firm i at time t. She sells 50 shares at time s. This case is one investment with both a realized outcome at time s and an unrealized outcome at $k = 12/31/2018$.

The firm identification number (*organisasjonsnummer*) is consistently used in all firm registries and allows the data to be merged to other databases. Thus, we merge the tax declarations to firm financial statements data, business registry data, bankruptcy registry data, firms' incorporation documents and data on CEOs and board members. We identify board members and executives among all individuals in the tax declarations by fuzzy matching on full names and exact matching on birth dates. In addition, we obtain individual-level wealth and income data for the sample period 2011–2018 from tax returns.

2.2 Identifying Firms with High Innovation Potential

To recognize firms potentially seeking early-stage equity financing from angel investors, we follow Kisseleva et al. (2024), who apply to the Norwegian context a methodology described in Andrews et al. (2022); Guzman and Stern (2015) and Guzman and Stern (2020). The process is described in detail in Appendix A here. A brief summary follows below. We begin by identifying all newly established limited liability companies (analogous to C-corporations in the US) that incorporated between 2004 and 2017. We remove financial services and real estate firms, newly formed subsidiaries of established companies, holding structures, and firms in industries that are heavily regulated or that have high governmental involvement. For our purposes to identify firms relevant for angel investing we apply a stricter industry filter than Kisseleva et al. (2024) and exclude firms operating in industries that are usually considered non-innovative.

Further, we use three indicators observable at founding to gauge a firm's likely innovation potential at the time it first appears in the tax registry data.[6] The first flag is whether the firm has an English-language firm name. The idea behind this flag is that, because Norway is a country of only approximately five million people, an English-language firm name helps the firm be recognizable to a broader, international audience and therefore is a natural choice for an entrepreneur who intends to grow. The second flag is whether the firm is located in a regional innovation hub in Norway. The four innovation hubs in our data are Oslo, Bergen, Stavanger and Trondheim. These are the four largest cities in the country, and each hosts a major research university and has an associated technology cluster (Hvide and Jones, 2018). The third flag tracks whether one of the company's non-executive board members lives in a geographically distant area from the city in which the company operates. The idea here is that the choice of a geographically distant board member in the year of establishment is a potential indication that the founders (or investors) have recruited a board member with specific technical or market expertise not readily found nearby. Thus, for a firm to be classed as high-innovation-potential (HIP), we require it to be in a potentially innovative industry and to meet the criteria for at least one of our three flags. This procedure yields a sample

[6] Kisseleva et al. (2024) use four flags including an additional indicator whether a firm operates in a potentially innovative industry. We have already excluded firms operating in industries considered as non-innovative, so that implicitly all our sample firms fulfill this flag requirement.

of 46,121 firms[7], among them 90% of all the firms that receive any VC funding in our data, which justifies our selection approach.

In Appendix A, Table A2 shows that each flag, both on its own and in combination with the others, is highly predictive of a firm's obtaining a patent, obtaining later-stage equity financing or government innovation grants, achieving an exit for investors, and having higher than average four-year revenue growth. Even more importantly, our HIP sample includes almost all firms selected by investors, accounting for over 90% of the total equity capital invested in all early-stage businesses in Norway in our sample period.[8]

2.3 Identifying Angel Investors

There is no standardized definition of an angel investor across various settings and previous research. We want to keep our definition as broad as possible, and for this purpose, we define an angel investor as an individual who, in her own name or through a fully owned holding company, invests at least once in a financing round of a HIP firm of which she is not a founder. We identify founders as a firm's CEO and/or contact person in the year of firm's inception and the two consecutive years. For firms that do not report a CEO or a contact person, we treat the chair of the board as founder.[9] Out of 46,121 HIP firms, 14,376 firms receive at least one investment from 36,749 angels, who comprise 6.1% of all Norwegian direct equityholders and 0.8% (1.3%) of the entire Norwegian (working) population.[10]

Table B1 in Appendix A evaluates who, among all individual investors, are most likely to make angel investments, i.e., invest in HIP firms. It shows that angels are typically younger and likelier to be men and to be founders (of different firms) themselves, and they also invest in the domestic public stock market. We also find that founders are less likely to invest in smaller and late-stage HIP firms, while being a public market and/or wealthy investor correlates with investing in late-stage and large HIP firms. The latter also tend to invest in more than just one HIP firm. In our sample, solely 12% of angel investors invest in more than one HIP firm (see Figure 1). Thus, in our analyses, we differentiate angels who invest in only one HIP firm (*single-firm angels*) and those who invest in multiple HIP firms (*repeat angels*) during our sample period. This distinction brings our definition of an angel investor closer to the focus on individuals with multiple investments in Bach et al.

[7]See Table A1 in the Appendix for the number of firms involved in each step of the selection procedure.
[8]See Table A3 in Appendix A for details.
[9]This applies to only 4% of our sample of HIP firms.
[10]Sources: The shareholder registry from the Norwegian Tax Authorities and Statistics Norway.

(2022).

Furthermore, we define investors as *wealthy angels* if their average wealth level is above the 90^{th} percentile of all angel investors in our sample. This aligns our definition of an angel investor with the US definition of an accredited angel investor and, thus, with the definition in Lindsey and Stein (2020) and Denes et al. (2023). In addition, we flag *board-experienced angels*, who are board members of at least one other firm at the time of their first angel investment. Last, we identify *family angels*, who share the last name and/or live on the same street as the founder of the firm.

2.4 Sample Description

To summarize the character of HIP firms, Table 1 provides descriptive statistics. On average, each HIP firm receives investments from three angel investors (median from one angel investor), although with a far thicker right tail ranging up to a consortium of over 30 angels. Angels invest early in a firm's life. Half of the angels invest in the year of the firm's inception – on average, when the firm is 1.2 years old (median 2.0 years). Firm size at the time of the (first) angel investment is highly right-skewed, with average total assets of 26 million NOK, but a median of only 890 thousand NOK.[11] The HIP firms report revenues in the year of the first angel investment of on average 1.3 times total assets (median 0.5 times), although still resulting in average losses of 1.4 times total assets (median 0.05 times). This is consistent with early-stage innovative firms' development and investment phase before they start generating profits. However, both revenues and net income have a thick right tail. Loans from financial institutions represent on average 15% and convertible loans 4% of the financing of angel-invested HIP firms at the year of their first angel investments. Due to accumulated losses, the average equity ratio at this time is -27% (median 39%). The firms hold large cash balances just after receiving angel financing, on average 39% (median 30%) of assets, while only on average 10% of assets (on the balance sheet) are intangibles (median 0%). The average sample firm has 4.4 employees (median 1.0 employees).

The vast majority of such firms remain independently operating at the end of our sample period (60%), and only 14% of them experience a positive exit event (13.9% through mergers and acquisitions and 0.2% through initial public offerings). A share of 26% of HIP firms officially file for bankruptcy and/or are liquidated. The average (median) firm age at the time of the (first) exit event is five (four) years old.

Table 2 describes our angel investors. They make on average 1.8 angel investments in 1.2

[11]The average exchange rate is 6.6 NOK per USD.

different HIP firms; these numbers are driven by a few angels, as most angels make only one investment in one firm, as illustrated in Figure 1. On average, angels realize only half of their investments by the end of our sample period. This highlights the importance of assigning implicit values to untraded shares for understanding the totality of investment returns. We describe our imputation method for untraded shares in Section 3.1.

In the year of their first angel investment, angel investors are on average 44 years old (median 43 years) with an average gross wealth of 6.9 million NOK (median 1.4 million NOK), equivalent to 1 million USD (0.2 million USD), which implies that they on average are wealthier than the average Norwegian household.[12] Angel investors also have a higher than average household annual income of 970 thousand NOK (median 540 thousand NOK), equivalent to 147 thousand USD (median 82 thousand USD).[13] Both in terms of age, wealth and income, angel investors show a fairly skewed distribution, which includes older and wealthier angels who have much higher income. A total of 83% of the angel investors in our sample are male, a figure that closely aligns with the gender mix in the sample of angel investors in contemporaneous work by Bach et al., 2022.

The realized portfolio return of our angel investors captures their overall realized performance as investors.[14] The average angel portfolio generates a *total value to paid-in capital* (TVPI)[15] of 2.31 (median 0.5), and only the top 25% of angels receive their invested capital back. Alternatively, we use buy-and-hold annualized returns (BHAR), which are the annualized TVPI returns, to account for the holding period of angel investments. An average angel experiences a total BHAR loss of 100% (median -30%) in her angel portfolio. Public market equivalent (PME) is TVPI adjusted by the Oslo Børs Benchmark Index (OSEBX) on each cashflow date. The average portfolio PME of 1.76 (median 0.40) is lower than that of TVPI, reflecting both time value of money and market-risk adjustment. Also the alternative return measures are heavily skewed, consistent with negative portfolio returns for a majority of angel investors.

Some angels are also active in other capital markets: 37% of angels invest directly in the domestic public stock market, and 9% of angels invest in private non-HIP firms. Using the realized TVPI measure for comparability, angel's portfolio returns in non-HIP firms, average 2.64 (median 0.57)

[12]Statistics Norway (SSB) reports that the average gross wealth of Norwegian households where the main income provider was between 45 and 54 years old is 4.3 million NOK (0.7 million USD) in 2015; see https://www.ssb.no/statbank/table/10317/. Wealth and income are measured in 2015 values and converted to USD amounts based on an exchange rate of 6.6 NOK per USD.

[13]For comparison, the average annual salary (before tax) across all sectors in 2015 was 516 thousand NOK (78 thousand USD); see https://www.ssb.no/statbank/table/11536/.

[14]Investment returns are weighted average returns (by purchase amount of realized shares) of each angel investor.

[15]See full description of the TVPI performance measure in Section 3.1.

are higher than in her angel portfolio, while the returns in the domestic public stock market, with the average TVPI of 1.28 (median 1.04), are lower than that of her angel portfolio. The returns in non-HIP firms are more volatile and skewed than for her angel portfolio, while the returns from investing in the far more liquid and efficient domestic public stock market are significantly less volatile and skewed.

3 Returns to Angel Investment

3.1 Measurement of Returns

To calculate angel investment returns, we use a measure commonly used in entrepreneurial finance, *total value to paid-in capital* (TVPI), which is the ratio of total nominal cash received by the investor from an investment to total nominal cash paid into the investment, with no adjustments for risk or the time value of money.

$$TVPI_{i,j,t,s} = \frac{\sum_{\tau=t}^{s} Distribution_{i,j,\tau}}{Contribution_{i,j,t}}$$

$Contribution_{i,j,t}$ is the amount invested in firm i by angel j at time t. For fully realized outcomes, whether through sales or liquidation, we directly observe each $Distribution_{i,j,\tau}$, which is the realization proceeds at time τ, calculated as the realization price per share multiplied by the number of realized shares. Thus, we calculate *Realized* $TVPI_{i,j,t,s}$ as the sum of the realized amounts divided by the purchase amount of the realized shares. Importantly, for some time $s, (s > t)$, the distributions associated with initial investment made at time t may not have yet arrived. To account for unrealized investments, we calculate two additional versions of $TVPI$. In addition to realized investments, *Adjusted TVPI* corrects for implicit losses by assuming that if a firm does not report revenues for five consecutive years after an angel investment, the implied $Distribution_{i,j,s}$ and, therefore, $TVPI_{i,j,t,s}$ is zero, even if we do not observe a formal bankruptcy or liquidation event. To account additionally for unrealized investments that are not total losses, we compute a *Full TVPI* by assigning the most recent share price (paid by any investor) observed in the latest financing round to any unrealized transactions. This implies that the Full TVPI includes all angel investments. In this case, $Distribution_{i,j,s} = Share\ price_{i,s} \times Untraded\ shares_{i,j,s}$, where $Share\ price_{i,s}$ is the most recent observed share price at time s. We then divide the estimated distribution by the purchase amount of unrealized shares.

To illustrate our procedure with regard to investments with several outcomes, we refer to our examples (a) and (c) introduced in Section 2.1. In example (a), an investor j purchases 100 shares for a price of 100 NOK/share in firm i at time t. She sells 50 shares at time s for 60 NOK/share and 50 shares for 75 NOK/share at a later point at time k. This implies $Realized\ TVPI = \frac{60\times50+75\times50}{100\times100} = 0.675$.

In example (c), an investor j purchases 100 shares in firm i at time t for a price of 100 NOK/share. She sells 50 shares at time s for 80 NOK/share. This case is one investment with both a realized outcome at time s and an unrealized outcome at time $k = 12/31/2018$. This implies that the $Realized\ TVPI = \frac{80\times50}{100\times50} = 0.8$, but the other return measures are dependent on the firm outcome. First, assume that the firm i does not earn any revenues throughout years $t + 5$. Then, $Adjusted\ TVPI = \frac{80\times50+0\times50}{100\times100} = 0.4$. Instead, assume that the firm does earn revenues, but has raised equity in a financing round on January 1, 2018, which is after the purchase date. The average share price in that financing round is 125 NOK/share. We calculate $Full\ TVPI = \frac{80\times50+125\times50}{100\times100} = 1.025$. In this case, $Realized\ TVPI = Adjusted\ TVPI = 0.8$, while $Full\ TVPI = 1.025$.

3.2 Return Distribution

In this section, we explore the distribution of returns to angel investments. Figure 2 illustrates how our methodology for calculating returns to unrealized investment affects the overall return distribution. Specifically, it plots the distributions of angel investment returns over return buckets and shows that angel returns are characterized by many losses and pronounced right-skewness, regardless of the particular measurement. The solid line, which represents Realized TVPI, shows that more than one-third of realized investments are total losses and that approximately 75% of investments do not yield a positive return in excess of the invested capital. At the same time, 11% of realized investments return more than three times the invested capital. This return distribution broadly aligns with the survey evidence from the UK in Mason and Harrison (2002) and from the US in DeGennaro and Dwyer (2014). Once we account for the implicit losses, represented by the dashed line for Adjusted TVPI, an additional 6% of investments are total losses, and a slightly higher share of investments do not yield a positive return. After the inclusion of all unrealized investments in Full TVPI, represented by the dotted line, the share of total losses is reduced to 21% of the entire return distribution, which now has a much higher proportion of returns that are equal to one. Still, only 10% of all investments return more than three times the invested capital, irrespective of the return measure applied.

Table 3 presents detailed statistics on the returns to angel investing for all investments (Panel A), separately for investments in financing rounds (Panel B) and in secondary trades from existing investors (Panel C).[16] Our sample consists of total 75,290 investments, whereas 2,149 investments (less than 3% of total investments)) have both realized and unrealized outcomes. Out of 36,525 realized investments, 4,726 (13%) investments have more than one realization dates.

The distribution of Realized TVPI indicates that realized angel investments return on average twice the invested capital. The average Adjusted TVPI decreases slightly because of the inclusion of implicit total losses, while the average Full TVPI increases slightly because of the large fraction of investments returning exactly the invested capital, i.e. median Full TVPI of one, higher than the medians of Realized TVPI and Adjusted TVPI. Full TVPI has also higher returns in the right tail.

Comparison of the returns earned in share purchases in financing rounds (Panel B) and in share purchases in secondary trades (Panel C) shows that the return distributions are similar. However, the average Full TVPI earned when shares are purchased in secondary trades is higher than when shares are purchased in financing rounds. This is driven by the thicker right tail of the secondary trade returns distribution, since the median returns from financing round purchases are higher than for secondary round purchases. The average holding period of angel investments is 1,725 days (4.7 years) and the median is 1,333 days (3.7 years). There is no significant difference (more than a couple of months) in the average holding period between angel investments in financing rounds and secondary trades, albeit in the right tail, secondary trades are held more than one year shorter than investments purchased in financing rounds.

Figure 3 plots the distributions of the average holding period (measured in days) over the same TVPI buckets as introduced in Figure 2. Overall, the distributions, regardless of the specific TVPI calculation, are U-shaped with longer holding periods in both ends of the return distributions. This implies that longer holding periods result either in extremely positive or negative outcomes, speaking against a hypothesis of consistently higher payoff for "patient" investors.[17]

Figure 4 shows the distribution of Full TVPI by investment size quartile. We observe that the return distribution has a heavier concentration in the third return bucket (*TVPI >0.50 to 1.00*) for the smallest investments and that this concentration declines with investment size. The share of investments that return more than three times the invested capital also declines in investment size

[16]We report average returns based on the at the 1^{th} and 99^{th} percentiles winsorized distributions given a couple of extreme values in their right tails.

[17]To further account for the effect of holding periods on return calculations, we replicate all our findings using several alternative measures of performance in Appendices B, C, and D.

from 11.5% for small investments to 7.1% for large investments, indicating that returns from small investments drive the right tail of the return distribution.

In addition, our data allow us to examine angel investments at different stages of firm development, gauged by whether the firm reports any revenues or any value of patents in its financial statements in the year of receiving an angel investment. For this purpose, Table B3 in Appendix B replicates Table 3 Panel A. The results suggest that the reduction in uncertainty from generating revenues or obtaining patents, as well as the positive survival bias, result in higher average returns. Specifically, post-revenue (post-patent) angel investments result in a higher median return and lower proportion of total losses across all three return measures compared to investments in pre-revenue (pre-patent) firms. The lower share of total losses is accompanied by overall less skewed return distributions.

4 Are Some Angels Better than Others?

4.1 Angels of a Different Kind

As outlined in Section 2.3, we intentionally keep our definition of angels as broad as possible, which allows us to differentiate between various, partially overlapping, angel types and to connect our study to existing research and different empirical settings. Table 4 replicates Table 3 Panel A for all investments for different angel types. Family angels perform on average and across the distributions, worse than other angel types. Their investments exhibit in particular a higher proportion of total losses and a lower right tail. First, such informal investors are thought to require lower returns from the founders because of the investors' information advantages or because they have non-pecuniary, altruistic motives. Second, despite the lower required returns, informal financing is often less preferred than institutional or angel financing because of the shadow costs if the startup fails – hence the reduced risk-taking behavior demonstrated by family-financed firms (Baik et al., 2023; Lee and Persson, 2016). For these reasons, we exclude this group of angels from our further analyses. This exclusion aligns with the approach in Bach et al. (2022), the study closest to ours, where the authors require that neither the angel investors themselves nor their family members work in the firm in which they invest.

The average Realized TVPI of board-experienced angels, wealthy angels and single-firm angels is approximately the same, ranging from 2.07 for single-firm angels to 2.19 for wealthy angels. The return distribution is the least right-skewed for single-firm angels. When we account for untraded shares, wealthy angels have the lowest average Full TVPI of 2.10, in comparison to 2.34 (2.29) for board-experienced (single-firm) angels. Wealthy angels also experience the highest proportion of total losses and the lowest median return.

Repeat angels earn the highest average returns among all angel types. Both the right and left tails of their return distribution are thicker than those for any other angel type. When we consider all investments by repeat angels, the average Realized TVPI (Full TVPI) is 2.62 (2.64), while their first investments yield a Realized TVPI (Full TVPI) of 2.90 (2.79)[18]. Figure 5 shows that between 11% and 17% of each angel investment calendar year cohort invests repeatedly in HIP firms. Figure 6 shows that 74% of repeat angels invest in two firms (Panel A), while approximately half of them realize only one angel investment (Panel B). Of course, some of the most recent investors may well become repeat investors after the end of our sample period since the median (mean) time period between two investments made by the same angel investor is 567 (952) days during our sample period.

In the remaining analyses we use Full TVPI as a measure of returns to account for all observable angel investments.

4.2 Cross-Sectional Variation in Angel Returns

This section attempts to explain the variation in angel investment performance documented in the previous section. To explore the systematic cross-sectional variation in returns to angel investing, we estimate the following ordinary least squares (OLS) regression model:

$$\begin{aligned} TVPI_{i,j,t,s} = \alpha &+ \beta_1 Repeat\ angel_j + \beta_2 Board\ experienced\ angel_j + \beta_3 Investor\ age_{j,t} \\ &+ \beta_4 Male_j + \beta_5 High\ wealth_j + \beta_6 Investment\ amount_{i,j,t} \\ &+ \beta_7 Secondary\ purchase_{i,j,t} + \beta_8 Holding\ period_{i,j,t,s} + \beta_9 Board\ seat_{i,j,t} \\ &+ \beta_{10} \%\ of\ investment\ realized_{i,j,t,s} \\ &+ \beta_{11} Public\ market\ return_{t,s} + \gamma_{i,t,s} + \delta_j + \theta_i + \upsilon_i + \varepsilon_{i,j,t,s} \end{aligned} \quad (1)$$

The dependent variable is one plus the natural logarithm of the Full TVPI. $Repeat\ angel_j$ is a dummy variable taking value one if angel j invests in several HIP firms. $Board\ experienced\ angel_j$ is a dummy variable taking value one if the angel investor holds a board seat in any other

[18]As we explore later, the relatively higher realized return of the first investment itself increases the likelihood of becoming a repeat angel investor.

firm at the time of her first angel investment. $Investor\ age_{j,t}$ is the natural logarithm of the investor's age at the time of investment t. $Male_j$ is a dummy variable taking value one for male angels. $High\ wealth_j$ a dummy variable taking value one for angel investors who are above the 90^{th} percentile in the investor wealth distribution over the time period 2011–2018. $Investment\ amount_{i,j,t}$ controls for the investment (purchase) amount of angel investor j into firm i at time t. $Secondary\ purchase_{i,j,t}$ is a dummy variable taking value one if the investor buys shares in a secondary trade. $Holding\ period_{i,j,t,s}$ is the natural logarithm of the holding period t to s of the investment measured in days. $Board\ seat_{i,j,t}$ is a dummy variable taking value one if the angel investor j receives a board seat in the firm i at the time of investment t. $\%\ of\ investment\ realized_{i,j,t,s}$ is the fraction of the investment that is realized at time s. $Public\ market\ return_{t,s}$ is the return on the Oslo Børs Benchmark Index (OSEBX) over the investment period from time t to s. $\gamma_{i,t,s}$ represents fixed effects for the purchase and realization calendar year and firm age at the time of investment, δ_j is investor fixed effects, θ_i is industry fixed effects, and υ_i is firm fixed effects. Standard errors are clustered at the firm level.

Table 5 shows the estimation results. Column (1) confirms in a more formal analysis that repeat angels earn on average 6% more than single-firm angels and angels with previous board experience. Observable investor and investment characteristics such as age, investment amount, board seat, investment amount, holding period and share of investment realized are strong predictors of returns, but collectively explain, when also controlling for public market return, firm age, year and industry, only 5.4% of the variation in returns. In particular, older investors, larger investment amounts, a longer holding period, a higher public market return and the fraction of the investment realized are associated with lower average returns, while having a board seat is weakly associated with a higher return.

Column (2) replicates Column (1) for the subsample of repeat angels, while Column (3) additionally includes investor fixed effects. The adjusted R-squared increases from 6.9% in Column (2) to 43.6% in Column (3). This result is robust when we limit the sample of repeat angels to those with at least three (Column (4)) or at least four (Column (5)) angel investments (thus it is not a mechanical artifact of the fixed effect being identified over small groups of observations). The large increase in explanatory power from introducing an investor fixed effect is evidence of large unobserved heterogeneity across investors, which plays a crucial role in understanding the returns from angel investing and connects our paper to findings in Bach et al. (2022).

In Column (6), we replace the investor fixed effects with firm fixed effects and use the same specification as in Column (1); i.e., we study only the variation in returns between different angel investors within the same firm. The adjusted R-squared increases further from 5.4% (Column (1)) to 59.3% (Column (6)), underscoring the importance of assortative matching between angel investors and firms. Overall, Table 5 provides evidence that angel investors vary systematically in their average angel investment performance and that unobserved differences across investors lie behind the observed variation in performance. Table B4 replicates this table for the subsample of realized returns, measured as Realized TVPI only and the results remain qualitatively unchanged. In fact, the increase in the adjusted R-squared after including investor fixed effects is even more pronounced, implying that investor's personal traits play an even more important role for explaining variation in realized returns.

4.3 Endogeneity of Repeat Investments

Some investors might shy away from repeat angel investing because of disappointing returns on their first investments. To better understand how the circumstances of the first investment predict whether a second investment occurs, we explore the relationship between the outcome of angels' first investment and their propensity to become a repeat angel. We estimate the following logit regression model:

$$\begin{aligned} Repeat\ angel_j = \alpha &+ \beta_1 First\ investment\ realized_j + \beta_2 First\ investment\ TVPI_j \\ &+ \beta_3 First\ investment\ amount_j + \beta_4 Board\ experienced\ angel_j \\ &+ \beta_5 Investor\ age_j + \beta_6 Male_j + \beta_7 High\ wealth_j + \gamma_j + \varepsilon_j \end{aligned} \tag{2}$$

The dependent variable is a dummy variable that takes the value of one if an angel j has made investments in more than one HIP firm. $First\ investment\ realized_j$ is a dummy variable taking value one if the angel's first investment has been realized during the sample period. $First\ investment\ TVPI$ is the return of the investor's first angel investment, measured as the natural logarithm of one plus the investment return, calculated as either Realized TVPI (realized investments only) or Full TVPI (including all unrealized investments). $First\ investment\ amount_j$ controls for the total amount invested in the first angel investment. $Board\ experienced\ angel_j$ is a dummy variable taking value one if the angel investor holds a board seat in any other firm at the time of her first angel investment. $Investor\ age_j$ is the natural logarithm of the investor's age at the time of her first angel investment. $Male_j$ is a dummy variable taking value one for male angels. $High\ wealth_j$ is a dummy variable taking value one for angel investors who are above the 90^{th} percentile in the investor wealth distribution over the time period 2011–2018. γ_j is a calendar year of the first angel investment fixed effect.

Table 6's Columns (1)–(3) estimate the propensity to become a repeat angel among all angel investors. Column (4) does so in the subsample of early-stage angels, while Column (5) does so in the subsample of late-stage angels. An angel is defined as early stage if her first angel investment occurs in the firm in the year of its inception or one year after. An angel is defined as late stage if her first angel investment occurs in the firm aged five years or older. Columns (6)–(7) estimate the propensity to become a repeat angel among small and large angel investors, respectively. An angel is defined as small if she invests less than 50 thousand NOK and as large if she invests 500 thousand NOK or more in her first angel investment.

Table 6 provides consistent evidence that the probability of an angel making repeat investments in different HIP firms is positively correlated with successful realization of her first angel investment. The statistically significant coefficient of 0.208 in Column (1) suggests that the odds of becoming a repeat angel is 1.2 times higher for angels whose first investment is realized than for angels whose first investment is not realized. The effect of the return to the realized first investment is higher in Column (2) than when we account for untraded shares (Full TVPI) in Column (3), confirming that the certainty of an investment realization matters. The probability of repeatedly investing in HIP firms is particularly positively correlated with angel wealth, being male, the size of the first investment and board experience, and negatively correlated with investor age. The positive effect of the first realized return is more pronounced for late-stage (Column (5)) and small (Column (6)) angels, while it does not matter for angels with deep pockets (Column (7)).

One concern is that right-truncation in our sample affects the measurement of repeat investors because we cannot distinguish repeat investors among those who make their first investment late in the sample period (and thus will later become repeat investors). Appendix B deals with this concern by repeating the analysis on the earlier portions of the sample, where this is not likely to be a concern.[19]

To disentangle the performance of the underlying asset from other firm characteristics and explore the drivers of repeatedly selecting successful or failing firms, we track our HIP firms from

[19]Specifically, Table B5 replicates Table 6 for a truncated sample of angel investors, where we include only those, who make her first investment no later than 2,591 days (around seven years) before the end of our sample period. At the same time, we define a repeat angel here as an angel who makes her repeat investment no more than 2,591 days after the first investment. 2,591 days represent the 90^{th} percentile in the distribution of days between two investments in different HIP firms in the entire sample of repeat angels as shown in Table 6.

their establishment up to the end of our sample period and record whether the firm is bankrupt or liquidated (representing failure) or has been merged, acquired or had an initial public offering (representing success). Thus, the investment performance is now measured by the firm's exit outcome. In the spirit of Kaplan and Schoar (2005), we include the lagged performance of the previous investment (in a different firm) as a right-hand-side variable and run a logit estimation of the following firm-level regression model:

$$Success(Failure)_{i,j,t} = \alpha + \beta_1 Success(Failure)_{i-1} + Controls_{i,j,t} + \varepsilon_{i,j,t} \tag{3}$$

The dependent variable $Success(Failure)_{i,j,t}$ is either a dummy variable taking value one if the firm the angel invests in has a successful exit event (merger, acquisition or IPO) or a dummy variable taking value one if the firm has an unsuccessful outcome (bankruptcy or liquidation). $Success_{i-1}$ ($Failure_{i-1}$) is a dummy variable taking value one if the firm in which the angel invested before had a successful (unsuccessful) exit event. Controls include the following investor and investment characteristics: investor age, gender, high net worth dummy, investment amount, fixed effects for industry and firm founding year, and fixed effects for the calendar year of investment. Standard errors are clustered at the firm level.

Table 7 presents the results for different angel types and investment characteristics. Panel A evaluates what predicts the selection of successful firms while Panel B does so for the selection of failed firms. Columns (1)–(4) in both panels differentiate between different angel types. In particularly, the persistence parameter in the subsample of board-experienced angels is significantly higher than in the subsample of board-inexperienced angels. At the same time, board-experienced angels are also likelier to repeatedly invest in successful firms than in failed firms. This result is consistent with the idea that greater sophistication increases an angel's ability to identify and avoid future failing firms. We also find a pronounced difference between high-wealth and low-wealth angels. High wealth angels are likelier to repeatedly invest in successful firms, while low-wealth are likelier to repeatedly invest in failed firms. Our results are consistent with findings in Fagereng et al., 2020 that returns to wealth are positively correlated with wealth and are persistent over time. They argue that this persistence reflects their financial sophistication, ability to process and use financial information, as well as their ability to overcome inertia.

A wider literature examining performance persistence in private equity finds that exposure to common market conditions may give rise to apparent performance persistence (see, for example, Korteweg and Sorensen, 2017). Columns (5)–(6) differentiate by the investment timing between firms i and $i-1$. Investments close in time (Column (5)) are sequential investments made 572 days (the median time between investments in our sample) or fewer apart, while investments not close in time (Column (6)) are sequential investments made more than 572 days apart. Indeed, angels are likelier to repeatedly invest in a successful firm if they do so close in time; the persistence parameter of 0.658 is the highest for these investments. In contrast, when investments are further apart, angels are likelier to repeatedly invest in failed firms. This speaks to the notion that innovative ideas or technologies come in waves and, thus, influence the persistence in firm selection. Columns (7)–(8) confirm this notion by differentiating by the industry focus of firms i and $i-1$. Angels are likelier to repeatedly invest in successful firms if they both operate in the same industry, while opposite is true for failed firms. This indicates that angels who repeatedly invest in the same industry gain industry expertise and are less prone to repeatedly investing in failing firms.[20]

5 Why Are Some Angels Better than Others?

Why do some angels earn higher returns than others? To explore this question we begin by examining whether the entire distribution of returns (not just the average return) varies according to angel performance. This offers insights into the selection process angels use, as well as the relationship between performance and risk-taking. Then we explore whether performance differences arise from patterns of co-investment, which would suggest an access-to-investment channel. We then explore the importance of angel's network, represented by her co-investors and fellow board members.

5.1 More Home Runs or Fewer Strike-Outs?

First we examine whether the performance differential is attributable to investors avoiding low-performing investments, or instead from their successfully seeking out high-performing investments. To use a baseball metaphor, do better performing angels strike out less often (i.e., hit more singles and doubles) or do they hit more home runs? To do this, we construct a measure of angel performance that is more closely tied to unobservable individual investor traits. We obtain it by recovering the error term from the regression in Equation 1 and as shown in Table 5 Column (1). Based on this measure, we group angel investors into performance quintiles, with the highest (top)

[20] Another alternative is that some angels approach angel investing like a lottery, intentionally favoring investments with low probability of success but high conditional payoffs. This would induce the opposite of performance persistence. Table B6 in Appendix B tests for this and finds no evidence of this behavior.

quintile representing the angel investors with the best investment performance not explained by the obsevable co-variates in the regression in Table 5 Column (1). Table 8 reports logit estimates from a regression model similar to Equation 1. The dependent variable is a dummy variable taking value one if the investment Full TVPI is within the stated percentile interval of the overall return distribution.

In columns (1) and (2), for returns just above the median, the estimated coefficients are lower for angels in the top quintile than for angels in the second, third and fourth quintiles, implying that better angels are no likelier than less well-performing investors to earn above-median returns. In contrast, Columns (5)–(8) demonstrate that high-performing angels are much likelier than other investors to achieve 90^{th} or 95^{th} percentile investment outcomes. The third-quintile angels have 9 times higher odds of having an investment outcome in the top 5% than first- and second-quintile angels, while angels in the top quintile have over 1,500 times higher odds of doing so. These results are robust to the inclusion of controls and fixed effects. Table B7 replicates the table for the subsample of realized returns, measured as Realized TVPI, and results remain qualitatively unchanged.

An alternative test is to explore whether better angels are more likely to invest in firms that attract venture funding. This is reported in Table 9. In Column (1), the dependent variable $VC\ Financing$ is a dummy variable taking value one if a VC investor invests through a financing round or secondary trades in the same firm as the angel investor at some point in time. Column (2) replaces the dependent variable with the natural logarithm of the total VC equity invested, conditional on receipt of VC financing. Columns (3) and (4) repeat columns (1) and (2), but require the VC investment to occur at a date strictly after the angel investment.

The results in Table 9 confirm that better angels are much likelier to invest in firms that raise VC funding. Consistently across all columns, larger angel investments are associated both with VC funding at all and with higher contemporaneous and future VC equity amounts. The logit estimates in Columns (1) and (3) imply that top-quintile angels have 2.0–2.3 times higher odds of investing in VC-backed firms than their counterparts in the lower quintiles. At the same time, Columns (2) and (4) provide evidence that, conditional on a firm's receiving VC funding, the provided VC equity amount is unrelated to angel performance. Our data do not allow us to go one step further and to determine whether the positive association with the follow-up VC financing arises because better angels *pick* better firms or whether they *create* better firms.

One may expect that unobserved, by investor and investment characteristics unexplained, angel performance is correlated with the financial performance of their portfolio firms. Figure 7 presents the evolution of firm performance by firm age (left column) and by the time prior to and after the first angel investment (right column). It demonstrates demonstrates that top-quintile-financed firms develop differently over time than their lower-quintile-financed counterparts. Specifically, at any firm age the first group displays higher revenues, employees, capital expenditures and intangible assets. The plots of firm development relative to the first angel investment reveal that the difference between these two groups is driven mostly by the period after the first angel investment. This is particularly the case for revenues and employees, for which we do not observe a significant difference in the pre-investment period. Our proxies for investments in tangible and intangible assets display more divergence in the pre-investment period, which might result from different types of angels matching to different business models.[21]

Overall, our findings provide evidence that better angels do not earn higher returns by avoiding left-tail realizations as much as they do by achieving extreme right-tail outcomes. To use a baseball metaphor, it is not that high-performing angels hit singles and doubles instead of striking out; instead, they are likelier than lower-performing investors to hit home runs.

5.2 Deal Access through Networks

Strictly speaking, our data do not allow us to determine whether better angels *pick* better firms or whether they *create* better firms. Nevertheless, we can ask whether some angel investors appear to have access to some investment opportunities that other angels do not, or whether instead angels differ in terms of their ability to discern promising opportunities from less attractive ones.

Network effects could potentially operate in a number of different ways. To measure the possibility that a small group of investors with privileged access to investment opportunities dominates the upper tail of the return distribution, we explore co-investments with other angels. A co-investment is defined as investing in the same firm in the same year as another angel investor. Figure 8 provides descriptive evidence on the repeat angels' co-investments in our sample of HIP firms. Only 6% of repeat angels do not co-invest with other angels, while a quarter of repeat angels co-invest at least once with a VC investor.[22] This illustrates that co-investing with other angels is an important component of repeat investing. Based on this, we assume that if we see groups

[21] Angel investments occur most often very early in firms' life with around 90% of firms receive their first angel investment by the end of their first year of operations, so that the analyses include solely 10% of our sample firms in the pre-investment period.

[22] In contrast, 23% of single-firm angels do not co-invest with other angels, and only 8% of single-firm angels co-invest at least once with a VC investor, as shown in Figure B1.

of angels repeatedly investing together, the correlation between performance and the strength of co-investing ties provides a test of whether performance is explained by differential access to deal flow.

To explore the relationship between an angel's performance and their co-investment with other angel investors, we develop a measure of co-investment concentration as follows. First, for each angel in our sample, we compute the fraction of the number of co-investments made by that angel with every other angels during our sample period to the total number of co-investments that angel made. So, for example, an angel who invested alongside three other angels in a total of ten co-investments would have the values $\frac{x_1}{10}$, $\frac{x_2}{10}$, and $\frac{x_3}{10}$, where x_i is a count of the number of investments made with each of the three angels. Then we take the maximum of this ratio for each angel investor and use this as a measure of their co-investment concentration. This assigns a higher concentration value to an angel whose investments are concentrated among a smaller number of total co-investors.

We then use this measure as the dependent variable in Table 10. Independent variables include a dummy variable $Top\ quintile$, which takes value one if the angel is grouped into the highest quintile based on the error term retrieved from the regression in Equation 1 and as shown in Table 5 Column (1), a dummy for repeat investors, investor's board experience, the natural log of investor's age, gender, a high-wealth dummy, the natural log of investor's total angel investment amount, the natural logarithm of the total number of HIP firms in which the angel investor has invested, the natural log of the number of co-investments with other angels, and fixed effects for the year of the angel's first angel investment.

Table 10 provides evidence that better angels invest with co-investors in a less concentrated manner. Columns (1)–(2) include all angel investments, while Columns (3)–(6) examine investment subsamples depending on whether the first angel investment has been realized, and, in case of realization, its return. We observe a consistently negative relationship between top angel performance and the co-investor concentration measure. The top-quintile angels have a 3.6% lower co-investor concentration compared to lower performing angels (Column (2)), i.e. better angels are characterized by having more dispersed co-investments with other angels. In the subsample of co-investments done after the first investment has been realized, the effect is strongest for the subsample of angels whose first investment has been realized with a positive return (Column (6)), but also the negative return subsample gets a weakly significant negative coefficient.[23] Overall,

[23]Since we do not include angels without co-investments in Table 10, Table B8 replicates Table 10, but in addition

since better angels do not invest alongside the same co-investors to the same extent as worse-performing angels, top-performing angels are less likely than lesser-performing angels to invest in tight-knit clusters. This speaks against the idea that a small group of angels has privileged access to high-quality deals from which others are potentially excluded.

We can also measure the connections that angels investors have to potential startup founders or, more generally, board members, through overlapping board memberships. This offers another perspective on access to deal flow. A board connections is defined as being together with another angel in a firm's board of directors at the same time. We calculate each angel investor's maximum number of board connections separately before and after her first angel investment and after her first angel investment realization. Joint board responsibilities represent a professional relationship with a significant duration, and in a network analysis, the hypothesis is that such relationships may increase the sharing of information related to investment opportunities in HIP firms.

Table 11 reports estimates from regressing the dummy variable taking value one if an angel investor has been connected through the boards to other people prior/after her first angel investment on the dummy variable $Top\ quintile$, which takes value one if the angel is grouped into the highest quintile based on the error term retrieved from the regression in Equation 1 and as shown in Table 5 Column (1). The dependent variable in Column (1) includes any such board connection, while Column (2) replaces the dependent variable with the dummy variable taking value one if an angel investor has been connected to other people in HIP firms only. Column (3) further narrows down the dependent variable to the connections to *founders* in HIP firms. Columns (4)–(7) replace the dependent variable by the change in the number of connections in HIP firms from the time period prior to the first angel investment either to the time period after the first angel investment (Column (4)) or the time period after the first angel investment realization (Columns (5)–(7)). Column (5) includes the change in connections in all HIP firms whilst Column (6) includes the change in HIP firm connections for the subsample of investors whose first angel investment was realized with a loss, and Column (7) equivalently for realizations with a positive return. Controls include; a dummy for repeat investors, investor's board experience, the natural log of investor's age, gender, a high-wealth dummy as introduced above, the natural log of investor's total angel investment amount, the natural logarithm of the total number of HIP firms in which the angel investor has invested, the natural log of the number of co-investments with other angels, and fixed effects for

includes angels who invest alone ($\sum co - investments_j = 0$), implying her co-investor concentration equal one. Results remain qualitatively unchanged.

the year of the angel's first angel investment.

Table 11 shows that angels who go on later to become top-performing angel investors in our sample are likelier to be connected to board members and founders of HIP firms *before* they make their first investment. These are professionally relevant connections as they are sharing the responsibilities as board members of at least one firm. In other words, they have business connections to founders of high-innovation potential firms before they themselves invest. This is not simply a matter of knowing more people in the business world: they are no likelier than lesser-performing angels to be connected to board members of non-HIP firms (Column (1)). The evidence in Column (6) confirms the importance of connections in potential investment opportunities. After realizing the first investment with a loss, top-quintile angels rely especially on their board networks, as evident by a large and statistically significant association of the change in the number of connections in HIP firms. If the angel has already established herself as a better-performing investor by her first angel realization yielding a positive return, we do not find any statistically significant increase in the number of connections (Column (5)). Seen together, the wider co-investor base and board network of angel investors allows us to interpret some of the unexplained better angel performance as deriving from larger professional networks in investment opportunities.

6 Conclusion

This paper provides some of the first large-scale evidence on the returns earned by angel investors. To develop these results, we assemble highly detailed investment-level time-series data linked back to individual investors in private companies from Norwegian equity transaction records to measure the performance of angel investors, to compare different types of angels, and to ask, ultimately, whether variation across investors is important for understanding this segment of the capital market and what factors drive it.

Using effectively the universe of angel investments in Norway from 2004-2018, we document enormous variation and skewness in performance. While around one third of all investments are complete write-offs, the average investment doubles its invested capital. This average is driven largely by the extreme right-tail of investment outcomes: nearly 75% of all investments involve some loss of invested capital, but the top percentile of investments returns around 50 times invested capital.

In spite of the lottery-like nature of angel investments, some angels are simply better than others. In other words, the distribution of angels returns inherits the skewness of the underlying investments. While observable characteristics explain variation in angel-level performance, unobservable characteristics are much more important. Persistent individual differences are critical for understanding this market. One explanation for these persistent differences is that some angel investors have better access to investments than others, such that, even if they choose randomly, they would do better. We do find evidence for this explanation.

This work connects entrepreneurship to household finance in new ways. While much previous work in entrepreneurship has connected household finance and entrepreneurship through the labor market decisions of entrepreneurs, ours is the first to link the performance in angel investments to performance in other investments, which helps orient the angel investment decision in the broader context of an individual's personal portfolio optimization problem. The results suggest that policy makers should proceed cautiously when trying stimulate private investment in early-stage companies.

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Figure 1: **The Distribution of Repeat Investments**

Figure 1 presents the distribution of the number of investments made by angels during our sample period (2003–2018).

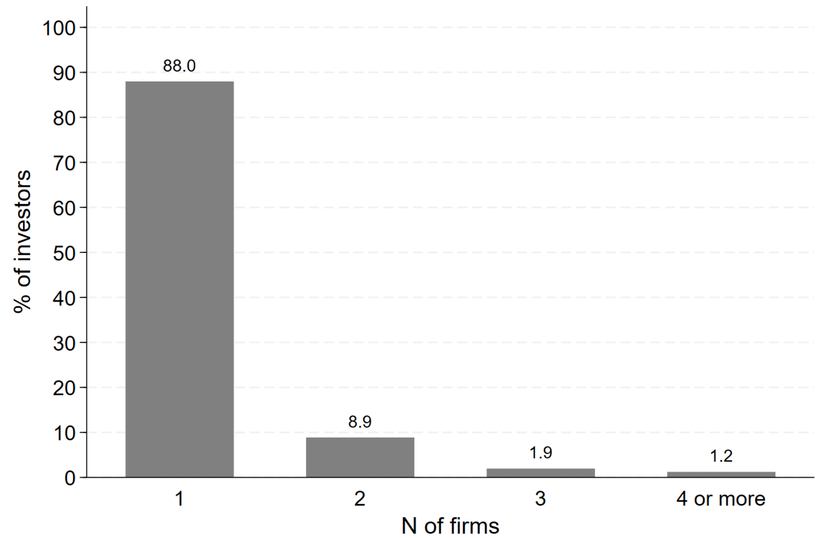

Figure 2: **The Distribution of Angel Investment Returns**

Figure 2 presents the distribution of returns to angel investment over our sample period (2003–2018). We measure returns as the *total value to paid-in capital (TVPI)*. We calculate TVPI as the realization amount (through sales or liquidation) divided by the purchase amount of the realized shares, Realized TVPI. For Adjusted TVPI, we additionally assume that if a firm does not report revenues in the time period of five consecutive years after the year of angel investment, the implied TVPI is zero. For Full TVPI, we compute for all remaining unrealized investments the untraded value of shares based on the most recent price observed in the latest financing round. This implies that Full TVPI includes all angel investments. For investments with multiple outcomes (e.g., partially realized, partially unrealized), TVPI is weighted by the purchase amount of the shares of the respective outcomes.

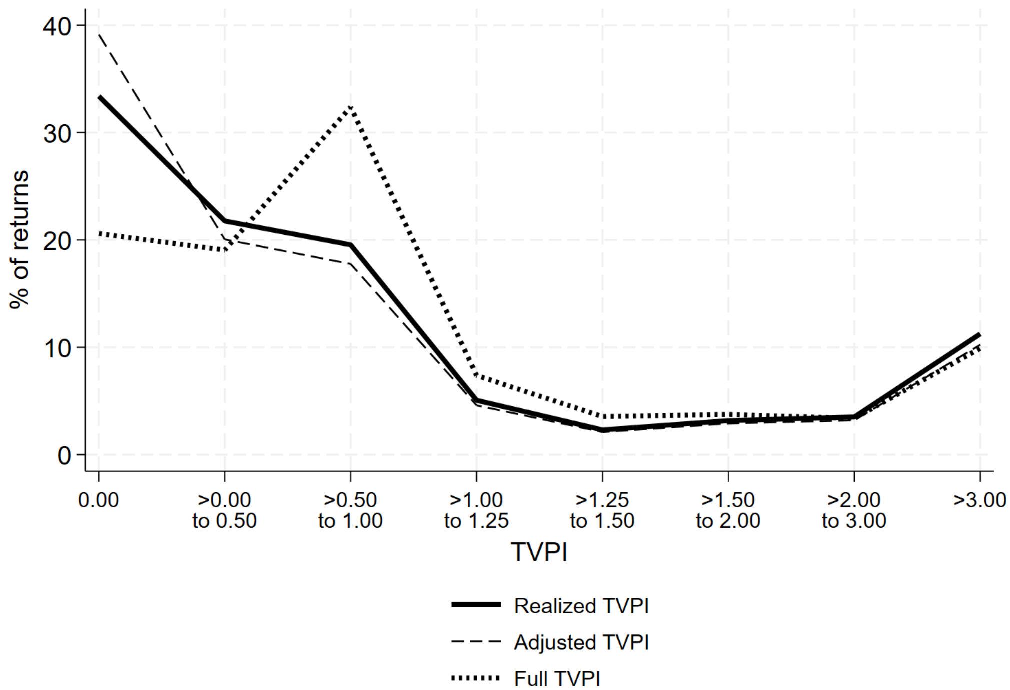

Figure 3: **The Distribution of Investment Holding Periods**

Figure 3 presents the distribution of average holding period (in days) of angel investments over our sample period (2003–2018). We measure returns as the *total value to paid-in capital (TVPI)*. We calculate TVPI as the realization amount (through sales or liquidation) divided by the purchase amount of the realized shares, Realized TVPI. For Adjusted TVPI, we additionally assume that if a firm does not report revenues in the time period of five consecutive years after the year of angel investment, the implied TVPI is zero. For Full TVPI, we compute for all remaining unrealized investments the untraded value of shares based on the most recent price observed in the latest financing round. This implies that Full TVPI includes all angel investments. For investments with multiple outcomes (e.g., partially realized, partially unrealized), TVPI is weighted by the purchase amount of the shares of the respective outcomes.

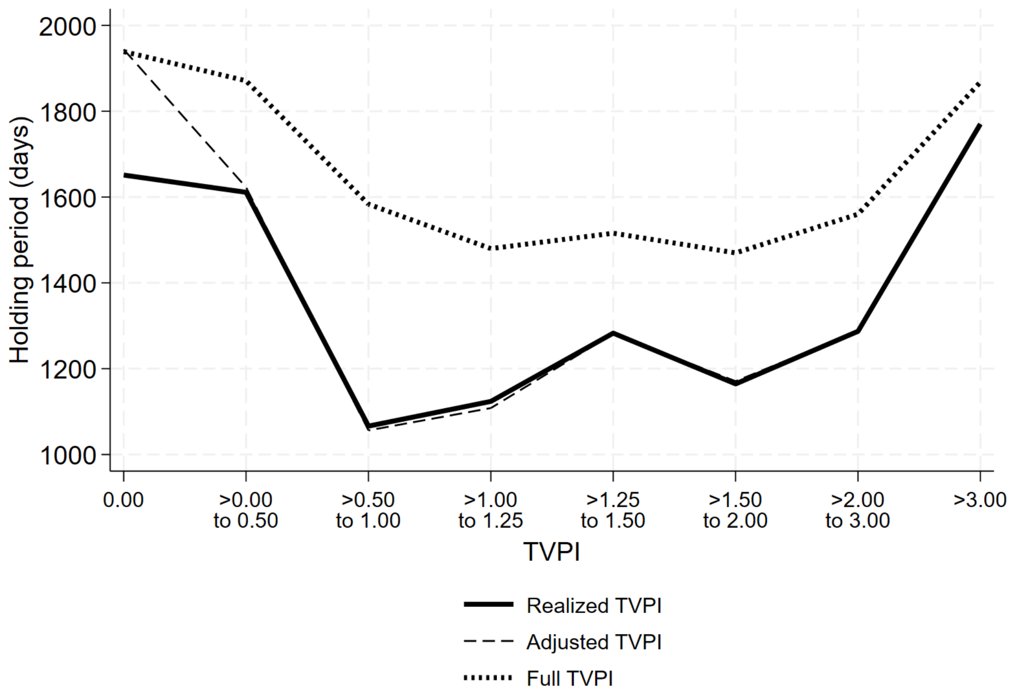

Figure 4: **The Distribution of Angel Returns by Investment Size**

Figure 4 presents the distribution of returns, measured as Full TVPI, by investment amount quartile. Size quartiles are defined as follows: less than 23 thousand Norwegian kroner (NOK) (4 thousand USD)=quartile 1, 23–54 thousand NOK (4–8 thousand USD)=quartile 2, 54–179 thousand NOK (8–27 thousand USD)=quartile 3, and more than 179 thousand NOK (27 thousand USD)=quartile 4. Amounts in USD are based on an exchange rate of 6.6 NOK per US dollar, the average daily interbank market midquote rate reported by Norges Bank over our sample period. We calculate TVPI as the realization amount (through sales or liquidation) divided by the purchase amount of the realized shares. In addition, we assume that if a firm does not report revenues in the time period of five consecutive years after the year of angel investment, the implied TVPI is zero. Finally, we compute for all remaining unrealized investments the untraded value of shares based on the most recent price observed in the latest financing round. For investments with multiple outcomes, (e.g., partially realized, partially unrealized), TVPI is weighted by the purchase amount of the shares of the respective outcomes.

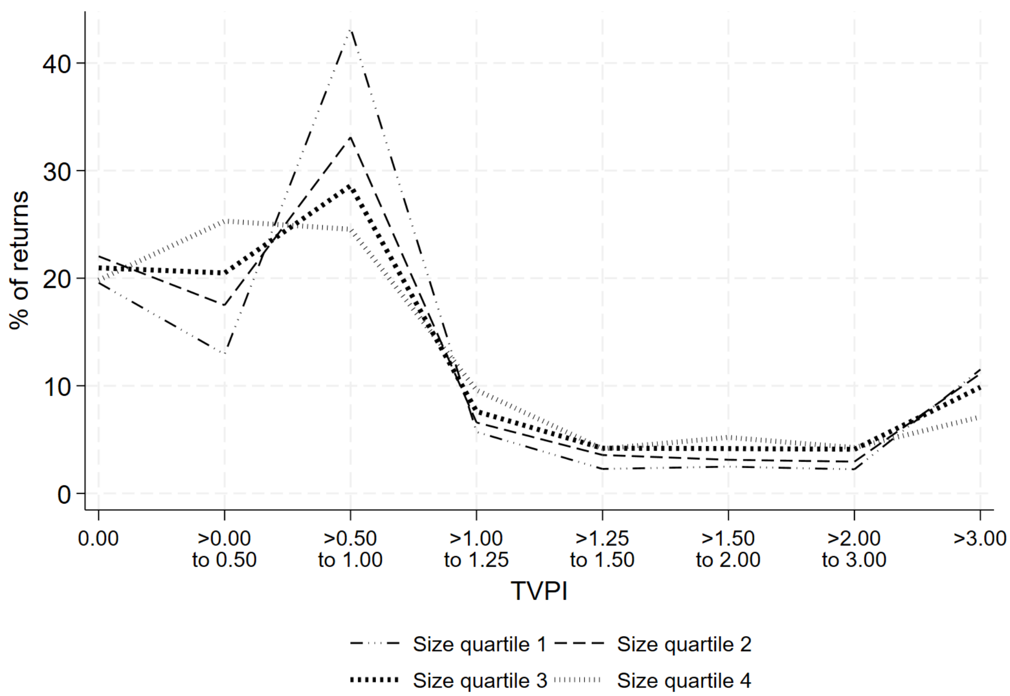

Figure 5: **The Proportion of Repeat Investors Over Time**

Figure 5 presents the distribution of the share of repeat angels among all angel investors by the calendar year of their first angel investment. A repeat angel is defined as an angel who invests in several HIP firms.

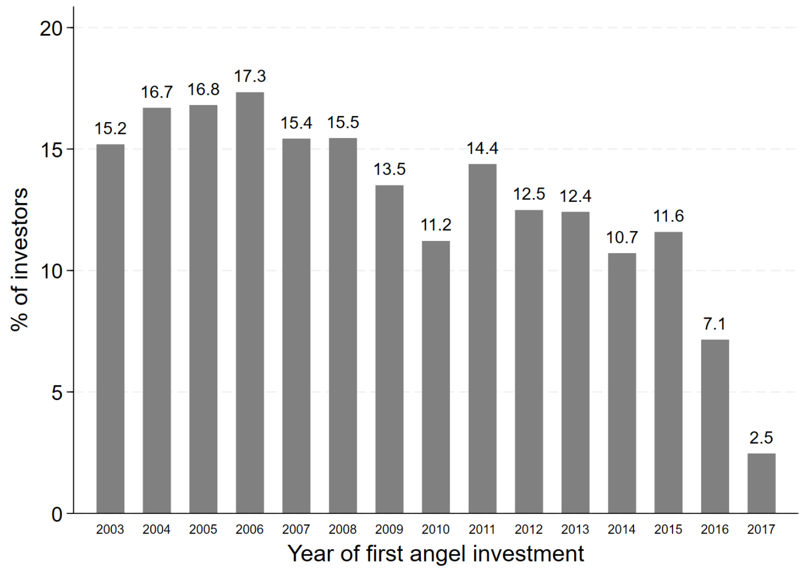

Figure 6: **The Distribution of Investments for Repeat Investors**

Figure 6 replicates Figure 1 for repeat angels only. A repeat angel is defined as an angel who invests in several HIP firms. Panel A is based on all investments, while Panel B is based on the subsample of investments that are realized (through sale or liquidation of shares) by the end of the sample period.

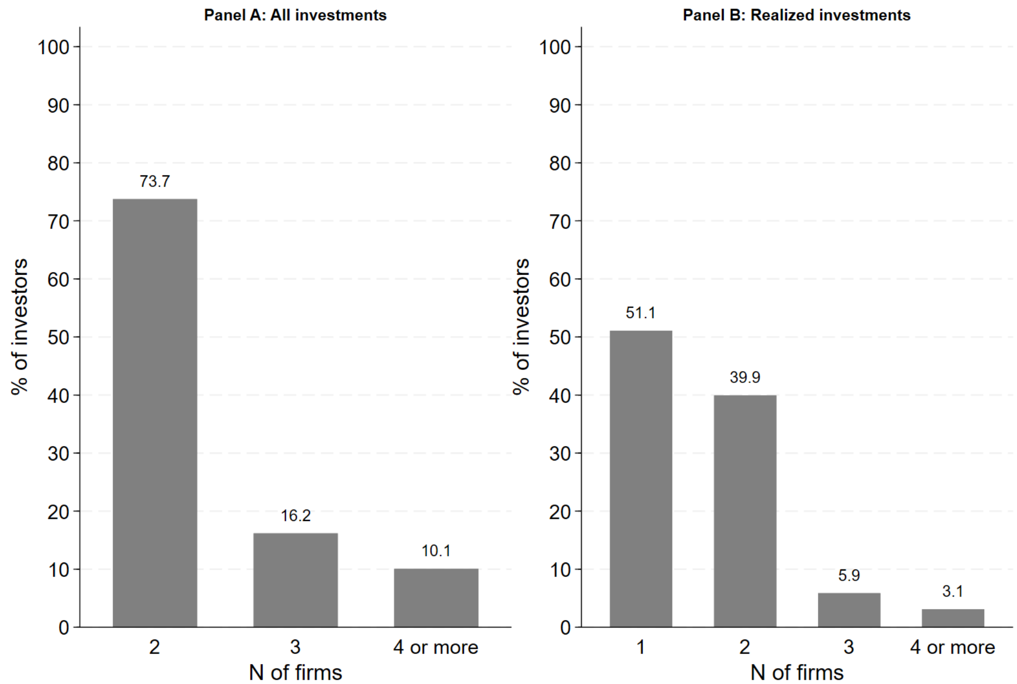

Figure 7: **Better Angels and Firm Performance**

Figure 7 presents the evolution of firm performance by firm age (left column) and by the time prior to and after the first angel investment (right column). Red dots represent firms with at least one angel investment from a top-quintile angel. Blue dots represent firms with at least one angel investment from a lower-quintile angels and no investments from top-quintile angels. Each row corresponds to a different firm performance measure: revenues, number of employees, capital expenditures, calculated as the change in the tangible assets plus total depreciation and amortization of fixed assets and (capitalized) intangible assets as reported on the balance sheet. All variables are measured in million NOK and are log-transformed.

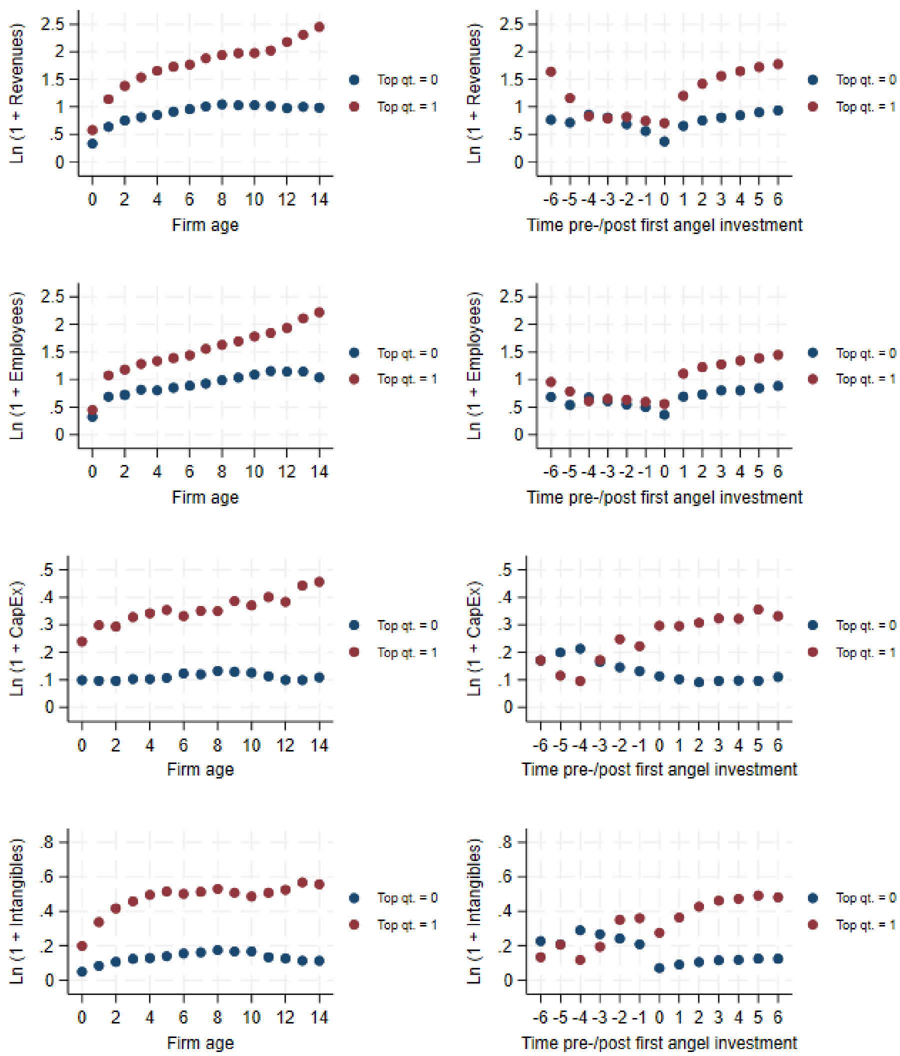

Figure 8: **Co-investments by Repeat Angels**

Figure 8 presents the distribution of the co-investments of repeat angel investors with other angel investors (Panel A) and with venture capital (VC) investors (Panel B). A co-investment with another angel investor (VC investor) is defined as an investment made in the same firm in the same year as another angel investor (VC investor). Figure B1 in Appendix B provides an overview of co-investments of single-firm angel investors.

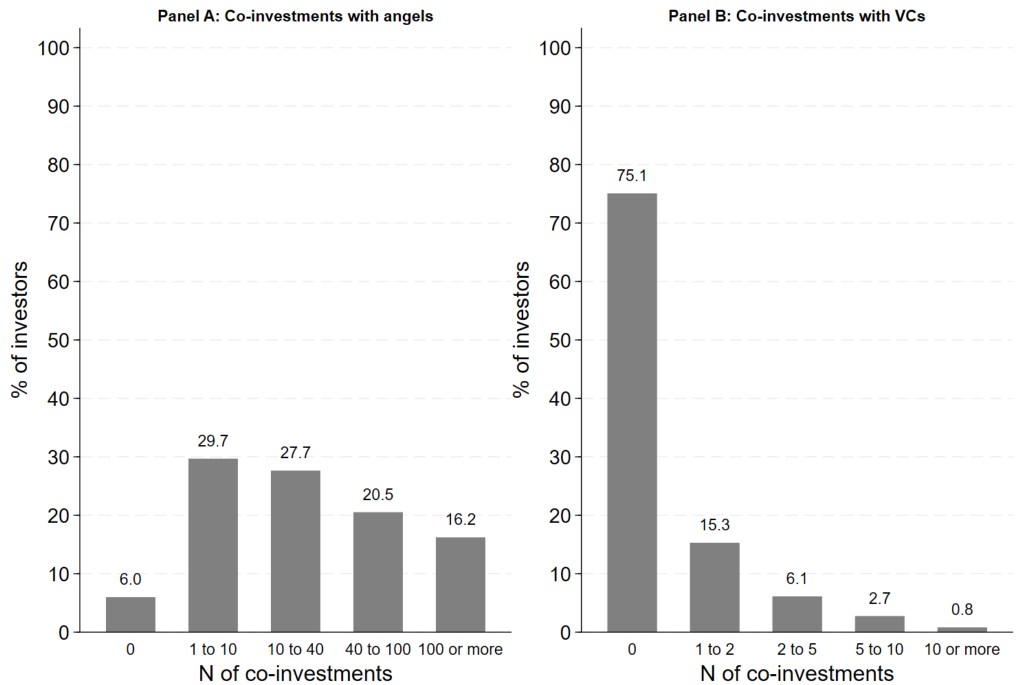

Table 1: Description of Sample Firms

Table 1 reports descriptive statistics of the sample of 14,376 HIP firms that receive angel investments. A HIP firm is a newly established firm (neither a holding nor a subsidiary) that operates outside financial services, real estate, and other non-innovative sectors. In addition, it satisfies at least one of the following criteria: English-language name, location near the largest university cities, and having at least one geographically distant board member. All amounts are in million NOK (1 USD is approximately 6.6 NOK over our sample period, based on the average daily interbank market midquotes reported by Norges Bank).

	N	mean	sd	skew.	p10	p25	p50	p75	p90	p95	p99
N of angels per firm	14,376	3.0	8.7	17.6	1.0	1.0	1.0	2.0	5.0	9.0	32.0
Firm characteristics in the year of angel investment											
Firm age	20,697	1.2	2.2	2.2	0.0	0.0	0.0	2.0	4.0	6.0	10.0
N of employees	13,532	4.4	14.3	14.2	0.0	0.0	1.0	4.0	10.0	18.0	52.0
Total assets (TA)	17,752	26.28	197.90	27.37	0.06	0.20	0.89	4.21	20.99	66.89	617.00
Revenues/TA	17,752	132.0%	7.53	67.19	0.0%	0.0%	46.8%	158.5%	288.9%	408.1%	952.6%
Net income/TA	17,752	-142.8%	29.08	-51.73	-116.5%	-36.0%	-4.6%	5.5%	25.6%	38.7%	61.4%
Bank loans/TA	17,752	15.5%	5.20	106.7	0.0%	0.0%	0.0%	0.0%	29.2%	54.8%	103.0%
Equity ratio	17,752	-26.8%	14.64	-49.00	-25.3%	10.8%	38.5%	77.2%	98.0%	100.0%	100.0%
Convertible loans/TA	17,752	4.4%	2.43	119.70	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	53.4%
Cash/TA	17,752	39.3%	0.38	8.38	1.1%	7.3%	29.8%	66.8%	100.0%	100.0%	100.0%
Intangible assets/TA	17,752	9.8%	0.26	20.73	0.0%	0.0%	0.0%	4.8%	41.6%	64.9%	89.3%
Firm status as of end of our sample period											
Independently operating	14,376	59.9%									
Bankruptcy/liquidation	14,376	26.0%									
M&A	14,376	13.9%									
IPO	14,376	0.2%									
Firm age at first exit event	14,376	5.2	3.6	0.8	1.0	2.0	4.0	7.0	11.0	13.0	14.0

Table 2: Description of Angel Investors

Table 2 reports descriptive statistics of of 36,749 angel investors in HIP firms. All amounts are in million NOK (1 USD is approximately 6.6 NOK over our sample period, based on the average daily interbank market midquotes reported by Norges Bank). Gross wealth represents taxable gross wealth after tax-related value discounts but before any debt deduction. Gross wealth and labor income data are available for 2011 onward and are expressed in 2015 values based on the consumer price index, adjusted for changes to duties and excluding energy goods, published by the statistical agency of Norway (SSB). We calculate *total value to paid-in capital (TVPI)* as the realization amount (through sales or liquidation) divided by the purchase amount of the realized shares. *Buy-and-hold annualized returns (BHAR)* are the annualized TVPI returns. *Public market equivalent (PME)* is TVPI adjusted by the Oslo Børs Benchmark Index (OSEBX) on each cashflow date. Investment returns are weighted average returns (by purchase amount of realized shares) of each angel investor.

	N	mean	sd	skew.	p10	p25	p50	p75	p90	p95	p99
Angel investors' portfolio characteristics											
N of portfolio firms	36,749	1.2	0.6	7.6	1.0	1.0	1.0	1.0	2.0	2.0	4.0
N of investments	36,749	1.8	2.0	7.5	1.0	1.0	1.0	2.0	3.0	5.0	10.0
% realized investments	36,749	50.2%	47.9%	-0.9%	0.0%	0.0%	50.0%	100.0%	100.0%	100.0%	100.0%
Angel characteristics in the year of her first angel investment											
Male	36,749	83.0%									
Investor age	36,749	43.9	12.4	0.4	28.0	34.0	43.0	52.0	61.0	66.0	75.0
Gross wealth	20,436	6.85	68.17	55.99	0.19	0.67	1.40	3.52	9.69	19.67	79.45
Annual labor income	20,436	0.97	3.45	23.48	0.10	0.31	0.54	0.92	1.72	2.88	8.89
Realized portfolio return											
TVPI angel investments	20,246	2.31	7.26	5.36	0.00	0.00	0.50	1.05	3.98	10.05	52.67
BHAR angel investments	20,246	100%	10.13	8.46	-100%	-100%	-30%	1%	66%	177%	9,340%
PME angel investments	20,246	1.76	5.39	5.38	0.00	0.00	0.40	0.99	3.01	7.18	39.13
TVPI non-HIP investments	1,920	2.64	8.67	5.82	0.00	0.00	0.57	1.14	4.73	11.68	66.70
TVPI public investments	13,483	1.28	0.83	2.63	0.72	0.95	1.04	1.32	2.05	3.03	5.33

Table 3: Returns to Angel Investment

Table 3 reports the distribution of returns to angel investment over our sample period (2003–2018). We measure returns as the TVPI. *Realized TVPI* is the realization amount (through sales or liquidation) divided by the purchase amount of the realized shares. *Adjusted TVPI* accounts for unrealized losses. For this, we assume that if a firm has had no reported revenues for five consecutive years after the angel investment, it is a total loss, and we assign a zero TVPI to the initial purchase. *Full TVPI* goes further to account for unrealized investments that are not total losses. Here, we assign the value of the most recent price observed in the last primary financing round to any unrealized share purchases. For investments with multiple outcomes (e.g., partially realized, partially unrealized), TVPI is weighted by the purchase amount of the shares of the respective outcomes. Panel A reports the distributions of the three measures of TVPI based on all investments in HIP firms. Panels B considers only HIP investments in financing rounds and Panel C only HIP investments in secondary trades. TVPIs are winsorized at the 1^{th} and 99^{th} percentiles.

		N per	TVPI										Total
	N	Angel	mean	sd	skew.	p10	p25	p50	p75	p90	p95	p99	Loss
Panel A: Angel Investments in HIP Firms													
Realized TVPI	36,525	1.6	2.16	7.12	5.59	0.00	0.00	0.23	1.00	3.62	9.15	53.21	33.4%
Adjusted TVPI	39,976	1.6	1.93	6.57	5.74	0.00	0.00	0.04	1.00	3.11	8.04	50.00	39.1%
Full TVPI	75,290	1.7	2.32	8.02	6.50	0.00	0.01	1.00	1.05	3.00	7.68	65.81	20.6%
Holding period (days)	75,290		1,725	1,282	1.00	433	719	1,333	2,445	3,798	4,392	5,261	
Panel B: Angel HIP Investments in Financing Rounds													
Realized TVPI	31,741	1.4	2.18	7.18	5.55	0.00	0.00	0.26	1.00	3.64	9.32	53.21	34.1%
Adjusted TVPI	34,926	1.4	1.94	6.60	5.72	0.00	0.00	0.05	1.00	3.05	7.89	50.00	40.1%
Full TVPI	65,891	1.6	2.28	7.89	6.60	0.00	0.00	1.00	1.02	2.93	7.19	62.50	21.1%
Holding period (days)	65,891		1,732	1,300	1.01	438	713	1,326	2,464	3,862	4,451	5,290	
Panel C: Angel HIP Investments in Secondary Trades													
Realized TVPI	4,784	5.4	2.04	6.72	5.87	0.00	0.00	0.08	1.11	3.56	9.00	52.68	28.8%
Adjusted TVPI	5,050	5.2	1.90	6.32	5.86	0.00	0.00	0.02	1.06	3.18	8.33	50.00	32.5%
Full TVPI	9,399	6.2	2.61	8.87	5.89	0.00	0.01	0.61	1.28	3.56	9.64	65.81	17.3%
Holding period (days)	9,399		1,673	1,153	0.84	410	752	1,389	2,381	3,366	4,017	4,812	

Table 4: Distribution of Returns by Angel Type

Table 4 replicates Table 3 and reports the distribution of returns to angel investments in HIP firms for different angel investor types. Family angels are individual investors who have the same last name as the firm founders. We differentiate between angels who invest in only one HIP firm (single-firm angels) and those who invest in two or more different HIP firms over our sample period (repeat angels). We also identify board-experienced angels; these are investors who at the time of their first angel investment hold a board seat in any other firm. Wealthy angels are individual investors who are above the 90^{th} percentile in the investor wealth distribution over 2011–2018 (the period for which wealth data are available). TVPIs are winsorized at the 1^{th} and 99^{th} percentiles.

		N per	TVPI										Total
	N	Angel	mean	sd	skew.	p10	p25	p50	p75	p90	p95	p99	Loss
Family angels													
Realized TVPI	3,720	1.2	1.63	6.30	6.64	0.00	0.00	0.00	1.00	2.06	5.65	45.45	44.4%
Adjusted TVPI	4,262	1.2	1.39	5.67	6.96	0.00	0.00	0.00	0.94	1.82	4.88	36.94	51.5%
Full TVPI	8,715	1.2	1.76	6.81	8.03	0.00	0.00	1.00	1.00	1.50	4.00	44.95	25.0%
Board-experienced angels													
Realized TVPI	20,948	1.7	2.14	7.21	5.62	0.00	0.00	0.24	1.00	3.23	8.70	53.21	32.8%
Adjusted TVPI	22,856	1.7	1.92	6.67	5.76	0.00	0.00	0.07	1.00	2.85	7.56	50.00	38.5%
Full TVPI	42,659	2.0	2.34	8.11	6.44	0.00	0.01	0.98	1.10	3.00	7.72	65.81	20.4%
Wealthy angels													
Realized TVPI	5,000	2.3	2.19	7.98	5.32	0.00	0.00	0.05	1.00	2.69	7.45	53.21	37.3%
Adjusted TVPI	5,584	2.3	1.91	7.28	5.56	0.00	0.00	0.00	1.00	2.30	6.22	50.00	43.8%
Full TVPI	10,812	2.9	2.10	7.77	6.77	0.00	0.00	0.75	1.06	2.50	5.55	57.04	22.4%
Single-firm angels													
Realized TVPI	23,605	1.4	2.07	6.80	5.74	0.00	0.00	0.30	1.01	3.33	8.32	46.67	32.0%
Adjusted TVPI	25,667	1.4	1.86	6.29	5.87	0.00	0.00	0.08	1.00	2.99	7.20	41.67	37.5%
Full TVPI	47,240	1.5	2.29	7.93	6.56	0.00	0.01	1.00	1.06	2.97	7.21	62.50	20.2%
Repeat angels													
Realized TVPI	9,200	2.7	2.62	8.14	4.98	0.00	0.00	0.25	1.13	5.03	12.01	53.21	32.3%
Adjusted TVPI	10,047	2.7	2.35	7.52	5.10	0.00	0.00	0.08	1.02	4.25	11.36	50.00	38.1%
Full TVPI	19,335	4.4	2.64	8.70	5.92	0.00	0.01	0.97	1.25	3.86	10.00	65.81	19.6%
Repeat angels' first investments													
Realized TVPI	4,956	1.7	2.90	8.54	4.65	0.00	0.00	0.26	1.20	6.63	12.86	53.21	31.8%
Adjusted TVPI	5,469	1.7	2.57	7.85	4.79	0.00	0.00	0.08	1.04	6.08	12.01	50.00	38.2%
Full TVPI	8,871	2.0	2.79	8.95	5.56	0.00	0.00	0.69	1.22	4.57	11.81	65.81	23.3%

Table 5: Cross-Sectional Variation in Angels' Returns

Table 5 reports OLS estimates from the regression model shown in Equation 1. The dependent variable is one plus the natural logarithm of the Full TVPI as described in Table 2. $Repeat\ angel$ is a dummy variable taking value one if angel invests in several HIP firms. $Board\ experienced\ angel$ is a dummy variable taking value one if the angel investor holds a board seat in any other firm at the time of her first angel investment. $Investor\ age$ is the natural logarithm of the investor's age at the time of investment. $Male$ is a dummy variable taking value one for male angels. $High\ wealth$ a dummy variable taking value one for angel investors who are above the 90^{th} percentile in the investor wealth distribution over the time period 2011–2018. $Investment\ amount$ controls for the investment (purchase) amount. $Secondary\ purchase$ is a dummy variable taking value one if the investor buys shares in a secondary trade. $Holding\ period$ is the natural logarithm of the holding period of the investment measured in days. $Board\ seat$ is a dummy variable taking value one if the angel investor receives a board seat at the time of investment. $\%\ of\ investment\ realized$ is the fraction of the investment that is realized. $Public\ market\ return$ is the return on the Oslo Børs Benchmark Index (OSEBX) over the investment period. Standard errors are clustered at the firm level and reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Angel's Total N of Investments	>=1	>=2	>=2	>=3	>=4	>=1
	(1)	(2)	(3)	(4)	(5)	(6)
Repeat angel (1/0)	0.061***					0.017*
	(0.023)					(0.010)
Board experienced angel (1/0)	0.006	-0.001				0.034***
	(0.013)	(0.020)				(0.007)
Investor Characteristics						
Ln (Investor age)	-0.128***	-0.205***				0.013
	(0.027)	(0.039)				(0.015)
Male (1/0)	0.033*	0.027				0.021***
	(0.019)	(0.028)				(0.007)
High wealth (1/0)	-0.026	-0.008				0.025**
	(0.020)	(0.022)				(0.011)
Investment Characteristics						
Ln (Investment amount)	-0.047***	-0.066***	-0.110***	-0.107***	-0.102***	-0.108***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.007)
Secondary purchase (1/0)	0.023	-0.013	-0.018	-0.027	-0.037	0.013
	(0.038)	(0.035)	(0.023)	(0.025)	(0.027)	(0.020)
Ln (Holding period)	-0.098***	-0.079***	0.027	0.026	0.026	0.060***
	(0.020)	(0.025)	(0.029)	(0.031)	(0.034)	(0.023)
Board seat (1/0)	0.057**	0.107***	0.110***	0.130***	0.130***	0.140***
	(0.024)	(0.026)	(0.028)	(0.029)	(0.031)	(0.013)
% of investment realized	-0.263***	-0.300***	-0.182***	-0.197***	-0.205***	-0.139***
	(0.059)	(0.075)	(0.058)	(0.061)	(0.066)	(0.044)
Public market return	-0.118**	-0.078	-0.028	-0.039	-0.038	-0.015
	(0.056)	(0.048)	(0.040)	(0.043)	(0.046)	(0.029)
Observations	66,575	42,096	42,096	29,120	22,073	59,149
Adjusted R-squared	5.4%	6.9%	43.6%	43.1%	40.4%	59.3%
Calendar year FE	Yes	Yes	Yes	Yes	Yes	Yes
Investment firm age FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	No	No	Yes	Yes	Yes	No
Firm FE	No	No	No	No	No	Yes

Table 6: Endogeneity of Repeat Investments

Table 6 reports logit estimates from the regression model shown in Equation 2. The dependent variable $Repeat\ angel$ is a dummy variable that takes the value of one if an angel has made investments in more than one HIP firm. Columns (1)–(3) estimate the propensity to become a repeat angel among all angel investors. Column (4) does so for the subsample of early-stage angels, while Column (5) does so for the subsample of late-stage angels. An angel is defined as early stage if her first angel investment occurs in the firm in the year of its inception or one year after. An angel is defined as late stage if her first angel investment occurs in the firm when it is aged five or older. Columns (6) and (7) estimate the propensity to become a repeat angel among small and large angel investors, respectively. An angel is defined as small if she invests less than 50 thousand NOK and as large if she invests 500 thousand NOK or more in her first angel investment. $First\ investment\ realized$ is a dummy variable taking value one if the angel's first investment has been realized during the sample period. $First\ investment\ TVPI$ is the return of the investor's first angel investment, measured as the natural logarithm of one plus the investment return, calculated as either as Realized TVPI (Column (2)) or Full TVPI(Column (3)). $First\ investment\ amount$ controls for the total amount invested in the first angel investment. $Board\ experienced\ angel$ is a dummy variable taking value one if the angel investor holds a board seat in any other firm at the time of her first angel investment. $Investor\ age$ is the natural logarithm of the investor's age at the time of her first investment. $Male$ is a dummy variable taking value one for male angels. $High\ wealth$ is a dummy variable taking value one for angel investors who are above the 90^{th} percentile in the investor wealth distribution over the time period 2011–2018. A fixed effect for the calendar year of the first angel investment is included in all specifications. Robust standard errors are reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Angel Investors	All (1)	All (2)	All (3)	Early-Stage (4)	Late-Stage (5)	Small (6)	Large (7)
First investment realized (1/0)	0.208***						
	(0.038)						
Ln (1 + first investment Realized TVPI)		0.197***		0.197***	0.531***	0.260***	-0.033
		(0.021)		(0.023)	(0.152)	(0.028)	(0.086)
Ln (1 + first investment Full TVPI)			0.139***				
			(0.017)				
Ln (First investment amount)	0.230***	0.250***	0.239***	0.250***	0.110	0.631***	0.159***
	(0.012)	(0.016)	(0.012)	(0.018)	(0.082)	(0.081)	(0.058)
Board experienced angel (1/0)	0.586***	0.571***	0.597***	0.598***	0.714***	0.603***	0.903***
	(0.040)	(0.050)	(0.040)	(0.057)	(0.244)	(0.078)	(0.199)
Ln (Investor age)	-0.542***	-0.553***	-0.534***	-0.590***	-0.035	-0.519***	-1.104***
	(0.064)	(0.082)	(0.065)	(0.093)	(0.397)	(0.128)	(0.259)
Male (1/0)	0.563***	0.578***	0.559***	0.602***	0.050	0.701***	0.447**
	(0.055)	(0.070)	(0.055)	(0.079)	(0.260)	(0.117)	(0.200)
High wealth (1/0)	0.934***	0.900***	0.928***	0.984***	1.082***	1.075***	0.936***
	(0.046)	(0.059)	(0.046)	(0.066)	(0.308)	(0.118)	(0.130)
Observations	36,749	19,545	36,749	15,971	959	9,383	1,628
Pseudo R-squared	9.7%	8.3%	9.8%	8.8%	11.8%	7.8%	10.6%
Calendar year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: What Explains the Persistence in Firm Selection?

Table 7 reports OLS estimates from the regression model shown in Equation 3 by subsamples of different angel types and investment characteristics. The dependent variable $Success(Failure)$ is either a dummy variable taking value one if the firm has a successful exit event (merger, acquisition or IPO) (Panel A) or a dummy variable taking value one if the firm has an unsuccessful outcome (bankruptcy or liquidation) (Panel B). $Success_{i-1}$ ($Failure_{i-1}$) is a dummy variable taking value one if the firm in which the angel invested before has a successful (unsuccessful) exit event. Columns (1)–(4) differentiate between angel investor types as defined in Table 3. Columns (5)–(6) differentiate by the investment timing between firms i and $i-1$. Investments close in time (Column (5)) are sequential investments made 572 days (median value in our sample) or fewer apart, while investments not close in time (Column (6)) are sequential investments made more than 572 days apart. Columns (7)–(8) differentiate by the industry focus of firms i and $i-1$. Firms $i-1$ and i operate in the same industry in Column (7), while they operate in different industries in Column (8). We employ a broad, 10-industry classification here. Controls include (untabulated) the following investor and investment characteristics: investor age, gender, high net wealth dummy (except for Columns (3)–(4)), investment amount, and a dummy for holding a board seat. All specifications include fixed effects for industry and firm founding and exit years, and fixed effects for the calendar year of investment. Standard errors are clustered at the firm level and reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Firm Success

	Angel Investor				Investment Timing		Industry Focus	
	Board-Experienced	Board-In-Experienced	High Wealth	Low Wealth	Close	Not close	Same	Different
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Success_{i-1}$ (1/0)	0.517***	0.205	0.630***	0.332	0.658**	0.179	0.564**	0.263
	(0.193)	(0.350)	(0.212)	(0.248)	(0.323)	(0.177)	(0.231)	(0.219)
Observations	4,994	1,347	2,087	4,233	3,176	3,167	2,571	3,554
Pseudo R-squared	40.9%	49.3%	45.1%	42.8%	47.0%	42.0%	48.7%	42.3%
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Firm Failure

	Angel Investor				Investment Timing		Industry Focus	
	Board-Experienced	Board-In-Experienced	High Wealth	Low Wealth	Close	Not close	Same	Different
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Failure_{i-1}$ (1/0)	0.371**	0.370	0.196	0.439**	0.181	0.437***	0.103	0.392**
	(0.145)	(0.310)	(0.206)	(0.170)	(0.210)	(0.169)	(0.226)	(0.177)
Observations	4,994	1,342	2,087	4,250	3,176	3,167	2,760	3,554
Pseudo R-squared	36.1%	41.3%	38.3%	36.6%	37.6%	40.1%	42.1%	34.3%
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Better Angels and the Tail of Returns

Table 8 reports logit estimates from a regression model similar to Equation 1. The dependent variable is a dummy variable taking value one if Full TVPI is within the stated percentile interval of the overall return distribution. $Performance\ error\ term$ is an investor-level measure of angel performance that is more closely tied to unobservable individual investor traits. We obtain it by recovering the error term retrieved from the regression in Equation 1 and as shown in Table 5 Column (1). Based on this measure, we group angel investors into performance quintiles, with the highest (top) quintile representing the best-performing angel investors. We control (untabulated) for all time-variant investor and all investment characteristics as described in Table 4. Standard errors are clustered at the firm level and reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Full TVPI Percentile (1/0)	50^{th} =<p <75^{th}		75^{th} =<p <90^{th}		90^{th} =<p <95^{th}		p>= 95^{th}	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Performance error term								
2nd quintile	2.394***	2.557***	1.936***	1.984***	3.158***	3.397***	0.705	0.975
	(0.110)	(0.102)	(0.228)	(0.231)	(1.027)	(1.027)	(0.885)	(0.888)
3rd quintile	3.464***	3.479***	3.307***	3.277***	4.724***	4.930***	2.150***	2.471***
	(0.123)	(0.112)	(0.254)	(0.258)	(1.009)	(1.009)	(0.750)	(0.756)
4th quintile	3.304***	3.552***	4.307***	4.334***	5.701***	6.036***	3.996***	4.771***
	(0.109)	(0.125)	(0.261)	(0.263)	(1.006)	(1.006)	(0.720)	(0.721)
5th quintile	1.825***	2.044***	4.655***	4.686***	7.877***	8.118***	7.334***	8.057***
	(0.108)	(0.128)	(0.256)	(0.260)	(1.003)	(1.003)	(0.710)	(0.712)
Observations	66,575	66,575	66,575	66,575	66,575	66,324	66,575	66,323
Pseudo R-squared	13.0%	32.9%	16.3%	21.0%	26.0%	28.6%	34.6%	45.4%
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Calendar year FE	No	Yes	No	Yes	No	Yes	No	Yes
Investment firm age FE	No	Yes	No	Yes	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes

Table 9: Better Angels and VC Financing

Table 9 reports logit estimates from regressing the dependent variable $VC\ Financing$, which is a dummy variable taking value one if a VC investor invests through a financing round or secondary trades in the same firm as the angel investor at some point in time, on the dummy variable $Top\ quintile$, which takes value one if the angel is grouped into the highest quintile based on the error term retrieved from the regression in Equation 1 and as shown in Table 5 Column (1) (Column (1)). Column (2) replaces the dependent variable with the natural logarithm of the total VC equity invested, conditional on receipt of VC financing. Columns (3) and (4) repeat columns (1) and (2), but require the VC investment to occur strictly after the angel investment. $Angel\ equity\ amount$ is the natural logarithm of the total equity amount provided by the respective angel investor to the firm. Calendar year, firm founding year and industry fixed effects are included in all specifications. Standard errors are clustered at the firm level and reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

			Follow-on	
	VC Financing (1/0)	Ln (VC Equity)	VC Financing (1/0)	Ln (VC Equity)
	(1)	(2)	(3)	(4)
Ln (Angel equity amount)	0.301***	0.234***	0.341***	0.100**
	(0.032)	(0.047)	(0.036)	(0.044)
Top quintile (1/0)	0.688***	0.209	0.820***	-0.022
	(0.132)	(0.168)	(0.145)	(0.167)
Observations	43,294	5,905	42,707	4,009
Pseudo/Adjusted R-squared	15.6 %	26.9 %	13.8 %	23.0 %
Fixed effects	Yes	Yes	Yes	Yes

Table 10: Do Better Angels Have the Same Co-investors?

Table 10 reports OLS estimates from regressing angel investor's co-investment concentration on the dummy variable $Top\ quintile$, which takes value one if the angel is grouped into the highest quintile based on the error term retrieved from the regression in Equation 1 and as shown in Table 5 Column (1). To develop a measure of co-investment concentration, for each angel in our sample, we compute fraction of the number of co-investments made by that angel with every other angels during the sample period to the total number of co-investments that angel made. Then we take the maximum of this ratio for each angel investor and use this as a measure of their co-investment concentration. This assigns a higher concentration value to an angel whose investments are concentrated among a smaller number of total co-investors. Columns (1)–(2) include all angel investors, while Columns (3)–(6) examine subsamples depending on whether the first angel investment has been realized. $Repeat\ angel$ is a dummy variable taking value one if angel invests in several HIP firms. $Board\ experienced\ angel$ is a dummy variable taking value one if the angel investor holds a board seat in any other firm at the time of her first angel investment. $Investor\ age$ is the natural logarithm of the investor's age at the time of her first angel investment. $Male$ is a dummy variable taking value one for male angels. $High\ wealth$ a dummy variable taking value one for angel investors who are above the 90^{th} percentile in the investor wealth distribution over the time period 2011–2018. $Total\ angel\ investment\ amount$ controls for the investment (purchase) amount an angel has invested in all HIP firms. $Portfolio\ firms$ controls for the total number of HIP firms in which the angel has invested, while $N\ of\ co-investments\ with\ angels$ does so for the angel's total number of co-investments with other angel investors during our sample period. Fixed effects for the year of the angel's first angel investment are included in Columns (2)–(6). Robust standard errors are reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Angel Investors	All	All	First Investment			
			Not Realized	Realized		
				All	$TVPI <= 1$	$TVPI > 1$
	(1)	(2)	(3)	(4)	(5)	(6)
Top quintile (1/0)	-0.028***	-0.036***	-0.030***	-0.026***	-0.020*	-0.032***
	(0.005)	(0.003)	(0.003)	(0.007)	(0.011)	(0.012)
Repeat angel (1/0)		-0.075***	-0.063***	-0.025*	-0.020	-0.031
		(0.007)	(0.012)	(0.013)	(0.015)	(0.024)
Board-experienced angel (1/0)		0.008***	0.011***	0.002	0.004	-0.004
		(0.002)	(0.003)	(0.008)	(0.009)	(0.013)
Ln (Investor age)		-0.003	-0.011**	-0.003	-0.015	0.035
		(0.004)	(0.004)	(0.013)	(0.016)	(0.024)
Male (1/0)		-0.003	0.000	0.008	0.006	0.007
		(0.003)	(0.003)	(0.010)	(0.012)	(0.016)
High wealth (1/0)		-0.006	-0.014***	-0.005	-0.001	-0.014
		(0.004)	(0.004)	(0.010)	(0.011)	(0.018)
Ln (Total angel investment amount)		0.002**	0.003***	0.010***	0.010***	0.011**
		(0.001)	(0.001)	(0.003)	(0.003)	(0.005)
Ln (Portfolio firms)		0.124***	0.175***	0.052***	0.052***	0.048**
		(0.008)	(0.014)	(0.011)	(0.014)	(0.020)
Ln (N of co-investments with angels)		-0.184***	-0.184***	-0.170***	-0.171***	-0.169***
		(0.001)	(0.001)	(0.002)	(0.003)	(0.005)
Observations	28,982	28,982	27,405	4,042	2,837	1,205
Adjusted R-squared	0.1 %	72.5 %	69.7 %	61.8 %	62.6 %	59.3 %
Calendar year FE	No	Yes	Yes	Yes	Yes	Yes

Table 11: Does Angel's (Board) Network Matter?

Table 11 reports logit estimates from regressing the dummy variable taking value one if an angel investor has been connected through the boards to other people prior to her first angel investment on the dummy variable $Top\ quintile$, which takes value one if the angel is grouped into the highest quintile based on the error term retrieved from the regression in Equation 1 and as shown in Table 5 Column (1) (Column (1)). Column (2) replaces the dependent variable with the dummy variable taking value one if an angel investor has been connected to other people in HIP firms only, while Column (3) further narrows down the dependent variable to the connections to founders in HIP firms. Columns (4)–(7) replace the dependent variable by the count variable, which captures the change in the number of connections in HIP firms from the time period prior to the first angel investment either to the time period after the first angel investment (Column (4)) or the time period after the first angel realization (Columns (5)–(7)). $Repeat\ angel$ is a dummy variable taking value one if angel invests in several HIP firms. $Investor\ age$ is the natural logarithm of the investor's age at the time of her first angel investment. $Male$ is a dummy variable taking value one for male angels. $High\ wealth$ a dummy variable taking value one for angel investors who are above the 90^{th} percentile in the investor wealth distribution over the time period 2011–2018. $Total\ angel\ investment\ amount$ controls for the investment (purchase) amount an angel has invested in all HIP firms and $Portfolio\ firms$ does so for the total number of HIP firms in which the angel has invested. Fixed effects for the year of the angel's first angel investment are included in all specifications and for the year of the angel's first realization in Columns (5)–(7). Robust standard errors are reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Angel Investors	Any Connections Before First Angel Investment			Change in Number of Connections After First Angel Investment			
					After First Angel Realization		
	All Firms	HIP Firms	HIP Founders	HIP Firms	HIP Firms All	HIP Firms $TVPI <= 1$	HIP Firms $TVPI > 1$
	Logit	Logit	Logit	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Top quintile (1/0)	-0.041	0.124***	0.061**	0.117**	0.252***	0.552***	-0.103
	(0.029)	(0.041)	(0.029)	(0.056)	(0.065)	(0.140)	(0.129)
Repeat angel (1/0)	0.105	0.283**	0.107	-2.959***	-2.474***	-2.542***	-2.454***
	(0.132)	(0.119)	(0.110)	(0.458)	(0.475)	(0.564)	(0.900)
Ln (Investor age)	1.965***	0.763***	1.505***	-0.772***	-0.927***	-0.950***	-0.804***
	(0.043)	(0.054)	(0.041)	(0.062)	(0.085)	(0.097)	(0.188)
Male (1/0)	0.634***	0.597***	0.594***	0.568***	0.418***	0.375***	0.505***
	(0.031)	(0.053)	(0.033)	(0.043)	(0.053)	(0.060)	(0.115)
High wealth (1/0)	2.025***	0.695***	1.339***	0.496***	0.222	-0.048	0.981***
	(0.070)	(0.050)	(0.043)	(0.105)	(0.142)	(0.157)	(0.319)
Ln (Total angel investment amount)	0.074***	0.040***	0.071***	-0.027*	0.059***	0.065***	0.038
	(0.008)	(0.012)	(0.008)	(0.016)	(0.021)	(0.025)	(0.040)
Ln (Portfolios firms)	0.485***	0.332**	0.551***	6.324***	5.275***	5.730***	4.254***
	(0.159)	(0.131)	(0.129)	(0.581)	(0.598)	(0.722)	(1.086)
Observations	36,749	34,556	36,749	36,749	20,246	15,036	5,210
Pseudo/Adjusted R-squared	12.0 %	6.6 %	9.8 %	15.4 %	17.0 %	18.1 %	15.7 %
Calendar year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

A Identifying Firms with High Innovation Potential applying Kisseleva, Mjøs and Robinson (2024)

A.1 Sample Selection

To construct our sample of interest, thus, firms potentially seeking early-stage equity financing from angel investors, we begin by identifying all newly established limited liability companies (analogous to C-corporations in the US) incorporated between 2004 and 2017. We remove financial services and real estate firms, newly formed subsidiaries of established companies, holding structures, and firms in industries that are also heavily regulated, have high levels of public-sector involvement or ownership, are heavily supported via taxes and/or subsidies, or are highly unlikely to engage in value-creating innovative growth projects. In such industries, we expect non-financial objectives such as government policies to be especially important. For our purposes to identify firms relevant for angel investing we apply a stricter industry filter than Kisseleva et al. (2024) and in addition exclude firms operating in industries that are usually considered non-innovative. We apply negative selection to rule out such industries. The excluded industries are the following: *agents/traders, agriculture, banks, brokers, cultural event producers, direct health services, education, fisheries, food production, gym/sports facilities, hotels, insurers, investment management, kindergartens, garages, mail-order, mining, museums, oil and gas production, physical shops, public services, publishing, real estate, restaurants, shipping companies, wholesale traders, and direct services (e.g., hairdressers, for tourists, car rental, lawyers, maintenance, accountants, auditors, builders, plumbers, electricians, undertakers, taxis).*

Table A1 shows that, out of the population of 79,196 newly formed firms, a total of 902 firms receive at least one investment from an institutional VC investor. For our purposes, VC investors comprise venture capital (traditional, corporate or government-affiliated) funds, early-stage investment funds associated with traditional private equity groups, and incubators.

Of course, it is unlikely that most of these 79,196 firms have growth aspirations or the intention to develop large-scale commercial innovation. Hurst and Pugsley (2011) show that most small business owners (in the US) have no desire to grow, operating their own businesses primarily for lifestyle purposes. Guzman and Stern (2015, 2020) start by recognizing that a practical first step for any growth-oriented entrepreneur in the US is to register her business in the state in which she operates: This facilitates paying payroll taxes, unemployment insurance, etc. Incorporated businesses are significantly likelier to grow than non-incorporated businesses. To adapt these insights to the Norwegian business context, we develop three flags that we use to gauge a firm's likely innovation potential at the time that it first appears in the tax registry data.[24] Population counts of the firms satisfying the criteria for these flags are reported in Table A1.

The first flag is whether the firm has an English-language firm name. A total of 26,452 firms, or approximately 33% of the sample, satisfy this criterion. The idea behind this flag is that because Norway is a country of only some five million people, an English-language firm name helps the firm be recognizable to a broader, international audience and therefore would be a natural choice for an entrepreneur intending to grow her firm. Giving the firm an English-language name would not necessarily confer a natural advantage if the firm's objective were to serve the local market, but if the firm developed a product or a service that appealed to customers in many national markets, an English-language firm name would be a logical choice, especially in northern Europe, where English is commonly spoken as a second language.

The second flag is whether the firm is located in a regional innovation hub in Norway. The

[24] Kisseleva et al. (2024) use four flags including an additional indicator whether a firm operates in a potentially innovative industry. We have already excluded firms operating in industries considered as non-innovative, so that implicitly all our sample firms fulfill this flag requirement.

four innovation hubs in our data are Oslo, Bergen, Stavanger and Trondheim. These are the four largest cities in the country, and each is home to a major research university with an associated technology cluster (Hvide and Jones, 2018). The idea here is to construct a geographical flag that would correspond to a US firm starting up in Silicon Valley, Route 128, Austin (Texas), or the Research Triangle Park area in the US. A total of 23,887 firms, or approximately 30% of the sample, were started in one of these innovation hubs during our sample period.

The final flag tracks whether one of the company's non-executive board members lives far from the city in which the company is based. For this, we use a zip code concordance and define "far" as a zip code difference of 1,500 zip code digits between the firm's and the board member's addresses. This implies an average beeline distance of more than 300 kilometers. Far fewer firms (14,148 firms, or approximately 18% of the sample) satisfy this criterion. The idea here is that the choice of a geographically distant board member in the year of establishment is a potential indication that the founders (or an investor) have recruited a board member with specific technical or market expertise not readily found nearby.

In some cases, these flags may overlap, while in other cases, the presence of one flag could make the presence of another unlikely. For example, a firm founded in a technology hub may not need to recruit a geographically distant board member for technical expertise. To remain agnostic about which of these flags is more or less salient in a particular setting, we define a firm as a HIP firm if we apply at least one flag to it, which results in a HIP sample of 46,121 firms. This sample contains 90% of all the firms that receive VC funding in our data. Within our HIP sample, 65% of the firms have only one ex ante innovation flag, 29% have two flags and only 5% match on all three selection flags. We label the remaining 33,075 firms, which operate in potentially innovative industries but are not designated with any of the ex ante innovation flags, as non-HIP firms in further analyses.

A.2 Validating the Sample Selection

To demonstrate the power of our flags to predict later-stage outcomes, Table A2 relates a series of firm outcomes to the presence of these flags, both individually and collectively. Panel A focuses on future financing events. In particular, this panel shows that each of these flags, either alone or in combination, is highly predictive of a firm's receiving VC investment or an innovation-related governmental grant.

Panel B focuses on future milestones related to growth and innovation. The first part of Panel B focuses on patents as an outcome.[25] In particular, firms with English names, but also firms with a geographically distant board member, are much likelier to apply for a patent at some point in time than firms not designated with any of these flags. All flags are highly predictive of the firm's achieving an exit through an IPO, merger or acquisition, as can be seen in the middle portion of Panel B. Last, the far-right portion of Panel B shows that these flags predict four-year revenue growth. The latter outcome also implicitly measures firm survival. Approximately one-third of our sample of newly established operating firms are still in operation after four years.

Another way to gauge the salience of these innovation flags is to look at capital flows into and out of these HIP firms and compare them to those of the overall firm population, as defined in Table A1 Panel A. This angle is especially important if we want to derive market valuations of these firms. Table A3 shows the amounts of equity capital invested, either in financing rounds or secondary trades, in the shares of all sample firms before their exit events and the amounts paid out through share sales or share liquidations. This offers a market-wide, macro-level overview of the capital that innovative firms garner relative to that drawn by other firms. In addition, Table A3

[25] We are grateful to Jorge Guzman for suggesting this outcome.

presents the historical and, if available, current values of untraded shares. We calculate the current value of untraded shares based on the latest observable secondary purchase price in the particular firm.

Our HIP sample received over 90% of the total equity capital invested in all newly established businesses in Norway in our sample period. The 810 ex post selected VC-backed firms with at least one ex ante innovation flag comprise only 1.8% of all HIP firms but garner 22% of the equity capital raised. The latter firms represent an even larger share of the volume in secondary purchase transactions. The vast majority of the total capital paid out through share sales or share liquidations occurs in the firms in our HIP sample. These statistics provide further evidence that our selection on ex ante flags captures firms with high odds of raising significant funding to support their investment.

Table A1: Sample Construction

Table A1 describes our sample construction process. Panel A begins with all firms newly founded in Norway between 2004 and 2017, from which we remove financial services and real estate firms, newly formed subsidiaries of established companies, holding company structures, and firms in non-innovative industries. Panel B describes our process for identifying the subsample of firms that have a high propensity to engage in innovation based on ex ante observable characteristics. Thus, we flag firms based on three alternative characteristics measured at year-end of their year of founding: founded with an English-language name, being located in one of the country's four innovation hubs, and having at least one geographically distant board member.

Panel A: Full Sample	Count	% of (A)
Firms (C-corps) founded in 2004–2017	321,548	
- Financial services and real estate firms	-143,496	
- Subsidiaries of established companies	-19,499	
- Holding structures	-6,275	
- Transaction data not matched	-27,930	
- Non-innovative industry	-45,152	
Newly established firms in potentially innovative industries: (A)	**79,196**	100.00%
***of which at least one VC investment:* (B)**	902	1.14%

Panel B: Ex Ante Innovation Flags	Firms	% of (A)
English name	26,452	33.40%
Located in an innovation hub (Oslo, Bergen, Stavanger, Trondheim)	23,887	30.16%
At least one geographically distant board member	14,148	17.86%

Panel C: HIP Firms	Firms	% of Baseline
At least one ex ante innovation flag (C)	46,121	58.24% of (A)
. . . and received at least one VC investment	810	89.80% of (B)
of which one ex ante innovation flag	30,166	65.41% of (C)
of which two ex ante innovation flags	13,544	29.37% of (C)
of which three ex ante innovation flags	2,411	5.23% of (C)

Table A2: Predicting Later-Stage Firm Outcomes with Ex Ante Innovation Flags

Table A2 reports the results of a regression of later-stage firm outcomes on the three flags used to define our HIP sample. In Panel A, the dependent variables are indicator variables for receiving any later VC financing or governmental innovation-related grant (logit estimations). In Panel B, in the first two sets of regressions, the dependent variables are indicator variables for the firm's having applied for a patent and having experienced a successful exit, defined as a merger, acquisition or IPO (logit estimations). In the final set of regressions, the dependent variable is the growth in revenues between the end of the first year and the end of the fourth year of the firm's life (OLS estimation). All regressions include a year-of-founding fixed effect. A constant term is estimated but suppressed for brevity. Robust standard errors are reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Predicting Future Financing

	VC Investment (1/0)				Governmental Innovation Grant (1/0)			
English name (1/0)	1.154***			0.984***	1.192***			1.131***
	[0.069]			[0.070]	[0.067]			[0.069]
Innovation hub (1/0)		1.120***		0.916***		0.358***		0.167*
		[0.068]		[0.070]		[0.068]		[0.069]
Distant board member (1/0)			1.181***	0.997***			0.709***	0.589***
			[0.071]	[0.074]			[0.070]	[0.072]
Observations	79,196	79,196	79,196	79,196	79,196	79,196	79,196	79,196
(Pseudo) R-squared	4.4%	4.2%	4.1%	8.4%	7.1%	4.3%	4.9%	7.9%

Panel B: Predicting Future Firm Outcomes

	Patent Application (1/0)				Value-Creating Firm Exit (1/0)				4-Year Revenue Growth			
English name (1/0)	1.209***			1.188***	0.255***			0.191***	1.755***			1.544***
	[0.069]			[0.070]	[0.027]			[0.028]	[0.330]			[0.334]
Innovation hub (1/0)		0.039		-0.153*		0.259***		0.175***		1.264***		0.940**
		[0.073]		[0.074]		[0.028]		[0.028]		[0.329]		[0.331]
Distant board member (1/0)			0.647***	0.559***			0.686***	0.651***			1.977***	1.732***
			[0.074]	[0.075]			[0.029]	[0.029]			[0.394]	[0.396]
Observations	79,196	79,196	79,196	79,196	79,196	79,196	79,196	79,196	27,137	27,137	27,137	27,137
(Pseudo) R-squared	4.7%	1.5%	2.2%	5.2%	8.2%	8.2%	9.2%	9.4%	0.3%	0.2%	0.3%	0.4%

Table A3: Total Capital in Private Capital Market

Table A3 shows the aggregated distribution of total capital invested in and paid out from our sample of newly established operating companies, denoted category (A) in Table A1, and our subsample of HIP firms. Amounts are reported in million USD, where NOK have been converted to dollars at the spot rate prevailing at the time of funding. Percentages are expressed in terms of the population amount indicated in each specific row. We calculate the current value of untraded shares based on the latest observable purchase price (either in a financing round or in a secondary trade) in each particular firm.

	Overall Population	HIP Firms			
				and VC-Backed	
Number of firms	79,196	46,121		*810*	
		58.2% of Total		*1.8% of Sample*	
Total amount:					
Invested in financing rounds	129,542	120,785	*93.2%*	28,518	*22.0%*
Invested in secondary trades	21,871	19,707	*90.1%*	5,392	*24.7%*
Paid out through share sales	20,961	19,079	*91.0%*	4,759	*22.7%*
Paid out through liquidation of shares	3,544	3,405	*96.1%*	684	*19.3%*
Historical value of untraded shares	61,864	54,476	*88.1%*	11,659	*18.8%*
Current value of untraded shares	149,328	136,146	*91.2%*	8,516	*5.7%*

B Additional Figures and Tables

Figure B1: **Co-investments of Single-Firm Angels**

Figure B1 presents the distribution of the co-investments of single-firm angel investors with other angels (Panel A) and with VC investors (Panel B). A co-investment with another angel investor (VC investor) is defined as an investment in the same firm in the same year as another angel investor (VC investor).

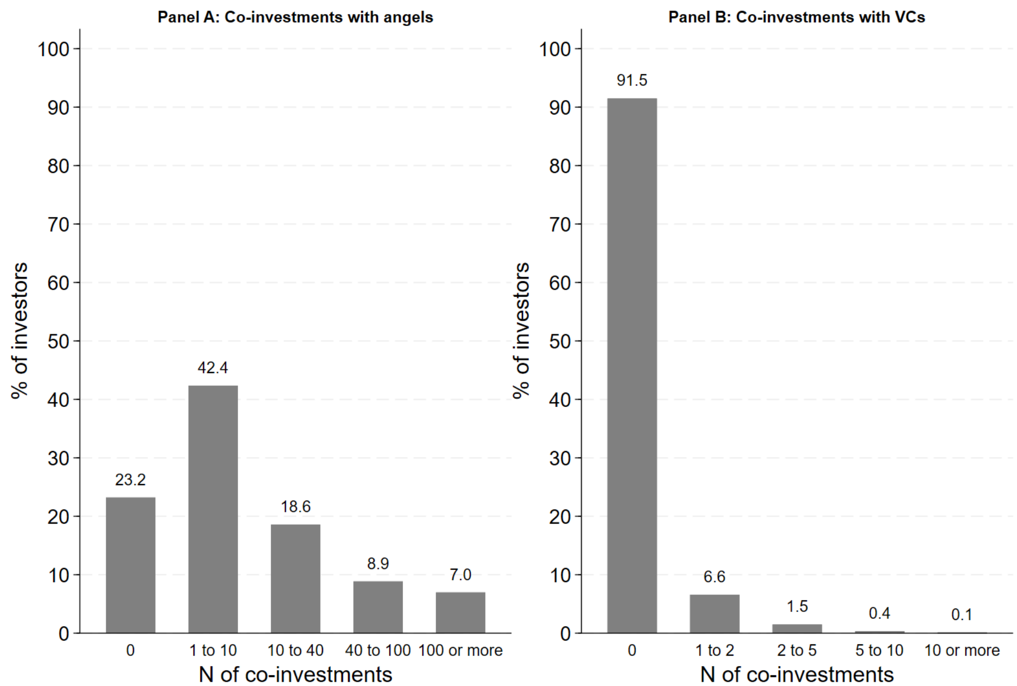

Table B1: Who Becomes an Angel Investor?

Table B1 reports logit estimates from a regression model where the dependent variable is a dummy variable taking value one if an individual invests in a HIP firm and is, thus, an angel investor. Column (1) estimates the propensity to become an angel investor among all individuals investing in both public and private stocks. Column (2) estimates the propensity to become an angel investor among individuals investing in privately held firms only. Columns (3)–(7) estimate the propensity to become a certain type of angel investor among all angel investors. An angel is defined as early stage if on average her angel investments occur in firms in the year of their inception or one year after (Column (3)). An angel is defined as late stage if her angel investments occur on average in firms aged five years or older (Column (4)). An angel is defined as small if she invests less than 50 thousand NOK (Column (5)) and as large if she invests 500 thousand NOK or more on average (Column (6)). A repeat angel is defined as an angel who invests in several HIP firms (Column (7)). $Age\ in$ 2017 is the natural logarithm of the investor's age in 2017. $Male$ is a dummy variable taking value one for male investors. $Founder$ is a dummy variable taking value one if the investor has founded any HIP firm. $Public\ stock$ is a dummy variable taking value one if the investor makes any direct investments in domestic public stocks during the sample period. $Board\ experienced\ angel$ is a dummy variable taking value one if the angel investor holds a board seat in any other firm at the time of her first angel investment. $High\ wealth$ is a dummy variable taking value one for angel investors who are above the 90^{th} percentile in the investor wealth distribution over the time period 2011–2018. Robust standard errors are reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Angel type	All	All	Early-Stage	Late-Stage	Small	Large	Repeat
N of Angel Investors	*36,749*	*36,749*	*24,795*	*3,155*	*17,062*	*3,192*	*4,419*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ln (Age in 2017)	-0.538***	-0.371***	-0.124***	-0.171**	-1.193***	1.191***	0.158**
	(0.016)	(0.029)	(0.044)	(0.072)	(0.043)	(0.086)	(0.065)
Male (1/0)	0.318***	0.243***	-0.030	-0.034	-0.004	0.044	0.397***
	(0.015)	(0.019)	(0.032)	(0.052)	(0.030)	(0.060)	(0.055)
Founder (1/0)	1.504***	0.795***	0.053	-0.155***	-0.071**	0.011	0.668***
	(0.017)	(0.027)	(0.032)	(0.056)	(0.032)	(0.052)	(0.040)
Public stock (1/0)		0.776***	-0.536***	0.542***	-0.566***	0.551***	0.607***
		(0.018)	(0.024)	(0.040)	(0.024)	(0.042)	(0.035)
Repeat angel (1/0)			-0.784***	-0.252***	-0.814***	0.580***	
			(0.034)	(0.062)	(0.038)	(0.049)	
Board-experienced angel (1/0)			0.064**	-0.119***	-0.096***	0.418***	0.361***
			(0.025)	(0.041)	(0.024)	(0.051)	(0.041)
High wealth (1/0)			-0.219***	0.099	-1.025***	1.447***	0.956***
			(0.039)	(0.064)	(0.048)	(0.048)	(0.045)
Observations	388,354	71,843	36,749	36,749	36,749	36,749	36,749
Pseudo R-squared	3.4%	3.9%	3.1%	1.0%	7.6%	12.9%	7.4%
Investor population	Public+Private	Private	Angel	Angel	Angel	Angel	Angel

Table B2: Alternative Measures of Returns to Angel Investment

Table B2 reports the distribution of returns to angel investment over our sample period (2003–2018) measured as buy-and-hold annualized returns (BHAR), which are the annualized TVPI returns or public market equivalent (PME), which is TVPI adjusted by either the Oslo Børs Benchmark Index (OSEBX), Russell 2000 or Russell 3000 on each cashflow date. All returns are winsorized at the 1^{th} and 99^{th} percentiles.

					Percentiles						
	N	mean	sd	skew.	p10	p25	p50	p75	p90	p95	p99
Realized BHAR	36,525	0.27	4.66	7.94	-1.00	-1.00	-0.46	0.00	0.67	1.80	41.91
Adjusted BHAR	39,976	0.05	3.46	7.54	-1.00	-1.00	-0.72	0.00	0.57	1.60	30.30
Full BHAR	75,290	-0.08	1.17	4.76	-1.00	-0.86	0.00	0.01	0.40	1.06	8.36
Oslo Børs Benchmark Index (OSEBX)											
Realized PME	36,525	1.65	5.42	5.77	0.00	0.00	0.17	0.96	2.73	6.68	41.59
Adjusted PME	39,976	1.46	4.84	5.78	0.00	0.00	0.03	0.91	2.47	6.02	36.88
Full PME	75,290	1.62	5.47	6.53	0.00	0.00	0.55	0.93	2.21	5.09	44.93
Russell 2000											
Realized PME	36,525	1.74	5.96	6.00	0.00	0.00	0.17	0.98	2.77	6.73	46.04
Adjusted PME	39,976	1.58	5.67	6.30	0.00	0.00	0.03	0.93	2.47	6.08	45.79
Full PME	75,290	1.79	6.19	6.65	0.00	0.00	0.60	1.04	2.36	5.47	51.04
Russell 3000											
Realized PME	36,525	1.77	6.09	6.03	0.00	0.00	0.17	0.97	2.80	6.81	47.23
Adjusted PME	39,976	1.60	5.77	6.32	0.00	0.00	0.03	0.93	2.49	6.09	46.68
Full PME	75,290	1.73	5.94	6.58	0.00	0.00	0.57	0.98	2.30	5.25	48.54

Table B3: Angel Returns and Firm Characteristics

Table B3 reports the distribution of returns to angel investment by the type of the firm. We measure returns as the TVPI. We calculate TVPI as the realization amount (through sales or liquidation) divided by the purchase amount of the realized shares, Realized TVPI. For Adjusted TVPI, we additionally assume that if a firm does not report revenues in the time period of five consecutive years after the year of angel investment, the implied TVPI is zero. For Full TVPI, we compute for all remaining unrealized investments the untraded value of shares based on the most recent price observed in the latest financing round. This implies that Full TVPI includes all angel investments. For investments with multiple outcomes (e.g., partially realized, partially unrealized), TVPI is weighted by the purchase amount of the shares of the respective outcomes. We report return distributions separately for investments made in firms depending on whether they have revenues and whether they have any patents on their balance sheet in the year of angel investment. TVPIs are winsorized at the 1^{th} and 99^{th} percentiles.

	N	N per Angel	mean	sd	skew.	Percentile p10	p25	p50	p75	p90	p95	p99	Total Loss
Pre-revenue firm													
Realized TVPI	12,958	1.4	1.87	7.01	6.12	0.00	0.00	0.18	1.00	2.14	6.30	53.21	35.0%
Adjusted TVPI	15,867	1.4	1.46	6.03	6.75	0.00	0.00	0.00	0.98	1.61	4.48	48.92	46.9%
Full TVPI	24,779	1.4	2.11	8.09	6.61	0.00	0.00	0.70	1.00	2.34	6.08	64.83	29.9%
Post-revenue firm													
Realized TVPI	19,847	1.5	2.45	7.32	5.15	0.00	0.00	0.33	1.25	4.71	11.74	50.23	30.3%
Adjusted TVPI	19,847	1.5	2.42	7.10	5.01	0.00	0.00	0.33	1.25	4.71	11.74	50.00	30.3%
Full TVPI	41,796	1.7	2.56	8.20	6.21	0.00	0.08	1.00	1.26	3.68	9.33	65.81	14.2%
Pre-patent firm													
Realized TVPI	27,695	1.5	2.14	7.18	5.60	0.00	0.00	0.24	1.00	3.24	8.98	53.21	32.9%
Adjusted TVPI	30,481	1.5	1.89	6.59	5.78	0.00	0.00	0.04	1.00	2.81	7.72	50.00	39.0%
Full TVPI	54,448	1.7	2.32	8.07	6.40	0.00	0.00	0.99	1.03	2.95	7.85	62.50	21.7%
Post-patent firm													
Realized TVPI	5,110	1.7	2.69	7.34	5.01	0.00	0.00	0.50	1.76	6.19	12.05	50.00	28.1%
Adjusted TVPI	5,233	1.7	2.60	7.06	4.93	0.00	0.00	0.44	1.68	6.04	12.02	50.00	29.8%
Full TVPI	12,127	1.9	2.69	8.57	6.15	0.00	0.06	1.00	1.41	4.13	10.00	65.81	12.6%

Table B4: Cross-Sectional Variation in Angels' Realized Returns

Table B4 reports OLS estimates from the regression model shown in Equation 1. The dependent variable is the natural logarithm (plus one) of the realized investment return calculated as Realized TVPI as described in Table 2. $Repeat\ angel$ is a dummy variable taking value one if an angel invests in several HIP firms. $Board\ experienced\ angel$ is a dummy variable taking value one if the angel investor holds a board seat in any other firm by the time of her first angel investment. $Investor\ age$ is the natural logarithm of the investor's age at the time of the investment. $Male$ is a dummy variable taking value one for male angels. $High\ wealth$ is a dummy variable taking value one for angel investors who are above the 90^{th} percentile in the investor wealth distribution over the time period 2011–2018. $Investment\ amount$ controls for the investment (purchase) amount. $Secondary\ purchase$ is a dummy variable taking value one if the investor buys shares in a secondary trade. $Holding\ period$ is the natural logarithm of the holding period of the investment measured in actual days. $Board\ seat$ is a dummy variable taking value one if the angel investor receives a board seat in the year of investment. $\%\ of\ investment\ realized$ is the fraction of the investment that is realized. $Public\ market\ return$ is the return on the Oslo Børs Benchmark Index (OSEBX) over the investment period. Standard errors are clustered at the firm level and reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Angel's Total N of Investments	>=1	>=2	>=2	>=3	>=4	>=1
	(1)	(2)	(3)	(4)	(5)	(6)
Repeat angel (1/0)	0.092***					0.013
	(0.032)					(0.014)
Board-experienced angel (1/0)	-0.030	-0.052*				0.017
	(0.019)	(0.030)				(0.011)
Investor Characteristics						
Ln (Investor age)	-0.157***	-0.261***				-0.006
	(0.034)	(0.058)				(0.021)
Male (1/0)	0.027	0.020				0.034***
	(0.027)	(0.037)				(0.010)
High wealth (1/0)	-0.009	0.012				0.041***
	(0.029)	(0.033)				(0.015)
Investment Characteristics						
Ln (Investment amount)	-0.046***	-0.063***	-0.094***	-0.085***	-0.081***	-0.083***
	(0.008)	(0.008)	(0.011)	(0.012)	(0.013)	(0.008)
Secondary purchase (1/0)	0.027	-0.006	-0.060**	-0.080***	-0.106***	-0.036*
	(0.057)	(0.053)	(0.026)	(0.028)	(0.032)	(0.021)
Ln (Holding period)	-0.157***	-0.136***	0.025	0.022	0.066	0.053**
	(0.020)	(0.027)	(0.034)	(0.037)	(0.043)	(0.027)
Board seat (1/0)	0.008	0.036	0.111***	0.123***	0.096*	0.079***
	(0.028)	(0.033)	(0.043)	(0.046)	(0.052)	(0.016)
% of investment realized	-1.059***	-1.221***	-0.947***	-0.839***	-0.847***	-0.832***
	(0.119)	(0.147)	(0.140)	(0.135)	(0.147)	(0.146)
Public market return	-0.060	-0.031	-0.029	-0.041	-0.046	-0.017
	(0.065)	(0.059)	(0.043)	(0.047)	(0.055)	(0.033)
Observations	32,805	18,403	18,403	11,680	8,330	27,703
Adjusted R-squared	7.7%	9.4%	53.9%	53.9%	54.3%	66.2%
Calendar year FE	Yes	Yes	Yes	Yes	Yes	Yes
Investment firm age FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	No	No	Yes	Yes	Yes	No
Firm FE	No	No	No	No	No	Yes

Table B5: Endogeneity of Repeat Investments - Truncated Sample

Table B5 replicates Table 6 for the truncated sample of angel investors, where we include only those, who make her first investment latest 2,591 days (around seven years) before the end of our sample period. At the same time, we define a repeat angel here as an angel who makes her repeat investment latest 2,591 days after the first investment. 2,591 days represent the 90^{th} percentile in the distribution of days between two investments in different firms in the entire sample of repeat angels as shown in Table 5. A fixed effect for the calendar year of the first angel investment is included in all specifications. Robust standard errors are reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Angel Investors	All (1)	All (2)	All (3)	Early-Stage (4)	Late-Stage (5)	Small (6)	Large (7)
First investment realized (1/0)	0.062						
	(0.058)						
Ln (1 + first investment Realized TVPI)		0.170***		0.167***	0.550	0.219***	-0.015
		(0.031)		(0.032)	(0.457)	(0.045)	(0.120)
Ln (1 + first investment Full TVPI)			0.091***				
			(0.024)				
Ln (First investment amount)	0.238***	0.246***	0.243***	0.230***	0.887***	0.498***	0.128*
	(0.020)	(0.024)	(0.020)	(0.027)	(0.312)	(0.125)	(0.073)
Board experienced angel (1/0)	0.537***	0.540***	0.547***	0.559***	-0.311	0.570***	0.745***
	(0.061)	(0.071)	(0.061)	(0.077)	(0.700)	(0.115)	(0.271)
Ln (Investor age)	-0.504***	-0.503***	-0.485***	-0.540***	2.039*	-0.424**	-0.977***
	(0.097)	(0.117)	(0.098)	(0.128)	(1.179)	(0.195)	(0.363)
Male (1/0)	0.580***	0.543***	0.575***	0.494***	-0.317	0.834***	0.351
	(0.084)	(0.099)	(0.084)	(0.105)	(0.848)	(0.189)	(0.279)
High wealth (1/0)	0.932***	0.943***	0.930***	0.985***	-0.066	1.152***	0.974***
	(0.066)	(0.078)	(0.066)	(0.084)	(0.981)	(0.156)	(0.179)
Observations	16,051	11,422	16,051	9,972	124	4,975	904
Pseudo R-squared	6.8%	7.2%	6.9%	7.1%	17.8%	6.1%	7.9%
Calendar year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table B6: Persistence in Total Losses

Table B6 reports logit estimates from the regression model shown in Equation 3. The dependent variable is a dummy variable taking value one if the investment return (investor–firm level) is within the stated percentile interval for the sample distribution of Full TVPI, calculated as described in Table 2. $Total\ loss_{t-1}$ ($Total\ loss_{t-2}$) is a dummy variable taking value one if the first (second) lagged angel investment in a different firm by the same angel investor is a total loss. $Same\ industry$ is a dummy variable taking value one if the investor's first lagged investment is in the same industry as the current investment. $Investment\ overlap$ is a dummy variable taking value one if the current investment year is before the exit year of the investor's first lagged investment. We control (untabulated) for the following investor and investment characteristics: $Investor\ age$, $Male$, $High\ wealth$, $Investment\ amount$, $Board\ seat$ and $\%\ of\ investment\ realized$. Calendar year, investment firm age and industry fixed effects are included in all specifications. Standard errors are clustered at the firm level and reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Full TVPI Percentile (1/0)	90^{th} =<p <95^{th}			p>= 95^{th}		
	(1)	(2)	(3)	(4)	(5)	(6)
$Total\ loss_{t-1}$	-0.358*	-0.335*	-0.378	0.135	0.150	0.563*
	(0.200)	(0.196)	(0.335)	(0.178)	(0.181)	(0.326)
Same industry (1/0)		0.256	-0.085		0.128	0.482*
		(0.263)	(0.234)		(0.172)	(0.278)
Investment overlap (1/0)		-0.140	0.241		0.037	0.398
		(0.304)	(0.356)		(0.172)	(0.451)
$Total\ loss_{t-2}$			-0.104			0.582**
			(0.252)			(0.264)
Observations	6,236	6,236	1,811	6,384	6,384	1,441
Pseudo R-squared	7.1%	7.4%	9.8%	12.5%	12.6%	16.4%
Investments	All	All	All	All	All	All
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Table B7: Better Angels and the Tail of Realized Returns

Table B7 reports logit estimates from a regression model similar to Equation 1. The dependent variable is a dummy variable taking value one if the realized investment return is within the stated percentile interval for the sample distribution of Realized TVPI. $Performance\ error\ term$ is an investor-level measure of angel investment performance due to unobservable characteristics, which we obtain by recovering the error term from the regression in Equation 1, as shown in Table B4 Column (1). The highest quintile represents the best-performing angel investors. We control (untabulated) for all time-variant investor and all investment characteristics as described in Table B4. Standard errors are clustered at the firm level and reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Realized TVPI Percentile (1/0)	50^{th} =<p $<75^{th}$		75^{th} =<p $<90^{th}$		90^{th} =<p $<95^{th}$		p>= 95^{th}	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Performance error term								
2nd quintile	0.227	0.904***	0.574**	0.829***				
	(0.199)	(0.164)	(0.272)	(0.274)				
3rd quintile	2.026***	2.847***	2.341***	2.567***	2.886***	3.159***		
	(0.237)	(0.183)	(0.259)	(0.252)	(0.530)	(0.527)		
4th quintile	2.952***	3.497***	3.991***	4.174***	3.999***	4.271***	3.233***	3.764***
	(0.201)	(0.146)	(0.257)	(0.250)	(0.522)	(0.522)	(0.435)	(0.434)
5th quintile	0.502**	0.976***	4.445***	4.612***	6.762***	6.896***	6.953***	7.381***
	(0.239)	(0.202)	(0.251)	(0.258)	(0.510)	(0.509)	(0.411)	(0.414)
Observations	32,805	32,802	32,805	32,802	32,805	32,688	32,805	32,609
Pseudo R-squared	18.6%	29.5%	22.7%	26.0%	32.5%	36.1%	38.8%	49.4%
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Calendar year FE	No	Yes	No	Yes	No	Yes	No	Yes
Investment firm age FE	No	Yes	No	Yes	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes

Table B8: Do Better Angels Have the Same Co-investors?

Table B8 replicates Table 10, but in addition includes angels who invest alone ($N\ of\ co-investments\ with\ angels = 0$), implying her co-investor concentration equal one. The table reports OLS estimates from regressing angel investor's co-investment concentration on the dummy variable $Top\ quintile$, which takes value one if the angel is grouped into the highest quintile based on the error term retrieved from the regression in Equation 1 and as shown in Table 5 Column (1). To develop a measure of co-investment concentration, for each angel in our sample, we compute fraction of the number of co-investments made by that angel with every other angels during the sample period to the total number of co-investments that angel made. Then we take the maximum of this ratio for each angel investor and use this as a measure of their co-investment concentration. This assigns a higher concentration value to an angel whose investments are concentrated among a smaller number of total co-investors. Columns (1)–(2) include all angel investors, while Columns (3)–(6) examine subsamples depending on whether the first angel investment has been realized. $Repeat\ angel$ is a dummy variable taking value one if angel invests in several HIP firms. $Board\ experienced\ angel$ is a dummy variable taking value one if the angel investor holds a board seat in any other firm at the time of her first angel investment. $Investor\ age$ is the natural logarithm of the investor's age at the time of her first angel investment. $Male$ is a dummy variable taking value one for male angels. $High\ wealth$ a dummy variable taking value one for angel investors who are above the 90^{th} percentile in the investor wealth distribution over the time period 2011–2018. $Total\ angel\ investment\ amount$ controls for the investment (purchase) amount an angel has invested in all HIP firms. $Portfolio\ firms$ controls for the total number of HIP firms in which the angel has invested, while $N\ of\ co-investments\ with\ angels$ does so for the angel's total number of co-investments with other angel investors during our sample period. Fixed effects for the year of the angel's first angel investment are included in Columns (2)–(6) .Robust standard errors are reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Angel Investors	All	All	First Investment			
			Not Realized	Realized		
				All	$TVPI <= 1$	$TVPI > 1$
	(1)	(2)	(3)	(4)	(5)	(6)
Top quintile (1/0)	-0.067***	-0.042***	-0.033***	-0.030***	-0.025**	-0.041***
	(0.005)	(0.003)	(0.003)	(0.007)	(0.011)	(0.013)
Repeat angel (1/0)		-0.109***	-0.081***	-0.022	-0.006	-0.054**
		(0.008)	(0.013)	(0.014)	(0.016)	(0.025)
Board-experienced angel (1/0)		0.010***	0.013***	0.013*	0.010	0.018
		(0.002)	(0.002)	(0.008)	(0.009)	(0.014)
Ln (Investor age)		-0.007*	-0.016***	-0.015	-0.020	0.001
		(0.004)	(0.004)	(0.013)	(0.015)	(0.025)
Male (1/0)		-0.006**	-0.004	0.010	0.007	0.016
		(0.003)	(0.003)	(0.009)	(0.011)	(0.018)
High wealth (1/0)		-0.004	-0.012***	0.003	0.010	-0.011
		(0.004)	(0.004)	(0.010)	(0.012)	(0.019)
Ln (Total angel investment amount)		-0.002**	0.000	0.005**	0.005*	0.005
		(0.001)	(0.001)	(0.002)	(0.003)	(0.005)
Ln (Portfolio firms)		0.162***	0.219***	0.055***	0.045***	0.074***
		(0.009)	(0.016)	(0.013)	(0.016)	(0.024)
Ln (N of co-investments with angels)		-0.229***	-0.228***	-0.208***	-0.207***	-0.210***
		(0.001)	(0.001)	(0.002)	(0.003)	(0.004)
Observations	36,749	36,749	34,964	5,162	3,668	1,494
Adjusted R-squared	0.4%	78.9%	76.1%	69.3%	69.7%	67.7%
Calendar year FE	No	Yes	Yes	Yes	Yes	Yes

C Replication of Analyses: PME

Table C1: Cross-Sectional Variation in Angels' Returns

Table C1 reports OLS estimates from the regression model shown in Equation 1. The dependent variable is the natural logarithm (plus one) of the investment return calculated as (3) PME. $Repeat\ angel$ is a dummy variable taking value one if an angel invests in several HIP firms. $Board\ experienced\ angel$ is a dummy variable taking value one if the angel investor holds a board seat in any other firm by the time of her first angel investment. $Investor\ age$ is the natural logarithm of the investor's age at the time of the investment. $Male$ is a dummy variable taking value one for male angels. $High\ wealth$ is a dummy variable taking value one for angel investors who are above the 90^{th} percentile in the investor wealth distribution over the time period 2011–2018. $Investment\ amount$ controls for the investment (purchase) amount. $Secondary\ purchase$ is a dummy variable taking value one if the investor buys shares in a secondary trade. $Holding\ period$ is the natural logarithm of the holding period of the investment measured in actual days. $Board\ seat$ is a dummy variable taking value one if the angel investor receives a board seat in the year of investment. $\%\ of\ investment\ realized$ is the fraction of the investment that is realized. Standard errors are clustered at the firm level and reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Angel's Total N of Investments	>=1	>=2	>=2	>=3	>=4	>=1
	(1)	(2)	(3)	(4)	(5)	(6)
Repeat angel (1/0)	0.054***					0.015
	(0.020)					(0.009)
Board-experienced angel (1/0)	0.007	0.001				0.031***
	(0.011)	(0.018)				(0.007)
Investor Characteristics						
Ln (Investor age)	-0.110***	-0.179***				0.008
	(0.024)	(0.034)				(0.014)
Male (1/0)	0.031*	0.025				0.019***
	(0.017)	(0.024)				(0.006)
High wealth (1/0)	-0.020	-0.004				0.021**
	(0.018)	(0.019)				(0.010)
Investment Characteristics						
Ln (Investment amount)	-0.039***	-0.056***	-0.098***	-0.094***	-0.090***	-0.095***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.006)
Secondary purchase (1/0)	0.036	0.002	-0.004	-0.013	-0.022	0.024
	(0.031)	(0.029)	(0.020)	(0.021)	(0.023)	(0.017)
Ln (Holding period)	-0.092***	-0.080***	0.007	0.005	0.003	0.038*
	(0.018)	(0.023)	(0.027)	(0.029)	(0.032)	(0.020)
Board seat (1/0)	0.039*	0.088***	0.094***	0.112***	0.113***	0.127***
	(0.022)	(0.022)	(0.025)	(0.026)	(0.028)	(0.012)
% of investment realized	-0.188***	-0.220***	-0.103**	-0.119**	-0.125**	-0.071**
	(0.049)	(0.060)	(0.048)	(0.050)	(0.053)	(0.036)
Observations	66,575	42,096	42,096	29,120	22,073	59,149
Adjusted R-squared	5.0%	6.4%	42.1%	41.3%	38.0%	58.6%
Calendar year FE	Yes	Yes	Yes	Yes	Yes	Yes
Investment firm age FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	No	No	Yes	Yes	Yes	No
Firm FE	No	No	No	No	No	Yes

Table C2: Endogeneity of Repeat Investments

Table C2 reports logit estimates from the regression model shown in Equation 2. The dependent variable $Repeat\ angel$ is a dummy variable taking value one if an angel invests in several HIP firms. Columns (1)–(3) estimate the propensity to become a repeat angel among all angel investors. Column (4) does so for the subsample of early-stage angels, while Column (5) does so for the subsample of late-stage angels. An angel is defined as early stage if her first angel investment occurs in the firm in the year of its inception or one year after. An angel is defined as late stage if her first angel investment occurs in the firm when it is aged five or older. Columns (6) and (7) estimate the propensity to become a repeat angel among small and large angel investors, respectively. An angel is defined as small if she invests less than 50 thousand NOK and as large if she invests 500 thousand NOK or more in her first angel investment. $First\ investment\ realized$ is a dummy variable taking value one if the angel's first investment has been realized during the sample period. $First\ investment\ PME$ is the PME of the investor's first angel investment, measured either as Realized PME (Column (2)) or Full PME (Column (3)). $First\ investment\ amount$ controls for the total amount invested. $Board\ experienced\ angel$ is a dummy variable taking value one if the angel investor holds a board seat in any other firm at the time of her first angel investment. $Investor\ age$ is the natural logarithm of the investor's age at the time of her first investment. $Male$ is a dummy variable taking value one for male angels. $High\ wealth$ is a dummy variable taking value one for angel investors who are above the 90^{th} percentile in the investor wealth distribution over the time period 2011–2018. A fixed effect for the calendar year of the first angel investment is included in all specifications. Robust standard errors are reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Angel Investors	All (1)	All (2)	All (3)	Early-Stage (4)	Late-Stage (5)	Small (6)	Large (7)
First investment realized (1/0)	0.208***						
	(0.038)						
Ln (1 + first investment Realized PME)		0.206***		0.204***	0.580***	0.275***	-0.068
		(0.023)		(0.025)	(0.179)	(0.030)	(0.096)
Ln (1 + first investment Full PME)			0.150***				
			(0.018)				
Ln (First investment amount)	0.230***	0.250***	0.239***	0.250***	0.108	0.632***	0.158***
	(0.012)	(0.016)	(0.012)	(0.018)	(0.082)	(0.082)	(0.058)
Board experienced angel (1/0)	0.586***	0.569***	0.596***	0.596***	0.708***	0.600***	0.903***
	(0.040)	(0.050)	(0.040)	(0.057)	(0.244)	(0.078)	(0.199)
Ln (Investor age)	-0.542***	-0.556***	-0.535***	-0.592***	-0.032	-0.520***	-1.107***
	(0.064)	(0.082)	(0.064)	(0.093)	(0.395)	(0.128)	(0.259)
Male (1/0)	0.563***	0.578***	0.559***	0.603***	0.054	0.700***	0.449**
	(0.055)	(0.070)	(0.055)	(0.079)	(0.259)	(0.117)	(0.200)
High wealth (1/0)	0.934***	0.900***	0.928***	0.984***	1.079***	1.077***	0.938***
	(0.046)	(0.059)	(0.046)	(0.066)	(0.309)	(0.118)	(0.130)
Observations	36,749	19,545	36,749	15,971	959	9,383	1,628
Pseudo R-squared	9.7%	8.2%	9.8%	8.8%	11.7%	7.7%	10.7%
Calendar year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table C3: Better Angels and the Tail of Returns

Table C3 reports logit estimates from a regression model similar to Equation 1. The dependent variable is a dummy variable taking value one if Full PME (OSEBX) is within the stated percentile interval of the overall return distribution. $Performance\ error\ term$ is an investor-level measure of angel performance that is more closely tied to unobservable individual investor traits. We obtain it by recovering the error term retrieved from the regression in Equation 1 and as shown in Table C1 Column (1). Based on this measure, we group angel investors into performance quintiles, with the highest (top) quintile representing the best-performing angel investors. We control (untabulated) for all time-variant investor and all investment characteristics as described in Table C1. Standard errors are clustered at the firm level and reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Full PME Percentile (1/0)	50^{th} =<p <75^{th}		75^{th} =<p <90^{th}		90^{th} =<p <95^{th}		p>= 95^{th}	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Performance error term								
2nd quintile	2.137***	2.252***	1.765***	1.854***	2.544***	2.710***	-0.860	-0.594
	(0.111)	(0.104)	(0.196)	(0.188)	(0.744)	(0.745)	(1.226)	(1.226)
3rd quintile	3.033***	3.151***	2.837***	2.810***	3.931***	4.083***	1.960**	2.345***
	(0.119)	(0.118)	(0.205)	(0.195)	(0.720)	(0.721)	(0.767)	(0.773)
4th quintile	3.341***	3.541***	3.805***	3.797***	5.037***	5.325***	3.805***	4.564***
	(0.116)	(0.127)	(0.196)	(0.194)	(0.717)	(0.717)	(0.720)	(0.719)
5th quintile	1.884***	2.014***	4.147***	4.312***	7.179***	7.388***	7.344***	8.008***
	(0.121)	(0.133)	(0.187)	(0.195)	(0.712)	(0.712)	(0.709)	(0.711)
Observations	66,575	66,575	66,575	66,575	66,575	66,436	66,575	66,510
Pseudo R-squared	11.8%	25.6%	14.3%	25.3%	25.7%	28.3%	35.5%	43.7%
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Calendar year FE	No	Yes	No	Yes	No	Yes	No	Yes
Investment firm age FE	No	Yes	No	Yes	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes

Table C4: Better Angels and VC Financing

Table C4 reports logit estimates from regressing the dependent variable $VC\ Financing$, which is a dummy variable taking value one if a VC investor invests through a financing round or secondary trades in the same firm as the angel investor at some point in time, on the dummy variable $Top\ quintile$, which takes value one if the angel is grouped into the highest quintile based on the error term retrieved from the regression in Equation 1 and as shown in Table C1 Column (1) (Column (1)). Column (2) replaces the dependent variable with the natural logarithm of the total VC equity invested, conditional on receipt of VC financing. Columns (3) and (4) repeat columns (1) and (2), but require the VC investment to occur strictly after the angel investment. $Angel\ equity\ amount$ is the natural logarithm of the total equity amount provided by the respective angel investor to the firm. Calendar year, firm founding year and industry fixed effects are included in all specifications. Standard errors are clustered at the firm level and reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

			Follow-on	
	VC Financing (1/0)	Ln (VC Equity)	VC Financing (1/0)	Ln (VC Equity)
	(1)	(2)	(3)	(4)
Ln (Angel equity amount)	0.301***	0.233***	0.341***	0.101**
	(0.032)	(0.047)	(0.036)	(0.045)
Top quintile (1/0)	0.641***	0.236	0.792***	0.042
	(0.130)	(0.171)	(0.142)	(0.169)
Observations	43,294	5,905	42,707	4,009
Pseudo/Adjusted R-squared	15.4 %	27.0 %	13.6 %	23.1 %
Fixed effects	Yes	Yes	Yes	Yes

Table C5: Do Better Angels Have the Same Co-investors?

Table C5 reports OLS estimates from regressing angel investor's co-investment concentration on the dummy variable $Top\ quintile$, which takes value one if the angel is grouped into the highest quintile based on the error term retrieved from the regression in Equation 1 and as shown in Table C1 Column (1). To develop a measure of co-investment concentration, for each angel in our sample, we compute fraction of the number of co-investments made by that angel with every other angels during the sample period to the total number of co-investments that angel made. Then we take the maximum of this ratio for each angel investor and use this as a measure of their co-investment concentration. This assigns a higher concentration value to an angel whose investments are concentrated among a smaller number of total co-investors. Columns (1)–(2) include all angel investors, while Columns (3)–(6) examine subsamples depending on whether the first angel investment has been realized. $Repeat\ angel$ is a dummy variable taking value one if angel invests in several HIP firms. $Board\ experienced\ angel$ is a dummy variable taking value one if the angel investor holds a board seat in any other firm at the time of her first angel investment. $Investor\ age$ is the natural logarithm of the investor's age at the time of her first angel investment. $Male$ is a dummy variable taking value one for male angels. $High\ wealth$ a dummy variable taking value one for angel investors who are above the 90^{th} percentile in the investor wealth distribution over the time period 2011–2018. $Total\ angel\ investment\ amount$ controls for the investment (purchase) amount an angel has invested in all HIP firms. $Portfolio\ firms$ controls for the total number of HIP firms in which the angel has invested, while $N\ of\ co-investments\ with\ angels$ does so for the angel's total number of co-investments with other angel investors during our sample period. Fixed effects for the year of the angel's first angel investment are included in Columns (2)–(6) .Robust standard errors are reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Angel Investors	All	All	First Investment			
			Not Realized	Realized		
				All	$TVPI <= 1$	$TVPI > 1$
	(1)	(2)	(3)	(4)	(5)	(6)
Top quintile (1/0)	-0.031***	-0.031***	-0.023***	-0.024***	-0.018*	-0.031**
	(0.005)	(0.003)	(0.003)	(0.007)	(0.011)	(0.013)
Repeat angel (1/0)		-0.075***	-0.064***	-0.025*	-0.020	-0.030
		(0.007)	(0.012)	(0.013)	(0.015)	(0.024)
Board-experienced angel (1/0)		0.008***	0.012***	0.002	0.004	-0.004
		(0.002)	(0.003)	(0.008)	(0.009)	(0.013)
Ln (Investor age)		-0.003	-0.011**	-0.003	-0.015	0.034
		(0.004)	(0.004)	(0.013)	(0.016)	(0.024)
Male (1/0)		-0.003	0.000	0.009	0.007	0.008
		(0.003)	(0.003)	(0.010)	(0.012)	(0.016)
High wealth (1/0)		-0.006	-0.014***	-0.005	-0.001	-0.014
		(0.004)	(0.004)	(0.010)	(0.011)	(0.018)
Ln (Total angel investment amount)		0.002**	0.003***	0.010***	0.010***	0.011**
		(0.001)	(0.001)	(0.003)	(0.003)	(0.005)
Ln (Portfolio firms)		0.124***	0.175***	0.052***	0.052***	0.046**
		(0.008)	(0.014)	(0.011)	(0.014)	(0.020)
Ln (N of co-investments with angels)		-0.184***	-0.184***	-0.170***	-0.171***	-0.168***
		(0.001)	(0.001)	(0.002)	(0.003)	(0.005)
Observations	28,982	28,982	27,405	4,042	2,837	1,205
Adjusted R-squared	0.1%	72.5%	69.7%	61.8%	62.6%	59.3%
Calendar year FE	No	Yes	Yes	Yes	Yes	Yes

Table C6: Does Angel's (Board) Network Matter?

Table C6 reports logit estimates from regressing the dummy variable taking value one if an angel investor has been connected through the boards to other people prior to her first angel investment on the dummy variable $Top\ quintile$, which takes value one if the angel is grouped into the highest quintile based on the error term retrieved from the regression in Equation 1 and as shown in Table C1 Column (1) (Column (1)). Column (2) replaces the dependent variable with the dummy variable taking value one if an angel investor has been connected to other people in HIP firms only, while Column (3) further narrows down the dependent variable to the connections to founders in HIP firms. Columns (4)–(7) replace the dependent variable by the count variable, which captures the change in the number of connections in HIP firms from the time period prior to the first angel investment either to the time period after the first angel investment (Column (4)) or the time period after the first angel realization (Columns (5)–(7)). $Repeat\ angel$ is a dummy variable taking value one if angel invests in several HIP firms. $Investor\ age$ is the natural logarithm of the investor's age at the time of her first angel investment. $Male$ is a dummy variable taking value one for male angels. $High\ wealth$ a dummy variable taking value one for angel investors who are above the 90^{th} percentile in the investor wealth distribution over the time period 2011–2018. $Total\ angel\ investment\ amount$ controls for the investment (purchase) amount an angel has invested in all HIP firms and $Portfolio\ firms$ does so for the total number of HIP firms in which the angel has invested. Fixed effects for the year of the angel's first angel investment are included in all specifications and for the year of the angel's first realization in Columns (5)–(7). Robust standard errors are reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Angel Investors	Any Connections Before First Angel Investment			Change in Number of Connections After First Angel Investment			
					After First Angel Realization		
	All Firms	HIP Firms	HIP Founders	HIP Firms	HIP Firms All	HIP Firms $TVPI <= 1$	HIP Firms $TVPI > 1$
	Logit	Logit	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Top quintile (1/0)	-0.022	0.108***	0.065**	0.141**	0.260***	0.534***	-0.065
	(0.029)	(0.041)	(0.029)	(0.056)	(0.065)	(0.136)	(0.129)
Repeat angel (1/0)	0.104	0.283**	0.107	-2.961***	-2.475***	-2.532***	-2.453***
	(0.132)	(0.119)	(0.110)	(0.457)	(0.475)	(0.564)	(0.900)
Ln (Investor age)	1.965***	0.762***	1.505***	-0.771***	-0.927***	-0.949***	-0.809***
	(0.043)	(0.054)	(0.041)	(0.062)	(0.085)	(0.096)	(0.189)
Male (1/0)	0.634***	0.597***	0.594***	0.568***	0.418***	0.375***	0.505***
	(0.031)	(0.053)	(0.033)	(0.043)	(0.053)	(0.060)	(0.115)
High wealth (1/0)	2.026***	0.694***	1.340***	0.497***	0.225	-0.042	0.980***
	(0.070)	(0.050)	(0.043)	(0.105)	(0.142)	(0.157)	(0.320)
Ln (Total angel investment amount)	0.074***	0.040***	0.071***	-0.028*	0.058***	0.065***	0.039
	(0.008)	(0.012)	(0.008)	(0.016)	(0.021)	(0.025)	(0.040)
Ln (Portfolios firms)	0.486***	0.331**	0.551***	6.325***	5.276***	5.722***	4.261***
	(0.159)	(0.131)	(0.129)	(0.581)	(0.598)	(0.722)	(1.087)
Observations	36,749	34,556	36,749	36,749	20,246	15,036	5,210
Pseudo/Adjusted R-squared	12.0%	6.6%	9.8%	15.4%	17.0%	18.1%	15.7%
Calendar year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

D Replication of Analyses: BHAR

Table D1: Cross-Sectional Variation in Angels' Returns

Table D1 reports OLS estimates from the regression model shown in Equation 1. The dependent variable is the natural logarithm (plus one) of the investment return calculated as (3) BHAR. $Repeat\ angel$ is a dummy variable taking value one if an angel invests in several HIP firms. $Board\ experienced\ angel$ is a dummy variable taking value one if the angel investor holds a board seat in any other firm by the time of her first angel investment. $Investor\ age$ is the natural logarithm of the investor's age at the time of the investment. $Male$ is a dummy variable taking value one for male angels. $High\ wealth$ is a dummy variable taking value one for angel investors who are above the 90^{th} percentile in the investor wealth distribution over the time period 2011–2018. $Investment\ amount$ controls for the investment (purchase) amount. $Secondary\ purchase$ is a dummy variable taking value one if the investor buys shares in a secondary trade. $Holding\ period$ is the natural logarithm of the holding period of the investment measured in actual days. $Board\ seat$ is a dummy variable taking value one if the angel investor receives a board seat in the year of investment. $\%\ of\ investment\ realized$ is the fraction of the investment that is realized. Standard errors are clustered at the firm level and reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Angel's Total N of Investments	>=1	>=2	>=2	>=3	>=4	>=1
	(1)	(2)	(3)	(4)	(5)	(6)
Repeat angel (1/0)	0.071***					0.021
	(0.027)					(0.017)
Board-experienced angel (1/0)	0.035**	0.032				0.044***
	(0.015)	(0.021)				(0.010)
Investor Characteristics						
Ln (Investor age)	-0.138***	-0.246***				-0.024
	(0.033)	(0.046)				(0.022)
Male (1/0)	0.039*	0.025				0.022*
	(0.021)	(0.031)				(0.011)
High wealth (1/0)	-0.045*	-0.026				0.002
	(0.025)	(0.026)				(0.017)
Investment Characteristics						
Ln (Investment amount)	-0.044***	-0.061***	-0.112***	-0.105***	-0.105***	-0.098***
	(0.008)	(0.009)	(0.013)	(0.014)	(0.015)	(0.009)
Secondary purchase (1/0)	0.055	0.011	-0.047	-0.089	-0.106	-0.051
	(0.061)	(0.060)	(0.060)	(0.064)	(0.071)	(0.053)
Ln (Holding period)	-0.637***	-0.717***	-0.625***	-0.668***	-0.711***	-0.543***
	(0.062)	(0.082)	(0.095)	(0.102)	(0.109)	(0.071)
Board seat (1/0)	0.049**	0.085***	0.058	0.096**	0.112**	0.115***
	(0.022)	(0.027)	(0.045)	(0.046)	(0.050)	(0.019)
% of investment realized	-0.312***	-0.335***	-0.244***	-0.254***	-0.248***	-0.204***
	(0.043)	(0.053)	(0.076)	(0.079)	(0.085)	(0.059)
Public market return	-0.093***	-0.071**	-0.005	-0.007	-0.004	0.010
	(0.036)	(0.035)	(0.038)	(0.038)	(0.041)	(0.029)
Observations	66,575	42,096	42,096	29,120	22,073	59,149
Adjusted R-squared	8.7%	10.4%	26.9%	27.5%	28.5%	43.7%
Calendar year FE	Yes	Yes	Yes	Yes	Yes	Yes
Investment firm age FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	No	No	Yes	Yes	Yes	No
Firm FE	No	No	No	No	No	Yes

Table D2: Endogeneity of Repeat Investments

Table D2 reports logit estimates from the regression model shown in Equation 2. The dependent variable $Repeat\ angel$ is a dummy variable taking value one if an angel invests in several HIP firms. Columns (1)–(3) estimate the propensity to become a repeat angel among all angel investors. Column (4) does so for the subsample of early-stage angels, while Column (5) does so for the subsample of late-stage angels. An angel is defined as early stage if her first angel investment occurs in the firm in the year of its inception or one year after. An angel is defined as late stage if her first angel investment occurs in the firm when it is aged five or older. Columns (6) and (7) estimate the propensity to become a repeat angel among small and large angel investors, respectively. An angel is defined as small if she invests less than 50 thousand NOK and as large if she invests 500 thousand NOK or more in her first angel investment. $First\ investment\ realized$ is a dummy variable taking value one if the angel's first investment has been realized during the sample period. $First\ investment\ BHAR$ is the BHAR of the investor's first angel investment, measured either as Realized BHAR (Column (2)) or Full BHAR (Column (3)). $First\ investment\ amount$ controls for the total amount invested. $Board\ experienced\ angel$ is a dummy variable taking value one if the angel investor holds a board seat in any other firm at the time of her first angel investment. $Investor\ age$ is the natural logarithm of the investor's age at the time of her first investment. $Male$ is a dummy variable taking value one for male angels. $High\ wealth$ is a dummy variable taking value one for angel investors who are above the 90^{th} percentile in the investor wealth distribution over the time period 2011–2018. A fixed effect for the calendar year of the first angel investment is included in all specifications. Robust standard errors are reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Angel Investors	All	All	All	Early-Stage	Late-Stage	Small	Large
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
First investment realized (1/0)	0.208***						
	(0.038)						
Ln (1 + first investment Realized BHAR)		0.030***		0.030***	0.045*	0.037***	0.009
		(0.007)		(0.008)	(0.023)	(0.010)	(0.023)
Ln (1 + first investment Full BHAR)			0.085***				
			(0.015)				
Ln (First investment amount)	0.230***	0.243***	0.235***	0.243***	0.067	0.612***	0.161***
	(0.012)	(0.016)	(0.012)	(0.018)	(0.079)	(0.081)	(0.058)
Board-experienced angel (1/0)	0.586***	0.556***	0.591***	0.581***	0.648***	0.586***	0.898***
	(0.040)	(0.051)	(0.040)	(0.057)	(0.242)	(0.078)	(0.199)
Ln (Investor age)	-0.542***	-0.575***	-0.547***	-0.608***	-0.223	-0.536***	-1.095***
	(0.064)	(0.081)	(0.064)	(0.092)	(0.386)	(0.125)	(0.259)
Male (1/0)	0.563***	0.588***	0.563***	0.613***	0.045	0.704***	0.445**
	(0.055)	(0.070)	(0.055)	(0.079)	(0.268)	(0.117)	(0.199)
High wealth (1/0)	0.934***	0.910***	0.929***	0.999***	1.083***	1.113***	0.938***
	(0.046)	(0.059)	(0.046)	(0.066)	(0.298)	(0.115)	(0.130)
Observations	36,749	19,545	36,749	15,971	959	9,383	1,628
Pseudo R-squared	9.7%	7.8%	9.7%	8.3%	8.6%	6.6%	10.6%
Calendar year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table D3: Better Angels and the Tail of Returns

Table D3 reports logit estimates from a regression model similar to Equation 1. The dependent variable is a dummy variable taking value one if Full BHAR is within the stated percentile interval of the overall return distribution. $Performance\ error\ term$ is an investor-level measure of angel performance that is more closely tied to unobservable individual investor traits. We obtain it by recovering the error term retrieved from the regression in Equation 1 and as shown in Table D1 Column (1). Based on this measure, we group angel investors into performance quintiles, with the highest (top) quintile representing the best-performing angel investors. We control (untabulated) for all time-variant investor and all investment characteristics as described in Table D1. Standard errors are clustered at the firm level and reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Full BHAR Percentile (1/0)	50^{th} =<p <75^{th}		75^{th} =<p <90^{th}		90^{th} =<p <95^{th}		p>= 95^{th}	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Performance error term								
2nd quintile	0.906***	1.254***	1.511***	1.429***	1.287***	1.346***	1.456***	2.550***
	(0.121)	(0.103)	(0.248)	(0.235)	(0.277)	(0.279)	(0.389)	(0.396)
3rd quintile	1.526***	1.875***	2.433***	2.248***	2.151***	2.296***	2.321***	3.968***
	(0.122)	(0.103)	(0.166)	(0.161)	(0.263)	(0.267)	(0.394)	(0.429)
4th quintile	1.594***	2.097***	2.980***	2.883***	2.770***	3.166***	3.113***	5.309***
	(0.125)	(0.109)	(0.154)	(0.150)	(0.257)	(0.255)	(0.399)	(0.427)
5th quintile	0.337***	0.937***	3.219***	3.216***	4.322***	4.580***	5.915***	8.039***
	(0.131)	(0.130)	(0.154)	(0.154)	(0.256)	(0.252)	(0.358)	(0.407)
Observations	66,575	66,575	66,575	66,575	66,575	66,575	66,575	66,575
Pseudo R-squared	5.6%	26.5%	9.6%	14.5%	16.8%	22.5%	29.6%	48.6%
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Calendar year FE	No	Yes	No	Yes	No	Yes	No	Yes
Investment firm age FE	No	Yes	No	Yes	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes

Table D4: Better Angels and VC Financing

Table D4 reports logit estimates from regressing the dependent variable $VC\ Financing$, which is a dummy variable taking value one if a VC investor invests through a financing round or secondary trades in the same firm as the angel investor at some point in time, on the dummy variable $Top\ quintile$, which takes value one if the angel is grouped into the highest quintile based on the error term retrieved from the regression in Equation 1 and as shown in Table D1 Column (1) (Column (1)). Column (2) replaces the dependent variable with the natural logarithm of the total VC equity invested, conditional on receipt of VC financing. Columns (3) and (4) repeat columns (1) and (2), but require the VC investment to occur strictly after the angel investment. $Angel\ equity\ amount$ is the natural logarithm of the total equity amount provided by the respective angel investor to the firm. Calendar year, firm founding year and industry fixed effects are included in all specifications. Standard errors are clustered at the firm level and reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

			Follow-on	
	VC Financing (1/0)	Ln (VC Equity)	VC Financing (1/0)	Ln (VC Equity)
	(1)	(2)	(3)	(4)
Ln (Angel equity amount)	0.305***	0.234***	0.345***	0.100**
	(0.032)	(0.047)	(0.036)	(0.044)
Top quintile (1/0)	0.573***	0.157	0.665***	-0.024
	(0.133)	(0.169)	(0.148)	(0.165)
Observations	43,294	5,905	42,707	4,009
Pseudo/Adjusted R-squared	15.2%	26.9%	13.1%	23.0%
Fixed effects	Yes	Yes	Yes	Yes

Table D5: Do Better Angels Have the Same Co-investors?

Table D5 reports OLS estimates from regressing angel investor's co-investment concentration on the dummy variable $Top\ quintile$, which takes value one if the angel is grouped into the highest quintile based on the error term retrieved from the regression in Equation 1 and as shown in Table D1 Column (1). To develop a measure of co-investment concentration, for each angel in our sample, we compute fraction of the number of co-investments made by that angel with every other angels during the sample period to the total number of co-investments that angel made. Then we take the maximum of this ratio for each angel investor and use this as a measure of their co-investment concentration. This assigns a higher concentration value to an angel whose investments are concentrated among a smaller number of total co-investors. Columns (1)–(2) include all angel investors, while Columns (3)–(6) examine subsamples depending on whether the first angel investment has been realized. $Repeat\ angel$ is a dummy variable taking value one if angel invests in several HIP firms. $Board\ experienced\ angel$ is a dummy variable taking value one if the angel investor holds a board seat in any other firm at the time of her first angel investment. $Investor\ age$ is the natural logarithm of the investor's age at the time of her first angel investment. $Male$ is a dummy variable taking value one for male angels. $High\ wealth$ a dummy variable taking value one for angel investors who are above the 90^{th} percentile in the investor wealth distribution over the time period 2011–2018. $Total\ angel\ investment\ amount$ controls for the investment (purchase) amount an angel has invested in all HIP firms. $Portfolio\ firms$ controls for the total number of HIP firms in which the angel has invested, while $N\ of\ co-investments\ with\ angels$ does so for the angel's total number of co-investments with other angel investors during our sample period. Fixed effects for the year of the angel's first angel investment are included in Columns (2)–(6) .Robust standard errors are reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Angel Investors	All	All	First Investment			
			Not Realized	Realized		
				All	$TVPI <= 1$	$TVPI > 1$
	(1)	(2)	(3)	(4)	(5)	(6)
Top quintile (1/0)	-0.026***	-0.029***	-0.022***	-0.009	-0.002	-0.005
	(0.005)	(0.003)	(0.003)	(0.008)	(0.012)	(0.012)
Repeat angel (1/0)		-0.077***	-0.065***	-0.026**	-0.019	-0.036
		(0.007)	(0.012)	(0.013)	(0.015)	(0.024)
Board-experienced angel (1/0)		0.008***	0.011***	0.003	0.004	-0.003
		(0.002)	(0.003)	(0.008)	(0.009)	(0.013)
Ln (Investor age)		-0.002	-0.010**	-0.003	-0.016	0.034
		(0.004)	(0.004)	(0.013)	(0.016)	(0.024)
Male (1/0)		-0.003	-0.000	0.008	0.006	0.007
		(0.003)	(0.003)	(0.010)	(0.012)	(0.016)
High wealth (1/0)		-0.005	-0.013***	-0.005	-0.001	-0.015
		(0.004)	(0.004)	(0.010)	(0.011)	(0.018)
Ln (Total angel investment amount)		0.001	0.003***	0.010***	0.010***	0.011**
		(0.001)	(0.001)	(0.003)	(0.003)	(0.005)
Ln (Portfolio firms)		0.125***	0.176***	0.054***	0.052***	0.054***
		(0.008)	(0.014)	(0.011)	(0.014)	(0.020)
Ln (N of co-investments with angels)		-0.184***	-0.184***	-0.169***	-0.170***	-0.167***
		(0.001)	(0.001)	(0.002)	(0.003)	(0.005)
Observations	28,982	28,982	27,405	4,042	2,837	1,205
Adjusted R-squared	0.1%	72.4%	69.7%	61.7%	62.6%	59.1%
Calendar year FE	No	Yes	Yes	Yes	Yes	Yes

Table D6: Does Angel's (Board) Network Matter?

Table D6 reports logit estimates from regressing the dummy variable taking value one if an angel investor has been connected through the boards to other people prior to her first angel investment on the dummy variable $Top\ quintile$, which takes value one if the angel is grouped into the highest quintile based on the error term retrieved from the regression in Equation 1 and as shown in Table D1 Column (1) (Column (1)). Column (2) replaces the dependent variable with the dummy variable taking value one if an angel investor has been connected to other people in HIP firms only, while Column (3) further narrows down the dependent variable to the connections to founders in HIP firms. Columns (4)–(7) replace the dependent variable by the count variable, which captures the change in the number of connections in HIP firms from the time period prior to the first angel investment either to the time period after the first angel investment (Column (4)) or the time period after the first angel realization (Columns (5)–(7)). $Repeat\ angel$ is a dummy variable taking value one if angel invests in several HIP firms. $Investor\ age$ is the natural logarithm of the investor's age at the time of her first angel investment. $Male$ is a dummy variable taking value one for male angels. $High\ wealth$ a dummy variable taking value one for angel investors who are above the 90^{th} percentile in the investor wealth distribution over the time period 2011–2018. $Total\ angel\ investment\ amount$ controls for the investment (purchase) amount an angel has invested in all HIP firms and $Portfolio\ firms$ does so for the total number of HIP firms in which the angel has invested. Fixed effects for the year of the angel's first angel investment are included in all specifications and for the year of the angel's first realization in Columns (5)–(7). Robust standard errors are reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Angel Investors	Any Connections Before First Angel Investment			Change in Number of Connections After First Angel Investment			
					After First Angel Realization		
	All Firms	HIP Firms	HIP Founders	HIP Firms	HIP Firms All	HIP Firms $TVPI <= 1$	HIP Firms $TVPI > 1$
	Logit	Logit	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Top quintile (1/0)	-0.137***	0.018	-0.035	0.065	0.213***	0.355***	-0.108
	(0.029)	(0.042)	(0.029)	(0.055)	(0.062)	(0.112)	(0.136)
Repeat angel (1/0)	0.102	0.289**	0.111	-2.952***	-2.461***	-2.528***	-2.468***
	(0.133)	(0.119)	(0.111)	(0.458)	(0.475)	(0.564)	(0.899)
Ln (Investor age)	1.970***	0.758***	1.504***	-0.775***	-0.936***	-0.954***	-0.800***
	(0.043)	(0.054)	(0.041)	(0.062)	(0.085)	(0.096)	(0.190)
Male (1/0)	0.633***	0.598***	0.594***	0.569***	0.422***	0.379***	0.501***
	(0.031)	(0.053)	(0.033)	(0.043)	(0.053)	(0.060)	(0.116)
High wealth (1/0)	2.024***	0.691***	1.337***	0.493***	0.219	-0.050	0.982***
	(0.070)	(0.050)	(0.043)	(0.105)	(0.142)	(0.157)	(0.320)
Ln (Total angel investment amount)	0.076***	0.043***	0.074***	-0.025	0.062***	0.072***	0.037
	(0.008)	(0.011)	(0.008)	(0.016)	(0.021)	(0.025)	(0.040)
Ln (Portfolios firms)	0.483***	0.321**	0.544***	6.317***	5.265***	5.729***	4.265***
	(0.159)	(0.130)	(0.129)	(0.581)	(0.598)	(0.722)	(1.086)
Observations	36,749	34,556	36,749	36,749	20,246	15,036	5,210
Calendar year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo/Adjusted R-squared	12.1%	6.5%	9.8%	15.4%	17.0%	18.0%	15.7%

Chapter 2

With a Little Help from My Family: Informal Startup Financing

With a Little Help from My Family: Informal Startup Financing*

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Abstract

Using a unique dataset that contains financial information of Norwegian startups and their investors, we depict the characteristics of informal financing, which are startup investments made by family of the entrepreneur. Consistent with theoretical predictions, we document that informal investments are associated with lower returns than external investments, and lower startup risk-taking behavior. On the other hand, firms that receive investments from both informal and external investors exhibit stronger forms of risk taking. Our instrumental variables (IV) regressions further support our findings. Reduced risk-taking behavior is mainly driven from wealthy informal investors, which is consistent with the argument that wealthy investors may be more risk averse. Collectively, our findings empirically illuminate an important source of startup financing that affects startup behavior.

Keywords: Early-stage financing, informal financing, risk-taking behavior, entrepreneurship.
JEL codes: D14, G40, G50, G51, G53, L26.

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1 Introduction

We investigate the role and returns of informal financing on startups. Informal financing is provided by individuals who have personal relationships with the founders (such as family and friends), and 3.8% of US startups receive such financing. This is substantially more common than venture capital (VC) investments (0.5%) (Cosgrove et al., 2023; Nanda and Phillips, 2023; Puri and Zarutskie, 2012). Robb and Robinson (2014) show that among the startups who use family equity the magnitude of informal equity is roughly the same as that of owner equity and many times larger than the magnitude of owner debt.

In addition to the economic magnitude, informal investors also yield different economic predictions than institutional investors or other sophisticated individual investors (e.g., angel investors) that invest in startups. First, informal investors are thought to require lower returns from the founders, due to the information advantages the investors have, or from altruistic motives. In an interview with Forbes, Ben Lipson, the founder of SportsTradex, shares his experience of receiving investments from his family and friends: "It is often quicker and easier than trying to attract angel investors or institutional money. Almost by definition, F&F [Family and Friends] investors trust the founders implicitly." (Forbes, 2015). Second, despite the lower required returns, informal financing is often less preferred than institutional or angel financing, because of the shadow costs when the startup fails, and therefore the reduced risk taking behavior demonstrated by these firms (S. Lee and Persson, 2016). Overall, the existing predictions on financing innovative firms may not be applicable for informal financing.

Although informal investments are prevalent in the economy and provide an interesting set of economic predictions, empirically not much is known about these investments and their impact on the startup firms that receive them, mainly due to lack of available data. For example, it is challenging to identify family investments in commercial datasets because they are rarely disclosed, not to mention their returns. In this paper, we overcome this challenge and empirically test the theoretical predictions of informal financing, by exploiting a unique dataset that covers Norwegian startup firms. This data contains not only financial statement information of the startups, but also rich information on their shareholders. Specifically, the data provides information on individual's personal equity investments (in both public and private firms), wealth, marital status, address, and much more. This enables us to (i) identify informal investments, and (ii) test the predictions not only at the startup firm level, but also at the investment level. Exploiting this information, we assume an investor to be closely related to the startup founder if the investor shares the surname with the founder.

One possible concern with our approach is that the firms that receive informal financing may be family businesses that could have substantially different motivations for growth (Bertrand and Schoar, 2006). To address the concern, we emphasize that we restrict our firms to a set of firms that have high innovation potential that are likely to seek other sources of early-stage financing, such as angel and VC investments. Following the filters developed by Guzman and Stern (2015), we restrict our sample to limited liability firms with English company names, firms that are located in one of the four regional innovation hubs in Norway, and firms with at least one non-executive board members live in an area outside of the company's headquarters.[1] By doing so, our assumption is that all firms in our sample (regardless of receiving informal financing) have similar growth and innovative aspirations (i.e., the founders hope to grow quickly and exit at some point), regardless of receiving informal financing.

Our empirical analyses are designed to test the following predictions: (i) informal investments have lower (even negative) required returns; and (ii) firms that receive informal investments take less risks compared to firms that do not. A theoretical model from S. Lee and Persson (2016) predicts that informal financing has lower returns than formal financing, possibly due to altruistic motives. To test the first prediction, we first examine the investor-level returns to the startup investments. Specifically, we test whether an individual investor's investments in startups founded by his/her family ultimately results in lower returns, compared to other investments. To test the second prediction, we examine whether startups that receives informal financing show evidence of reduced risk taking, both in terms of ultimate startup outcomes and financial performance.

It is important to emphasize the significance of selection in testing our predictions. As mentioned above, informal financing is predicted to be less preferred than external investments, and therefore entrepreneurs may seek informal financing when the startup is low quality. Conversely, if the startup receives financing from both informal and external investors, the reduced information asymmetry story could be driving the investment decision. We test these two mechanisms by separately identifying firms that receive financing solely from informal investors, and firms that

[1] Kisseleva et al. (2024) link these flags to later firm outcomes. Each flag, both on its own and in combination with the others, is highly predictive of a firm's obtaining a patent, obtaining later-stage equity financing, achieving an exit for investors, and having higher 4-year revenue growth. Even more importantly, our ex ante innovation sample—that is, firms with any two flags—received over 90% of the total equity capital invested in all businesses in Norway in our sample period.

receive investments from both types of investors.[2]

We first provide some stylized facts on the characteristics of informal investments. A number of interesting insights arise from this exercise. First, many informal investments are made at much earlier (mean 0.9 years since startup incorporation) compared to external investments, which on average are made 2.4 years since startup inception, and have lower realized returns and longer holding periods. These two statistics are consistent with the altruism hypothesis, as informal investors take more risk by investing in the startup earlier but resulting in lower returns. Further, only 41.3% of these investors have above-median wealth (compared to 55.1% for external investors), which is consistent with our conjecture that informal investors are less likely to be wealthy investors that invest in multiple startups. Second, startups that do receive informal financing at some point in our sample are smaller in size for the first five years (in terms of revenue and total assets), incur less expenses, and are more profitable.

In our initial set of regressions, we investigate whether informal investments are associated with lower returns than formal investments by external investors. The first return metric, total value to paid-in capital (TVPI), measures the realized investment returns, where investors buy and sell (or liquidate) their equity shares. Our second metric, monthly internal rate of return (IRR), takes the holding period into consideration. Consistent with our prediction, informal investments are associated with significantly lower (73.2%p) TVPI (approximately 38% of the unconditional mean) and 7.3%p lower IRRs than external investments into startup firms. The results are slightly weaker when we test for unrealized returns.

We then analyze whether informal firms have different types of financing and exit outcomes, which further illuminates our understanding of the return characteristics of informal investments. Specifically, we document that informal firms are less likely to receive any forms of institutional financing, while informal $\times$ external firms demonstrate similar levels compared to external firms, if not higher. In terms of ultimate startup outcomes, we analyze and find that informal firms are associated with the following long-term outcomes: higher probability of a non-exit (i.e., remaining as an active firm), and lower probability of them being acquired/merged or going public. On the other hand, informal $\times$ external firms share similar characteristics with external only firms in terms of having an exit event. There are two possible interpretations of the results. First, it may be that the presence of informal investors may reduce myopia (Bertrand and Schoar, 2006; J. C. Stein, 1989).

[2] For brevity, we use 'informal firm', 'external firm', and 'informal $\times$ external firm' to indicate startups that receive financing from informal investors only, external investors only, and both types of investors, respectively.

Second, informal financing can influence the startup founder to take less desired risks, which we discuss more in the following sections. These results are consistent with the prediction that, while informal firms have lower returns (which is consistent with S. Lee and Persson (2016)), informal $\times$ external firms demonstrate similar levels (at least in terms of firm outcomes).

Next, we test our second prediction by investigating whether entrepreneurs take less risks when firms receive informal investments, doing so by testing for firm financial performance. Specifically, we examine firm-years that have informal investors as equity investors against those that do not, as well as the interaction of informal investor dummy with external investor dummy, do investigate whether informal $\times$ external firms have different effects. As proxies for risk taking, we use various financial statement measures, such as profitability, innovation, and growth. Our regressions show that startups that receive informal financing experience are associated with higher profitability (9.8%p of total assets), but lower intangibles (2.3%p), patent applications, and lower revenue growth (7.7%p). Meanwhile, informal $\times$ external startups exhibit significantly stronger levels of risk taking, even compared to external firms. These results support our argument that informal firms are associated with reduced risk-taking, whereas informal $\times$ external firms are associated with even stronger risk taking than external startups.

Our above analysis, however, is subject to alternative interpretations from omitted variables. To mitigate the concerns and take a step towards causality, we conduct instrumental variables (IV) regressions by exploiting the mean distance between the startup headquarters and *individual* investors' residential address as the instrument. Because many informal (family) investors are expected to live close to the startup's headquarters (as the founders are likely to live at the same location or close with the family investor), we expect and find a strong first-stage correlation between our distance measure and the informal investment indicator. More importantly, we anticipate the exclusion restriction to hold for two reasons. First, our sample filters restrict the sample to startups with high innovation potential. Second, we focus on startups that have at least one external individual investor, and validate that the external-startup distance for startups *with informal financing* have longer distance than startups without informal financing. By doing so, our underlying assumption is that the quality/sophistication of external investors are similar between both groups. Our IV estimates suggest similar conclusions from our OLS regressions; that is, informal (informal $\times$ external) firms are related to weaker (stronger) startup risk taking, compared to external firms.

We explore the heterogeneous nature of our effects. In particular, we investigate whether informal investments made by wealthy investors have different risk taking behavior than our main analysis. The motivation of this test is that informal investments made by wealthy individuals are more likely to resemble that of angel investments, as they may have more investment experience, as Bach et al. (2020) and Fagereng et al. (2020) document that expected returns on wealthy individuals are strongly persistent. Rather, wealthy investors in general may be associated with stronger risk aversion (Paravisini et al., 2017), leading to reduced risk taking behavior on the startups. We extend our analysis by re-estimating the main regressions mentioned above (using financial performance variables as dependent variables), on the interaction of the informal investment indicator with an indicator that classifies individuals who have above-median wealth in our sample. We find that both informal firms and informal×external firms are correlated with less risk-taking when the informal investors are wealthy.

We contribute to two streams of academic literature. First, we contribute to the literature that studies the role of financing on startups and innovation, by providing empirical evidence on an important but understudied source of entrepreneurial financing.[3] Specifically, our innovation is to examine the characteristics of *informal* financing sources (e.g., family and friends), which is distinguished from angel investors (e.g., Bach et al., 2022; Hellmann and Thiele, 2015; Hellmann et al., 2021; Kerr et al., 2014; Lerner et al., 2018; Lindsey and L. S. Stein, 2020; Wong, 2002) or VC investors (e.g., Bernstein et al., 2016; Hellmann and Puri, 2002; Sorensen, 2007), who are thought to be more sophisticated. Not only these investments are economically significant, but also generate different economic predictions than angel/VC investments (e.g., reduced information asymmetry with the entrepreneur, and their altruistic motives). We provide insights of how informal investments are related to different startup risk-taking behavior and different returns.

Second, we contribute to the literature on individual/retail investors. Several studies have demonstrated the lower returns of retail/unsophisticated individuals, compared to institutional investors (e.g., Barber and Odean, 2000; Barber et al., 2008). While most of the studies in this area of research have focused on retail investments in *public* equity markets where the investors have limited influence in firm behavior, our innovation is that we document a certain group of retail investments (i.e., informal investments into startups) is associated with lower returns (which is consistent with existing behavior) than those of sophisticated investors, but more importantly, because the existence of these investors as shareholders is associated with startup's operational outcomes and risk-taking behavior.

[3]See Kerr and Nanda (2015) for a detailed review.

2 Data and Sample Construction

2.1 The Norwegian Administrative Data

Norwegian administrative data are recognized for their quality and detail and have been used prominently in research in labor economics, finance and innovation (for recent examples, see Fagereng et al., 2021; Hvide and Jones, 2018; Ring, 2023). Our main data comes from the annual tax declarations of the population of Norwegian public and private limited liability companies and their shareholders. These declarations have been digitally collected and stored in a data warehouse since 2004, and we obtain data up through to the end of calendar year 2018. The data identify firms' shareholders and their shareholdings and all equity purchase, sale and liquidation transactions. Each transaction comprises dates, amounts, number of shares transacted, and whether a purchase transaction is a primary (issuance of new shares) or secondary (purchase of shares from an existing investor) purchase. We process the transaction data such that an equity purchase is defined by a unique combination of investor, purchase date, firm, share class and purchase type (primary or secondary). This implies that, while the raw data may correctly show two purchase transactions of the same purchase type by the same investor on the same date of shares in the same firm that are of the same share class, we aggregate these two records to one observation. Correspondingly, we process realization transactions such that an equity realization is defined by a unique combination of investor, purchase date, realization date, firm, share class, purchase type (primary or secondary) and realization type (sale or liquidation). From the same data source, we obtain additional personal-level annual wealth information for the shareholders for the sample period 2011–2018.

The transaction records also include a unique national firm identification number (*organisasjonsnummer*), which is allocated to all firms registered in Norway and to foreign institutional shareholders of these firms. This firm identification number is consistently used in all firm registries and allows the data to be merged to other databases. Ultimately, we merge the tax declarations to financial statements data, business registry data, firms' incorporation documents and board data. We identify board members and executives among all individuals in the tax declarations by fuzzy matching on full names and exact matching on birth dates.

2.2 Sample Construction

To construct our sample of interest, we begin by identifying all newly established limited liability companies (analogous to C-corporations in the U.S.) that have been incorporated between 2004 and 2017. We remove financial services and real estate firms, newly formed subsidiaries of established companies, holding structures and firms operating in non-innovative industries, which are also either heavily regulated, or have high levels of public-sector involvement or ownership, or that are highly supported via taxes and/or subsidies.[4] Of course, it is unlikely that most of these firms have growth aspirations or the intention to develop large-scale commercial innovation. As Hurst and Pugsley (2011) shows, most small business owners (in the U.S.) have no desire to grow, operating their businesses primarily for lifestyle purposes.

To identify firms with high potential for innovation, we follow the spirit of the Startup Cartography Project (Andrews et al., 2022; Guzman and Stern, 2020; Guzman and Stern, 2015) and its application to the Norwegian business context in Kisseleva et al. (2024). We use a series of observable firm-level indicators to gauge a firm's likely innovation potential at the time it first appears in the tax registry data. The first flag is whether the firm has an English-language firm name. The idea behind this flag is that, because Norway is a country of only approximately five million people, an English-language firm name helps the firm be recognizable to a broader, international audience and therefore is a natural choice for an entrepreneur who intends to grow. The second flag is whether the firm is located in a regional innovation hub in Norway. The four innovation hubs in our data are Oslo, Bergen, Stavanger and Trondheim. These are the four largest cities in the country, and each hosts a major research university and has an associated technology cluster (Hvide and Jones, 2018). The third flag tracks whether one of the company's nonexecutive board members lives in a geographically distant area from the city in which the company operates. The idea here is that the choice of a geographically distant board member in the year of establishment is a potential indication that the founders (or an investor) have recruited a board member with specific technical or market expertise not readily found nearby. To remain agnostic about which of these flags is more or less salient in a particular setting, we define the firm as a high-innovation-potential (HIP) firm if at least one flag can be applied to it. This criterion yields a sample of 46,121 firms and contains

[4] We apply negative selection to rule out such industries. Excluded industries are: *agents/traders, agriculture, banks, brokers, cultural event producers, direct health services, education, fisheries, food production, gym/sports facilities, hotels, insurers, investment management, kindergartens, garages, mail-order, mining, museums, oil and gas production, physical shops, public services, publishing, real estate, restaurants, shipping companies, wholesale traders, direct services (e.g., hairdressers, for tourists, car rental, lawyers, maintenance, accountants, auditors, builders, plumbers, electricians, undertakers, taxis).*

87% of all the firms that receive any VC funding in our data. The HIP sample selection process is presented in Table A1.

Out of the entire pool of HIP firms, 4,475 HIP firms have an informal investor who invested at least NOK 10,000 (approximately eight Norwegian kroner to the US dollar over the sample period) in the firm's equity, either in a financing round or through a secondary transaction. We define an informal investor as an individual investor who shares the last name with the founder of the firm. All other individual investors are classified as external investors. Out of 4,475 firms with an informal investor, 2,960 firms have only informal but no external individual investors (informal-financed firms) and 1,515 both informal and external individual investors (informal $\times$ external firms). 15,874 HIP firms have at least one external investor and none informal investors (external-financed firms).[5] Informal-financed, informal $\times$ external-financed and external-financed firms represent our final sample.

Figure 1 plots the relative frequency of startup age at the year of informal financing. The figure shows that the most informal financing is provided in the very beginning of the firm life. Approximately 70% of informal financing occurs in the year of startup's business registration, which validates the idea that informal investors are willing to provide capital at the earliest stages of the startup. The mean startup age for informal investments is 0.95, which is lower than that of external financing (2.46) and (professional) angel investments from Hellmann et al. (2021), who report a mean firm age of 4.5 years.

Figure 2 plots the industry composition of startups that receive informal and external financing. Panel A and Panel B report the classification based on Pitchbook and International Standard Industry Classification (ISIC), respectively. For each panel, we decompose the sample of firms into informal, external, and informal $\times$ external firms. In both panels, we observe similar industry distributions for startups with or without informal financing. Particularly, the most common industry is Research and development and IT, which comprises approximately 50% of our sample startups. This composition validates our startup filter to restrict firms to HIP firms.

2.3 Sample Description

Table 1 presents descriptive statistics of equity investments made in our sample firms, partitioned by whether the investment has been made by an informal or external investor. A number of

[5] 571 external-financed firms have an external investor, who happens to be an informal investor in another firm in our sample. We will exploit this information in Section 4.2.

interesting characteristics emerge. First, informal investments on average have lower realized returns (TVPI); specifically, mean TVPI of informal investments (external investments) is 1.47 (1.96). This is consistent with the prediction that informal investments have lower returns on average, as well as the findings from the retail investor literature that demonstrate underperformance compared to benchmarks (see Barber and Odean, 2013, for a review.). This also applies to the internal rate of return (IRR), whereby informal investor lose on average (and also in median terms) monthly more money (-48.9%) than their external counterparts (-36.3%). The low IRRs are mainly driven by the fact that realized investments often are zero, which translates into an IRR of -100%. In fact, informal investors lost completely their money in 47.2% of investments, which is 12%p more than external investors. The IRRs are significantly lower than the reported IRRs in the literature; for instance, Ljungqvist and Richardson (2003) report a mean IRR of 19.8% for VC funds. This disconnect, however, also can be an evidence how risky very early-stage startup investments are for individuals in comparison to VC investors, who invest later in the startup life-cycle.

Second, in terms of investment characteristics, similar to Figure 1, we find informal financing is made at an earlier startup age (0.95 years old) than external financing (2.46 years old). In addition, informal investments take almost three times higher ownership stake (mean 29.8%) than external investments (mean 11.9%), and has approximately 34%p higher probability of being assigned a board seat (mean 70.9% for informal investments vs. mean 36.6% for external investments).

Finally, there are also significant differences with regards to investor characteristics. Informal investors are younger, less likely to be male, less likely to be an experienced repeat angel investor and public, and is less wealthy (i.e., 40.9% of informal investors have above-median wealth vs. 55.2% of external investors). Collectively, these statistics validates our assumption of family being defined as investors with the same surname as entrepreneur. Moreover, informal investors are less wealthy and have less investing experience (both in startups and public equities).

Table 2 describes our informal-financed and external-financed firms. Specifically, we decompose our set of firms into external, informal $\times$ external, and informal firms. In terms of the overall firm trajectory, informal firms show lower higher likelihood of no exit event (69.4% vs. 62% for external and informal$\times$external firms, and lower probability of M&A/IPO (5.6%, compared to 13% for other types). These statistics is consistent with the notion that informal startups take less risk and therefore yield lower firm returns than external-financed ones.

On overage, external-financed firms receive three times as much equity. Interestingly, informal$\times$external firms are much more likely to receive investments from repeat angel investors (28.6%), individuals who have experience in investing in startups, than other startup types (18.4% for external firms, 6.1% for informal firms). This pattern is also consistent across different institutional investor types, such as venture capital, corporate, or foreign investors. This statistic aligns with our argument that informal×external startups possess at least comparable quality against external startups.

In addition, we examine the firm financials to understand the nature of our sample firms. Informal×external firms are the largest among the three groups, with NOK 6.97 million (approximately USD 0.64 million) in revenues and NOK 9.79 million in total assets, and also strongest levels of risk taking, in terms of profitability, growth, leverage, and innovation. Informal firms show the smallest size (NOK 3.43 million revenues and NOK 5.25 million total assets) and growth (77.0% revenue growth and 67.9% asset growth, compared to 104.4% revenue growth for external firms). Conversely, informal firms have highest ROA and lowest leverage, suggesting that these firms take lowest risk among the three groups. Overall, the results are consistent with the notion that informal firms take less risks, while informal×external firms take more.

3 Empirical Analyses

3.1 Returns to Informal Investments

To test the prediction that informal investments have lower returns than external financing, we estimate the following ordinary least squares (OLS) regression model:

$$\begin{aligned} Return_{i,j,t,s} = {} & \beta_1 Informal_j + \beta_2 Investor\ age_{j,t} + \beta_3 Male_j + \beta_4 Repeat\ angel_j \\ & + \beta_5 Public\ stock_j + +\beta_7 Ownership_{i,j,t} + \beta_7 Holding\ Period_{i,j,t,s} \\ & + \beta_8 Board\ Seat_{i,j,t} + \gamma_{i,j,t,s} + \varepsilon_{i,j,t,s}. \end{aligned} \tag{1}$$

The dependent variable is the realized or unrealized investment return $Return_{i,j,t,s}$, measured either as $TVPI$ or $Monthly\ IRR$. For unrealized investments, we take the price at the latest financing round. $TVPI$ is total value to paid in capital and is calculated as realization amount divided by purchase amount of realized shares. $Monthly\ IRR$ is computed as $TVPI^{(30/holding\ period\ in\ days)} - 1$. Both $TVPI$ and IRR are winsorized at the 1^{st} and 99^{th} percentiles. Our main variable of interest, $Informal_j$, is a dummy variable taking the value of one if the investment is done by an informal investor (i.e., investors who shares the same last name with the founder). $Investor\ age_{j,t}$ is the natural logarithm of the investor's j age at the time of investment t. $Male_j$ is a dummy variable taking the value of one for male investors. $Repeat\ angel_j$ is a dummy variable taking the value of one for an individual investor who has invested at least in two firms with high innovation potential in our sample. $Public\ stock_j$ is a dummy variable taking the value of one for investors who have made at least one direct investment in public stock in prior to the investment. $Ownership_{i,j,t}$ is the natural logarithm of the ownership stake of the investment in firm i. $Holding\ Period_{i,j,t,s}$ is the number of days between the investment date t and realization date s. $Board\ Seat_{i,j,t}$ is a dummy variable taking the value of one if the investor holds a board seat in the firm i at the time of investment t. $\gamma_{i,j,t,s}$ includes investment calendar year, firm age at time of investment, industry and region fixed effects. We cluster standard errors at the firm level.

Table 3 reports the regression results of Equation 1. The first two columns use realized returns as the dependent variable, while the last two use unrealized returns. Consistent with the predictions, for realized returns we find a negative and significant coefficient for $Informal_j$, which suggests that informal investments yield lower realized returns compared to external investments. Economically, the TVPI is 73.2%p lower than that of external investors. The results are consistent when we use monthly IRR as the dependent variable, such that informal investment realize a 7.3%p lower returns than external investments. An interpretation of this is that, consistent with Nadauld et al. (2019), realized investments are often purchased at a discount due to sellers' liquidity constraints. Informal investors may suffer liquidity constraints more so than external investors, and thus the realized price may be much lower. Furthermore, we expect the high write-off frequency to drive the lower returns.

When unrealized returns are used as the dependent variable, we observe much weaker results, although the directions remain the same. This supports the notion that conditional on remaining active, informal investors' returns are less negative.

Overall, the results suggest that informal investments into startups are associated with lower returns than external financing. This is consistent with the prediction from S. Lee and Persson (2016), who predict informal investors have lower required returns than external investors. Moreover, this result is also consistent with the findings from the retail investor literature, which documents lower returns compared to benchmarks.

3.2 Outcomes of Informal-Financed Startups

Institutional financing

Next, we investigate whether startups that receive informal financing have different firm outcomes than startups without. The underlying motivation for this test is to validate and explore whether informal-financed startups have lower probability of positive and negative outcomes than startups without informal financing. We test this idea in two ways. First, we explore whether startups with informal financing have different probabilities of receiving different types of sophisticated financing, such as investments from angels, VC, corporate, or foreign investors. To do so, we estimate the following logit regression model:

$$\begin{aligned} Financing_{i,t} &= \beta_1 Informal_i + \beta_2 Informal \times External_i \\ &+ \beta_3 \ln(Revenues_{i,t}) + \beta_4 \ln(Total\ assets_{i,t}) + \beta_5 Asset\ growth_{i,t-1;t} \\ &+ \beta_6 ROA_{i,t} + \beta_7 Leverage_{i,t} + \beta_8 Ownership\ concentration_{i,t} + \gamma_{i,t} + \varepsilon_{i,t}. \end{aligned} \tag{2}$$

The dependent variable $Financing_{i,t}$ is a dummy variable taking value of one if the firm receives an equity injection in year t from a repeat angel investor, venture capital (VC) investor, corporate investor or foreign investor, respectively. $Informal_i$ is a dummy variable taking the value of one if the firm has been financed by at least one informal investor. $Informal \times External_i$ is an interaction term taking the value of one if the firm has been financed by both informal and external investors. $\ln(Revenues_{i,t})$ is the natural logarithm (+1) of revenues (in Tsd. NOK) in year t. $\ln(Total\ assets_{i,t})$ is the natural logarithm (+1) of total assets (in Tsd. NOK) in year t. $Asset\ growth_{i,t-1;t}$ measures the one-year growth in total assets in year t. $ROA_{i,t}$ is the return on assets and $Leverage_{i,t}$ the leverage of the firm, each measured in year t. $Ownership\ concentration_{i,t}$ is the Herfindahl-Hirschman index (HHI), based on the ownership stakes of all shareholders in year t. γ_i, t includes industry x calendar year, industry x firm age, and region fixed effects. We cluster standard errors at the firm level.

Table 4 shows the results of Equation 2. Informal firms have 86.7% lower odds of receiving experienced (repeat) angel money (Column (1)), while informal×external firms have net 84.6% higher odds to receive one.[6] The results are similar when different types of institutional financing are used as dependent variables. While informal firms demonstrate a significantly lower probability (compared to external firms) of receiving angel/VC/corporate/foreign investments,

[6] $e^(2.634 - 2.021) - 1 = 0.846$.

informal×external firms showcase a higher odds of doing so.

The control variable coefficients also yield insights into the determinants of institutional financing. Across all columns that include firm-level controls, institutional financing is positively related to higher growth (asset growth) and lower profitability, which is consistent with the notion that higher firm risk taking is associated with favorable financing outcomes.

Ultimate firm outcomes

Second, we analyze the ultimate outcomes of the startup firms. In particular, we investigate whether informal firms exhibit different paths than other types of firms. To do so, we estimate the following logit regression model:

$$\begin{aligned} Firm\ outcome_{i,T} = {} & \beta_1 Informal_i + \beta_2 Informal \times External_i \\ & + \beta_3 \ln(Revenues_{i,T-1}) + \beta_4 \ln(Total\ assets_{i,T-1}) \\ & + \beta_5 Asset\ growth_{i,T-1;T} + \beta_6 ROA_{i,T-1} + \beta_7 Leverage_{i,T-1} \\ & + \beta_8 Ownership\ concentration_{i,T-1} + \gamma_{i,T} + \varepsilon_{i,T}. \end{aligned} \tag{3}$$

The dependent variable $Firm\ outcome_i$ is a dummy variable taking the value of one if the firm is still operating independently and, thus, has had no exit event as of 2018, the firm has gone bankrupt, or the firm has experienced a successful exit, such as merger, acquisition or IPO during our sample period. $Informal_i$ is a dummy variable taking the value of one if the firm has been financed by at least one informal investor. $Informal \times External_i$ is an interaction term taking the value of one if the firm has been financed by both informal and external investors. $\ln(Revenues_{i,T-1})$ is the natural logarithm (+1) of revenues (in Tsd. NOK) and $\ln(Total\ assets_{i,T-1})$ is the natural logarithm (+1) of total assets (in Tsd. NOK). $Asset\ growth_{i,T-1;T}$ measures the one-year growth in total assets, $ROA_{i,T-1}$ the return on assets and $Leverage_{i,T-1}$ the leverage of the firm, each measured in the latest observable year prior to the exit event or 2018, in case the startup is not exited by the end of our sample period. $Ownership\ concentration_{i,T-1}$ is the Herfindahl-Hirschman index (HHI), based on the ownership stakes of all shareholders, measured at the same time. γ_i includes industry, region and founding year fixed effects. Standard errors are robust.

Table 5 shows regression results for Equation 3. Columns (1) and (2) show results that use an indicator variable which equals one if the startup has not exited at the most recent year (2018) in our sample. In column (2), the coefficient $Informal$ suggests that startups with informal investors are associated with 47.6% higher odds of not exiting and staying as an active firm. The interaction term $Informal \times External$ is negative but statistically insignificant. Through columns (3)-(5), we analyze whether informal and informal×external startups have different likelihood of going bankrupt. While we do not find significant results in columns (3) and (4), informal×external firms show longer time to reach bankruptcy conditional on going bankrupt. Columns (6)-(8) test for probabilities of firms being acquired or going public. Column (7) suggests that, informal firms have significantly lower probability (61.1% lower odds) of M&A or IPO; informal×external firms show 36.4% lower odds than external firms.

The control variables in this table again confirms the growth and profitability measure as indicators of risk taking. In columns (4) and (7), asset growth (ROA) is positively (negatively) associated with the probability of bankruptcy (an extreme negative outcome) as well as the probability of M&A and IPO (an extreme case of positive outcome).

Overall, the results are consistent with the notion that informal startups have lower variance in terms of long-term outcomes. We interpret the results as consistent with the argument that altruistic ties can increase the entrepreneur's aversion to failure (longer time to go bankrupt) and undermines the entrepreneur's willingness to take risk (lower probability to go M&A). However, we also acknowledge that informal financed startups tend to favor long-run decisions than startups without informal financing.

4 Do Entrepreneurs Reduce Risk-Taking if They Receive Informal Financing?

4.1 Baseline Results

In this section, we further investigate whether the informal-financed startups take less risks, by exploiting the financial statement information through the Norwegian administrative data. In particular, we estimate the following Poisson/OLS regression model:

$$\begin{aligned} Y_{i,t} = \beta_1 Informal_i + \beta_2 Informal \times External_i \\ \beta_3 \ln(Revenues_{i,t}) + \beta_4 \ln(Total\ assets_{i,t}) + \beta_5 Asset\ growth_{i,t-1;t} \\ + \beta_6 ROA_{i,t} + \beta_7 Leverage_{i,t} + \beta_8 Ownership\ concentration_{i,t} + \gamma_{i,t} + \varepsilon_{i,t}. \end{aligned} \tag{4}$$

The dependent variable $Y_{i,t}$ measures different proxies for firm's risk-taking in year t: return on assets (ROA), intangible assets scaled by total assets, number of total patent applications, and one-year revenue growth. $Informal_i$ is a dummy variable taking the value of one if the firm has been financed by at least one informal investor. $Informal \times External_i$ is an interaction term taking the value of one if the firm has been financed by both informal and external investors. $\ln(Revenues_{i,t})$ is the natural logarithm (+1) of revenues (in Tsd. NOK) in year t. $\ln(Total\ assets_{i,t})$ is the natural logarithm (+1) of total assets (in Tsd. NOK) in year t. $Asset\ growth_{i,t-1;t}$ measures the one-year growth in total assets in year t. $ROA_{i,t}$ is the return on assets and $Leverage_{i,t}$ the leverage of the firm, each measured in year t.[7] $Ownership\ concentration_{i,t}$ is the Herfindahl-Hirschman index (HHI), based on the ownership stakes of all shareholders in year t. γ_i, t includes firm age, calendar year, industry, region, calendar year by industry as well as firm age by industry fixed effects. We cluster standard errors at the firm level.

Table 6 reports the results of Equation 4. Across the proxies, we find results consistent with the reduced risk-taking behavior for startups with informal financing. We document that startups that receive informal financing associated with higher return on assets (ROA) (9.8%p), but lower intangibles ratio (-2.3%p) and patent applications (-36.3%p). These coefficients suggest that informal startups are associated with stronger profitability and lower R&D output, which is consistent with the reduced risk-taking hypothesis.

On the other hand, the interaction term $Informal \times External$ overall show results consistent with *additional* risk-taking even compared to external firms. ROA, intangible assets, patent applications, and revenue growth are all statistically significant and are consistent with risk-taking behavior.

The regression coefficients overall imply that while informal firms show significantly less risk taking behavior, informal×external firms are associated with stronger risk taking, consistent with our predictions. The reduced risk taking may be a mechanism behind the lower informal investment returns we observe in the previous section. On the other hand, a possible explanation why we find *stronger* risk-taking behavior from informal×external firms could be that informal×external investments may be *better* startups among the three groups of firms. In this scenario, informal investors would have lower information asymmetry than external investors, which enables them to invest earlier in the startup.

[7] We do not include ROA for regressions that use ROA as the dependent variable.

4.2 Instrumental Variables

A potential issue with our baseline results is that there may exist omitted variables that may introduce room for alternative interpretations, and do not warrant a causal statement. To address the concern, we utilize an instrument exploiting the rich and granular data we have on the individual investors of the startups. Specifically, we take the average geographical distance between the startup's headquartered location and the individual investors' residential address, as the instrument, $Mean\ Distance_{i,t}$.[8] Our logic is that, because many family investors commonly live with or close to the entrepreneur (and therefore the startup's location), having informal investors as shareholders will significantly reduce the investor-startup distance. Ultimately, we expect a strong first-stage correlation between our distance measure and the informal investment indicator ($Informal_i$). More importantly, we expect the exclusion restriction to hold. Recall that our distance measure calculates the mean distance between *individual* investors and the startup location. We do not consider the distance between institutional investors and the startup location, because doing so can introduce a correlation between investor-startup distance and startup quality. On the other hand, we assume that individual investors' distance from the startups are indicative of startup quality only through the informal investor channel, for the following reasons. First, our HIP filters ensure that the startups in our sample have a certain quality. For example, one of the filters require the startups to be located in one of the four Norwegian innovation hubs. Second, more importantly, the average distance between *external* investors and the startup headquarters is *higher* for startups with informal financing than startups without. Table A2 shows that the average distance between an external investor and the firm at an informal-financed startup is 94.17 kilometers, and 69.86 kilometers for startups without informal financing. If the investor-startup distance is a critical measure to capture startup quality, we would anticipate to observe opposite results.

The first stage is estimated using the following model:

$$\begin{aligned} Informal_i = {} & \beta_1 \ln(Mean\ Distance_{i,t}) + \beta_2 \ln(Revenues_{i,t}) + \beta_3 \ln(Total\ assets_{i,t}) \\ & + \beta_4 Asset\ growth_{i,t-1;t} + \beta_5 ROA_{i,t} + \beta_6 Leverage_{i,t} \\ & + \beta_7 Ownership\ concentration_{i,t} + \gamma_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{5a}$$

[8] We measure the distance between the zip codes with geographical coordinates as inputs. The data on all Norwegian zip code coordinates is publicly provided by Erik Bolstad: https://www.erikbolstad.no/postnummer-koordinatar/?postnummer=0010.

while the second-stage equation replicates our Equation 4:

$$\begin{aligned} Y_{i,t} = {} & \beta_1 \widehat{Informal}_i + \beta_2 \ln(Revenues_{i,t}) + \beta_3 \ln(Total\ assets_{i,t}) \\ & + \beta_4 Asset\ growth_{i,t-1;t} + \beta_5 ROA_{i,t} + \beta_6 Leverage_{i,t} \\ & + \beta_7 Ownership\ concentration_{i,t} + \gamma_{i,t} + \varepsilon_{i,t}. \end{aligned} \tag{5b}$$

Table 7 Panels A–C report the IV regression results. Panel A represents the pooled estimations; Panel B restricts the sample to informal firms and external firms; Panel C restricts the sample to informal×external firms and external firms. Subsampling our sample into these groups helps us to separately analyze the effects, as we did in previous regressions.

Our first stage regressions in the pooled estimations in Panels A (Columns (1)-(3)) indicate a strong relationship (a strongly statistically significant coefficient of -0.023***) between our distance measure and the informal investment dummy, regardless of the inclusion of an additional control and varying number of observations. We record a first-stage F-statistic of approximately 109 for most specifications, which is above D. S. Lee et al. (2022)'s suggested threshold of 104.7 to be considered as a strong instrument without any need to adjust the second stage's standard errors. In column (7), where our F-statistics is lower than 104.7 (79.31), we adjust our standard errors accordingly and the results are still statistically significant.

The second-stage regression results are even stronger than our baseline results in Table 6. The combination of higher profitability, lower intangibles and revenue growth suggests that the higher profitability is achieved by less investment activities. The results confirm that informal firms demonstrate reduced risk-taking behavior, by focusing on profitability than on innovation and growth. To further mitigate the concern that informal investors have different (worse) selection abilities than external investors, we re-estimate our pooled IV regressions, but include only the sub-sample of external-financed firms, whereby external investors are at the same time informal investors in the other firms in our sample. That implies that both informal- and external-financed firms are selected by the same set of individual investors. The only difference is that they invest in some of the firms as external investors and in some of the firms as informal investors. Results in Table A3 remain qualitatively unchanged and, even become stronger in the second stage. The results suggest that the difference in the firm risk-taking is driven by different motives of the same individual investors.

Table 7 Panel B compares informal only-financed firms to external only-financed firms. The results resemble those in Panel A, implying that our pooled estimations are driven by the comparison of these subsamples. In Panel C, when informal×external firms are compared to external firms, we find similar results to Table 6, which suggest that informal×external firms take more risks even compared to external firms.

In an attempt to attenuate any concerns with the regard to our instrument, in Table A4 we replicate the results from Table 7 Panel C, but instead exploiting inheritance of an individual investor as an instrumental variable. Specifically, the instrument $Inheritance$ $(1/0)$ is the dummy variable that measures whether the investor receives an inheritance in up to three years before making the investment. The logic for this instrument is that individuals who are endowed with (unanticipated) wealth may make more investments when they experience windfall gains, and these individuals are more susceptible to invest in family entrepreneurs. While F-statistic (14.9-25.4) shows that this instrument is weaker than our distance measure, the results remain qualitatively unchanged (even after applying adjusted standard errors).

5 The Role of Investor Wealth in Informal Financing

Subsequently, we analyze the role of wealth when providing/receiving informal financing. Wealthy investors may be more sophisticated and have more investing experience, and may resemble angel investors in terms of return characteristics. Alternatively, as Paravisini et al. (2017) suggest, wealthy investors in general may be more risk averse, which may also influence the entrepreneurs' behavior. We test this claim by interacting the $Wealth_{i,t}$ indicator (which equals one if the investor has an above-median wealth and zero otherwise) with the informal indicator.[9]

Table 8 reports the results. Similar to the IV regressions in Table 7, we decompose our sample into pooled (Panel A), informal firms vs. external firms (Panel B), and informal×external firms vs. external firms. The pooled regressions suggest that firms that have a wealthy informal investor are associated with statistically significant 11.4%p higher profitability, 2.1%p lower intangibles ratio and 0.338% less patent applications than firms that have a non-wealthy informal investor. The interaction term coefficients for the one-year revenue growth is also negative, albeit statistically not significant. Interestingly, both Panels B and C depict similar results.

Note that the main effect of wealth suggests that external wealthy investors are associated with stronger risk taking behavior. We interpret these results as evidence consistent with the

[9]Note that the wealth data only contains information from 2011. Hence the number of observations is lower than our main regressions.

argument that, while wealthy investors may be more sophisticated and encourage risk for their investments, they may be more risk averse especially in settings where shadow costs are high (i.e., family investments). Overall, our regressions imply that receiving investments from wealthy family members reduces entrepreneurs' risk-taking behavior.

6 Conclusion

In this paper, we explore the characteristics of informal investments. Consistent with extant literature and its theoretical predictions, we find that informal investments are related to lower returns. The startups that only receive informal financing are associated with lower risk-taking behavior, while firms that receive from both types showcase stronger risk taking behavior. Our findings are further supported by IV regressions. On the contrary, informal investments by wealthy entrepreneurs are associated with even less risk taking, consistent with the argument that wealthy investors are more risk averse.

We contribute to the academic literature by empirically demonstrating the investment characteristics of informal investments, which are economically significant and yield different theoretical predictions than other seasoned investors, such as angels and VC funds. Furthermore, our analyses on informal investor returns also characterizes retail investor returns in a startup setting.

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Figure 1: **Timing of the Investments**

Figure 1 shows the distribution of the timing when informal and external investments are made. Blue (grey) bars represent firm age when informal (external) investments occur.

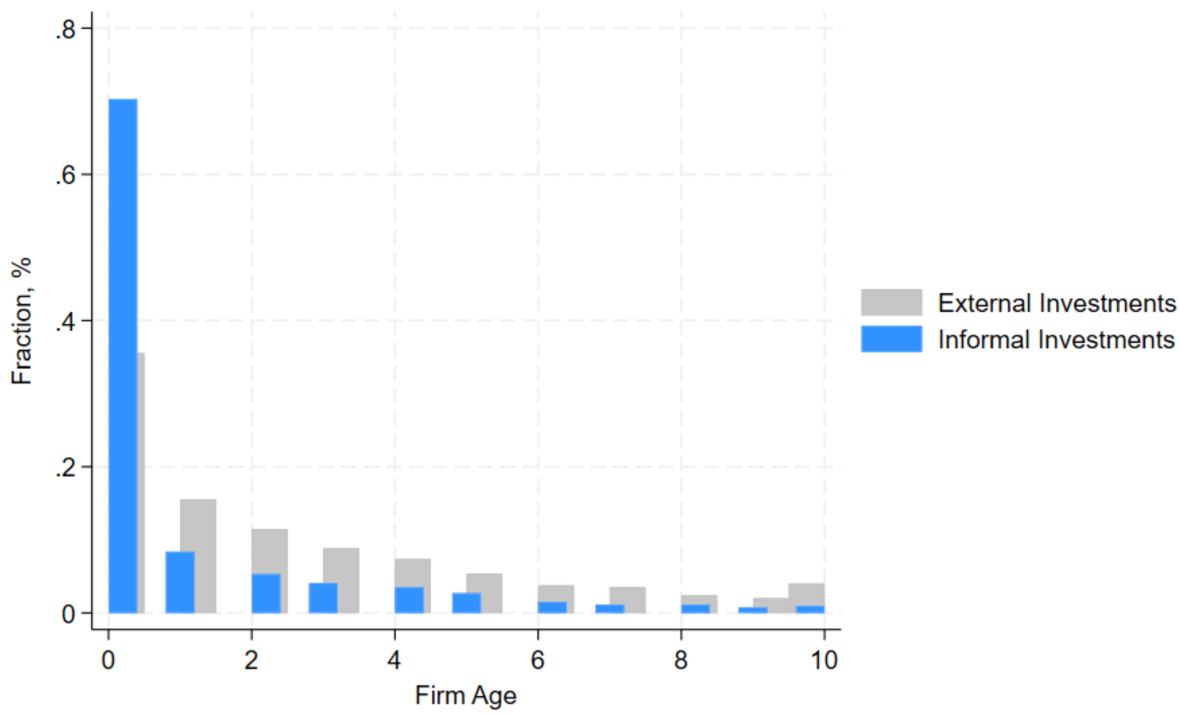
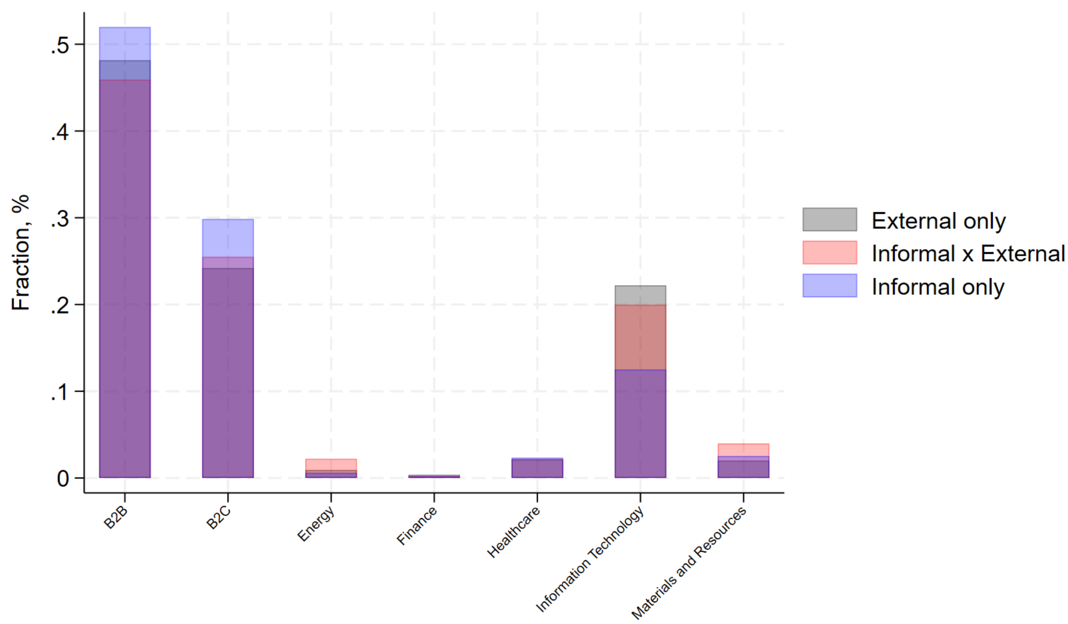


Figure 2: **Distribution of Operating Industries**

Figure 2 Panels A and B show the distribution of the firms' operating industries by financing type. Panel A follows the industry classification by the startup-specialized data provider Pitchbook. Panel B follows the more traditional ISIC classification. Grey represents firms that receive external financing only. Blue represents firms that receive informal financing only. Red represents firms that receive both informal and external financing.

Panel A: Pitchbook Industry Classification



Panel B: ISIC Industry Classification

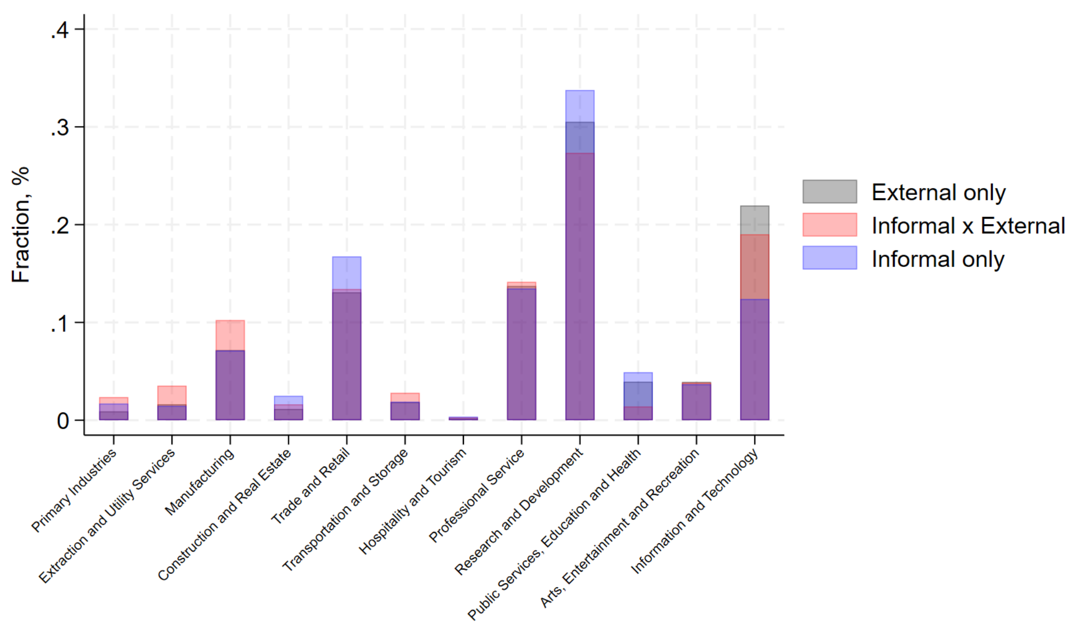


Table 1: Description of Equity Investments

Table 1 describes equity investments in our sample of informal-financed and external-financed firms in the period 2004–2018. We define an informal investor as an individual investor, who shares the last name with the founder of the firm. All other individual investors are classified as external investors. $TVPI$ is total value to paid in capital and is calculated as realization amount (purchase price in the latest financing round multiplied by the number of shares purchased) divided by purchase amount of realized (untraded) shares. $Monthly\ IRR$ is computed as $TVPI^{(30/holding\ period\ in\ days)} - 1$. Both $TVPI$ and IRR are winsorized at the 1^{st} and 99^{th} percentiles. $Firm\ age$ is the firm age in the year of the investment. $Ownership\ stake$ is the ownership stake of the investment. $Board\ seat$ indicates whether the investor takes a board seat in the firm at the time of the investment. $Holding\ period\ (years)$ is the holding period of realized investments, measured in years. $Investor\ age$ is the age of the investor in the year of the investment. $Male$ is a dummy variable whether the investor is male. $Public\ stock\ investor$ is a dummy variable taking the value of one if the investor has previously invested in public stocks. $Repeat\ angel\ investor$ indicates whether the investor previously has invested in any other sample firm. $Above\ median\ wealth$ is a dummy variable taking the value of one if the investor is above median wealthy, relative to other investors within the year of the investment. Information about investors' wealth is available for the time period 2011–2018.

	External Investments			Informal Investments		
	N	p50	Mean	N	p50	Mean
Realized returns						
Total value paid in (TVPI)	40,541	0.30	1.96	2,895	0.00	1.47
Monthly internal rate of return (IRR)	40,541	-3.6 %	-36.3 %	2,895	-23.8 %	-48.9 %
Total Loss	40,541		35.2 %	2,895		47.2 %
Unrealized returns						
Total value paid in (TVPI)	26,959	1.00	4.29	841	1.00	7.26
Monthly internal rate of return (IRR)	26,959	0.0 %	0.3 %	841	0.0 %	1.2 %
Investment characteristics						
Firm age	87,812	1.00	2.46	6,824	0	0.948
Ownership stake	87,812	1.6 %	11.4 %	6,824	25.0 %	29.3 %
Board seat	87,812		37.3 %	6,824		73.8 %
Holding period (years)	40,541	2.8	3.5	2,895	3.9	4.7
Investor characteristics						
Investor age	87,812	45.0	45.77	6,824	43.0	44.55
Male	87,812		84.9 %	6,824		62.9 %
Public stock investor	87,812		39.1 %	6,824		19.9 %
Repeat angel investor	87,812		19.5 %	6,824		7.5 %
Above median wealth	59,967		55.1 %	3,853		41.3 %

Table 2: Description of Sample Firms

Table 2 describes our sample of informal-, external- and informal $\times$ external-financed firms. $Firm\ Outcomes$ represent firm's first exit event. $Firm\ Financing$ shows equity injected into the firm (in financing rounds) over our sample period, in total and by investor type. We measure $Ownership\ concentration$ as Herfindahl-Hirschman index (HHI) based on the ownership stakes of all shareholders. $Financials$ comprise all firm-years from the firm's inception until its first exit event. All amounts are in million Norwegian kroner (MNOK) (approximately eight Norwegian kroner to the US dollar over the sample period). Financial ratios are winsorized at the 1^{st} and 99^{th} percentiles. $Innovation\ Output$ presents proxies for the firm's innovation creation over our sample period.

	External-Financed Firms		Informal $\times$ External-Financed Firms		Informal-Financed Firms	
	N	Mean	N	Mean	N	Mean
Firm Outcomes						
No exit event	15,874	62.5 %	1,515	62.1 %	2,960	69.4 %
Bankruptcy	15,874	24.2 %	1,515	24.9 %	2,960	25.0 %
Merger/Acquisition/IPO	15,874	13.3 %	1,515	13.0 %	2,960	5.6 %
Firm Financing (in Mio NOK)						
Total equity injection	15,874	32.51	1,515	15.43	2,960	1.73
Equity injection from	%N		%N		%N	
Entrepreneur	77.7 %	0.33	82.4 %	0.86	88.3 %	0.43
Informal investor			83.6 %	0.90	94.3 %	0.86
External investor	89.6 %	10.99	88.8 %	2.67		
Repeat angel investor	18.4 %	5.92	28.6 %	3.10	6.1 %	1.65
Venture Capital investor	2.7 %	44.08	4.0 %	30.26	0.1 %	1.03
Corporate investor	35.5 %	40.37	41.4 %	19.39	8.4 %	6.26
Foreign investor	6.1 %	112.90	11.6 %	20.47	1.1 %	0.36
Ownership concentration	78,224	50.0 %	9,345	41.8 %	15,858	56.8 %
Financials (Amounts in Mio NOK)						
Revenues	78,971	6.59	9,428	6.97	16,004	3.43
1-yr revenue growth	48,128	104.4 %	5,979	105.3 %	9,543	77.0 %
Total assets	78,971	7.72	9,428	9.79	16,004	5.25
1-yr asset growth	62,661	86.4 %	7,862	85.0 %	12,961	67.9 %
Return on assets	78,971	-0.40	9,428	-0.49	16,004	-0.24
Leverage	78,971	141.1 %	9,428	147.5 %	16,004	120.8 %
Innovation Output						
Intangibles / total assets	78,971	6.3 %	9,428	8.3 %	16,004	3.1 %
Total patent applications	78,971	0.05	9,428	0.08	16,004	0.01

Table 3: Do Informal Investors Realize Lower Returns?

Table 3 presents OLS estimates from running the regression as defined in Equation 1. The dependent variables are the realized and unrealized investment return $Return_{i,j,t,s}$, measured either as $TVPI$ (Columns (1) and (3)) or $Monthly\ IRR$ (Columns (2) and (4)). $TVPI$ is total value to paid in capital and is calculated as realization amount (purchase price in the latest financing round multiplied by the number of shares purchased) divided by purchase amount of realized (untraded) shares. $Monthly\ IRR$ is computed as $TVPI^{(30/holding\ period\ in\ days)} - 1$. Both $TVPI$ and IRR are winsorized at the 1^{st} and 99^{th} percentiles. Our main variable of interest, $Informal_j$, is a dummy variable taking the value of one if the investment is done by an informal investor (i.e., investors who shares the same last name with the founder). $Investor\ age_{j,t}$ is the natural logarithm of the investor's j age at the time of investment t. $Male_j$ is a dummy variable taking the value of one for male investors. $Repeat\ angel_j$ is a dummy variable taking the value of one for an individual investor who has invested at least in two firms with high innovation potential in our sample. $Public\ investor_j$ is a dummy variable taking the value of one for investors who have made at least one direct investment in public stock in prior to the investment. $Ownership_{i,j,t}$ is the natural logarithm of the ownership stake of the investment in firm i. $Holding\ Period_{i,j,t,s}$ is the number of days between the investment date t and realization date s. $Board\ Seat_{i,j,t}$ is a dummy variable taking the value of one if the investor holds a board seat in the firm i at the time of investment t. A constant term is estimated but suppressed for brevity. Standard errors are clustered at firm level and are reported in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1% level, respectively.

	Realized Returns		Unrealized Returns	
	TVPI	Monthly IRR	TVPI	Monthly IRR
	(1)	(2)	(3)	(4)
Informal investor (1/0)	-0.732***	-0.073***	-0.207	-0.010*
	(0.153)	(0.014)	(1.151)	(0.006)
Investor characteristics				
Ln (Investor age)	-0.542***	-0.049***	-3.338***	-0.020***
	(0.148)	(0.018)	(0.668)	(0.005)
Male (1/0)	0.171	0.016*	0.496	0.003
	(0.130)	(0.009)	(0.348)	(0.002)
Repeat investor (1/0)	0.380**	-0.030**	-0.552	-0.005
	(0.160)	(0.014)	(0.351)	(0.003)
Public investor (1/0)	-0.231**	-0.010	-1.236***	-0.009***
	(0.106)	(0.011)	(0.274)	(0.003)
Investment characteristics				
Ln (Ownership)	0.060	-0.000	1.284***	0.012***
	(0.041)	(0.004)	(0.124)	(0.001)
Ln (Holding period)	-0.072	-0.141***	1.047	-0.027
	(0.099)	(0.015)	(0.739)	(0.027)
Board seat (1/0)	0.074	0.009	2.853***	0.010***
	(0.130)	(0.013)	(0.549)	(0.004)
Observations	43,432	43,432	27,799	27,799
Adjusted R-squared	4.9 %	18.3 %	10.7 %	15.7 %
Calendar year FE	Yes	Yes	Yes	Yes
Investment firm age FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes

Table 4: Do Firms Receive Different Types of Financing?

Table 4 presents logit estimates from running the regression as defined in Equation 2. The dependent variable $Financing_{i,t}$ is a dummy variable taking value of one if the firm receives an equity injection in year t from a repeat angel investor (Columns (1)–(2)), venture capital (VC) investor (Columns (3)–(4)), corporate investor (Columns (5)–(6)) or foreign investor (Columns (7)-(8). $Informal_i$ is a dummy variable taking the value of one if the firm has been financed by at least one informal investor. $Informal \times External_i$ is an interaction term taking the value of one if the firm has been financed by both informal and external investors. $\ln(Revenues_{i,t})$ is the natural logarithm (+1) of revenues (in Tsd. NOK) in year t. $\ln(Total\ assets_{i,t})$ is the natural logarithm (+1) of total assets (in Tsd. NOK) in year t. $Asset\ growth_{i,t-1;t}$ measures the one-year growth in total assets in year t. $ROA_{i,t}$ is the return on assets and $Leverage_{i,t}$ the leverage of the firm, each measured in year t. $Ownership\ concentration_{i,t}$ is the Herfindahl-Hirschman index (HHI), based on the ownership stakes of all shareholders in year t. $1 - yr\ asset\ growth$, $Return\ on\ assets$ and $Leverage$ are winsorized at the 1^{st} and 99^{th} percentiles. A constant term is estimated but suppressed for brevity. Standard errors are clustered at firm level and are reported in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1% level, respectively.

	Financing Source:							
	Repeat Angel		Venture Capital		Corporate Investor		Foreign Investor	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Informal (1/0)	-1.623***	-2.021***	-3.708***	-3.530***	-1.932***	-1.810***	-2.289***	-2.547***
	[0.079]	[0.209]	[0.533]	[0.738]	[0.070]	[0.148]	[0.188]	[0.375]
Informal × External (1/0)	2.274***	2.634***	4.157***	3.539***	2.373***	2.254***	3.055***	3.007***
	[0.100]	[0.221]	[0.551]	[0.759]	[0.088]	[0.163]	[0.208]	[0.389]
Ln (Revenues)		-0.081***		-0.055***		-0.078***		-0.071***
		[0.008]		[0.017]		[0.007]		[0.011]
Ln (Total assets)		0.507***		0.695***		0.536***		0.618***
		[0.018]		[0.034]		[0.015]		[0.024]
1-yr asset growth		0.059***		0.040***		0.065***		0.046***
		[0.004]		[0.007]		[0.003]		[0.005]
Return on assets		-0.350***		-0.438***		-0.394***		-0.372***
		[0.015]		[0.025]		[0.015]		[0.020]
Leverage		-0.115***		-0.627**		-0.121***		-0.116***
		[0.019]		[0.257]		[0.015]		[0.034]
Ownership concentration		-5.021***		-3.865***		-4.344***		-3.776***
		[0.259]		[0.397]		[0.194]		[0.354]
Observations	92,796	67,417	92,796	59,531	92,796	68,101	92,796	64,522
Pseudo R-squared	2.8 %	30.3 %	3.3 %	35.1 %	3.5 %	28.8 %	3.2 %	29.4 %
Firm Age FE	No	Yes	No	Yes	No	Yes	No	Yes
Calendar Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Region FE	No	Yes	No	Yes	No	Yes	No	Yes

Table 5: Difference in Firms' Pathways

Table 5 presents logit and OLS estimates from running the regression as defined in Equation 3. The dependent variable is a dummy variable is taking the value of one if the firm does not have an exit event as of 2018 and, thus, is still operating independently (Columns (1)–(2)). The dependent is taking the value of one if the firm has gone bankrupt (Columns (3)–(4)), and, conditional that the firm goes bankrupt, the firm age at the time of the bankruptcy (Column (5)). The dependent variable is taking the value of one the firm has been merged, acquired or gone IPO (Columns (6)–(7)), and, conditional on such a successful exit event, the firm age at the time of it (Column (8)). $Informal_i$ is a dummy variable taking the value of one if the firm has been financed by at least one informal investor. $Informal \times External_i$ is an interaction term taking the value of one if the firm has been financed by both informal and external investors. $\ln(Revenues_{i,T-1})$ is the natural logarithm (+1) of revenues (in Tsd. NOK) and $\ln(Total\ assets_{i,T-1})$ is the natural logarithm (+1) of total assets (in Tsd. NOK). $Asset\ growth_{i,T-1;T}$ measures the one-year growth in total assets, $ROA_{i,T-1}$ the return on assets and $Leverage_{i,T-1}$ the leverage of the firm, each measured in the latest observable year prior to the exit event or 2018, in case the startup is not exited by the end of our sample period. $Ownership\ concentration_{i,T-1}$ is the Herfindahl-Hirschman index (HHI), based on the ownership stakes of all shareholders, measured at the same time. Return on assets, leverage and growth ratios are winsorized at the 1^{st} and 99^{th} percentiles. A constant term is estimated but suppressed for brevity. Standard errors are clustered at firm level and are reported in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1% level, respectively.

	No Exit Event		Bankruptcy			Merger/Acquisition/IPO		
	1/0	1/0	1/0	1/0	Firm Age	1/0	1/0	Firm Age
	Logit	Logit	Logit	Logit	OLS	Logit	Logit	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Informal (1/0)	0.299***	0.390***	0.048	0.008	0.118	-0.935***	-0.944***	0.347
	[0.043]	[0.056]	[0.046]	[0.060]	[0.116]	[0.083]	[0.099]	[0.241]
Informal × External (1/0)	-0.307***	-0.123	-0.024	-0.020	0.506***	0.912***	0.492***	0.370
	[0.067]	[0.083]	[0.073]	[0.092]	[0.192]	[0.110]	[0.132]	[0.308]
Ln (Revenues)		-0.014**		0.022***	-0.085***		0.003	0.029*
		[0.006]		[0.008]	[0.014]		[0.008]	[0.017]
Ln (Total assets)		0.093***		-0.287***	0.088***		0.212***	0.174***
		[0.011]		[0.014]	[0.027]		[0.014]	[0.032]
1-yr asset growth		-0.048***		0.034***	-0.051***		0.041***	-0.048***
		[0.006]		[0.007]	[0.012]		[0.007]	[0.013]
Return on assets		0.119***		-0.078***	0.076***		-0.065***	0.049
		[0.011]		[0.012]	[0.017]		[0.015]	[0.033]
Leverage		0.033***		-0.048***	0.064***		0.013**	0.063***
		[0.005]		[0.005]	[0.008]		[0.007]	[0.013]
Ownership concentration		0.714***		-0.541***	1.071***		-0.534***	0.264
		[0.079]		[0.093]	[0.185]		[0.099]	[0.266]
Observations	20,349	17,272	20,349	17,272	3,280	20,349	17,247	1,983
Pseudo/Adjusted R-squared	0.2 %	19.1 %	0.0 %	16.4 %	24.2 %	1.1 %	17.4 %	22.8 %
Founding Year FE	No	Yes	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	No	Yes	Yes	No	Yes	Yes
Region FE	No	Yes	No	Yes	Yes	No	Yes	Yes

Table 6: Informal Financing and Firm Risk: OLS Estimations

Table 6 presents Poisson/OLS estimates from running the regressions as defined in Equation 4. The dependent variable $Y_{i,t}$ measures different proxies for firm's risk-taking in year t: return on assets (ROA), measured as net income divided by total assets (Column (1)), intangible assets scaled by total assets (Column (2)), number of total patent applications (Column (3)), and one-year revenue growth (Column (4)). $Informal_i$ is a dummy variable taking the value of one if the firm has been financed by at least one informal investor. $Informal \times External_i$ is an interaction term taking the value of one if the firm has been financed by both informal and external investors. $\ln(Revenues_{i,t})$ is the natural logarithm (+1) of revenues (in Tsd. NOK) in year t. $\ln(Total\ assets_{i,t})$ is the natural logarithm (+1) of total assets (in Tsd. NOK) in year t. $Asset\ growth_{i,t-1;t}$ measures the one-year growth in total assets in year t. $ROA_{i,t}$ is the return on assets and $Leverage_{i,t}$ the leverage of the firm, each measured in year t. $Ownership\ concentration_{i,t}$ is the Herfindahl-Hirschman index (HHI), based on the ownership stakes of all shareholders in year t. $1-yr\ asset\ growth$, $Return\ on\ assets$ and $Leverage$ are winsorized at the 1^{st} and 99^{th} percentiles. A constant term is estimated but suppressed for brevity. Standard errors are clustered at firm level and are reported in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1% level, respectively.

	Return on Assets (1)	Intangibles/ Total Assets (2)	Total Patent Applications (3)	1-yr Revenue Growth (4)
Informal (1/0)	0.098***	-0.023***	-0.977**	-0.077*
	(0.015)	(0.003)	(0.402)	(0.041)
Informal × External (1/0)	-0.214***	0.041***	1.261***	0.307***
	(0.031)	(0.007)	(0.407)	(0.080)
Ln (Revenues)	0.020***	-0.005***	-0.069***	0.219***
	(0.002)	(0.001)	(0.014)	(0.007)
Ln (Total assets)	0.127***	0.015***	0.448***	-0.086***
	(0.005)	(0.001)	(0.032)	(0.014)
1-yr asset growth	0.025***	-0.001***	0.014**	0.563***
	(0.001)	(0.000)	(0.006)	(0.025)
Return on assets		-0.004***	-0.204***	-0.035**
		(0.000)	(0.021)	(0.015)
Leverage	-0.255***	-0.000*	0.021*	0.000
	(0.007)	(0.000)	(0.012)	(0.006)
Ownership concentration	0.483***	-0.038***	-2.114***	-0.599***
	(0.041)	(0.008)	(0.427)	(0.099)
Observations	68,092	68,092	61,909	51,691
Pseudo/Adjusted R-squared	44.8 %	5.6 %	26.4 %	17.9 %
Mean of dependent variable	-0.36	0.06	0.06	1.04
Calendar Year*Industry FE	Yes	Yes	Yes	Yes
Firm Age*Industry FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes

Table 7: Informal Financing and Firm Risk: Instrumental Variables

Table 7 Panels A–C present first- and second-stage estimates from running the regressions as defined in Equations 5 (first-stage) and 5 (second-stage). Column (1) corresponds to Column (4), Column (2) to Columns (5)–(6), while Column (3) to Column (7). The dependent variable in Columns (1)–(3) is $Informal\ (1/0)$, a dummy variable taking the value of one if the firm has at least one informal investor. The main independent variable of interest, $Ln\ (Mean\ distance)$, is our instrument, which measures the average geographical distance between the startup's headquarters location and its individual investors residual addresses. The dependent variables in Columns (4)–(7) are proxies for firm's risk-taking in year t as in Table 6. Control variables as in Table 6, calendar year by industry, firm age by industry and region fixed effects are included in all stages and specifications. A constant term is estimated but suppressed for brevity. Standard errors are clustered at firm level and are reported in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1% level, respectively.

Panel A: Pooled estimations

	First-Stage Estimates			Second-Stage Estimates			
				Return on Assets	Intangibles/ Total Assets	Total Patent Applications	1-yr Revenue Growth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Informal (1/0)				1.134***	-0.346***	-0.250***	-2.061***
				(0.184)	(0.045)	(0.084)	(0.487)
Ln (Mean distance)	-0.024***	-0.024***	-0.023***				
	(0.002)	(0.002)	(0.003)				
Observations	67,146	67,146	51,061	67,146	67,146	67,146	51,061
R-squared	7.1 %	7.1 %	7.5 %				
F-statistic				109.09	108.56	108.56	79.31
Mean of dependent variable				-0.36	0.06	0.06	1.04

Panel B: Informal-financed only vs. external-financed only firms

	First-Stage Estimates			Second-Stage Estimates			
				Return on Assets	Intangibles/ Total Assets	Total Patent Applications	1-yr Revenue Growth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Informal (1/0)				0.034	-0.141***	-0.022	-0.806**
				(0.122)	(0.027)	(0.067)	(0.360)
Ln (Mean distance)	-0.030***	-0.030***	-0.029***				
	(0.002)	(0.002)	(0.002)				
Observations	62,392	62,392	47,459	62,392	62,392	62,392	47,459
R-squared	12.7 %	12.7 %	12.9 %				
F-statistic				191.7	191.7	191.7	138.4
Mean of dependent variable				-0.34	0.06	0.05	1.03

Panel C: Informal × external-financed firms vs. external-financed firms

	First-Stage Estimates			Second-Stage Estimates			
				Return on Assets	Intangibles/ Total Assets	Total Patent Applications	1-yr Revenue Growth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Informal (1/0)				-2.895***	0.877***	0.501**	5.325***
				(0.619)	(0.160)	(0.252)	(1.575)
Ln (Mean distance)	0.010***	0.010***	0.009***				
	(0.002)	(0.002)	(0.002)				
Observations	55,090	55,090	42,140	55,090	55,090	55,090	42,140
R-squared	7.5 %	7.5 %	8.0 %				
F-statistic				41.4	40.5	40.5	29.6
Mean of dependent variable				-0.39	0.07	0.06	1.10

Table 8: Does Wealth Reduce Risk-Taking Frictions?

Table 8 presents Poisson/OLS estimates from running an adjusted regression model defined in Equation 2. The dependent variable $Y_{i,t}$ measures different proxies for firm's risk-taking in year t as in Table 6. Our main variable of interest, $Informal_j$, is a dummy variable taking the value of one if the investment is done by an informal investor (i.e., investors who shares the same last name with the founder). $Above\ median\ wealth$ (1/0) is a dummy variable taking the value of one if the investor has gross wealth above the median gross wealth of all individual investors in the year of investment t. $Informal \times above\ median\ wealth$ is the interaction term of these two dummy variables. Control variables as in Table 6, calendar year by industry, firm age by industry and region fixed effects are included in all stages and specifications. A constant term is estimated but suppressed for brevity. Standard errors are clustered at firm level and are reported in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1% level, respectively.

Panel A: Pooled estimations

	Return on Assets (1)	Intangibles/ Total Assets (2)	Total Patent Applications (3)	1-yr Revenue Growth (4)
Informal (1/0)	-0.015	0.004	0.730**	-0.055
	(0.030)	(0.005)	(0.356)	(0.098)
Above median wealth (1/0)	-0.176***	0.017***	0.664***	0.075
	(0.024)	(0.004)	(0.198)	(0.078)
Informal × above median wealth	0.114**	-0.021***	-1.143***	-0.131
	(0.045)	(0.008)	(0.431)	(0.145)
Observations	27,430	27,430	22,274	19,452
Pseudo/Adjusted R-squared	48.7 %	6.2 %	30.4 %	19.5 %
Mean of dependent variable	-0.45	0.07	0.042	1.44

Panel B: Informal-financed only vs. external-financed only firms

	Return on Assets (1)	Intangibles/ Total Assets (2)	Total Patent Applications (3)	1-yr Revenue Growth (4)
Informal (1/0)	0.062**	-0.008	-0.936*	-0.191**
	(0.030)	(0.005)	(0.521)	(0.097)
Above median wealth (1/0)	-0.189***	0.021***	0.822***	0.109
	(0.024)	(0.004)	(0.184)	(0.078)
Informal × above median wealth	0.121***	-0.028***	-0.781	-0.086
	(0.047)	(0.008)	(0.688)	(0.152)
Observations	25,930	25,930	20,697	18,414
Pseudo/Adjusted R-squared	49.1 %	6.0 %	31.4 %	19.7 %
Mean of dependent variable	-0.44	0.06	0.04	1.42

Panel C: Informal & external-financed firms vs. external-financed firms

	Return on Assets (1)	Intangibles/ Total Assets (2)	Total Patent Applications (3)	1-yr Revenue Growth (4)
Informal (1/0)	-0.302***	0.046***	1.518***	0.425
	(0.081)	(0.013)	(0.337)	(0.271)
Above median wealth (1/0)	-0.180***	0.015***	0.731***	0.062
	(0.025)	(0.004)	(0.190)	(0.079)
Informal × above median wealth	0.243**	-0.028	-1.299***	-0.448
	(0.103)	(0.018)	(0.427)	(0.331)
Observations	22,624	22,624	18,398	16,072
Pseudo/Adjusted R-squared	49.0 %	7.3 %	30.9 %	19.8 %
Mean of dependent variable	-0.48	0.07	0.05	1.53

A Additional Results

Table A1: Selection of Firms with Innovation Potential

Table A1 describes the selection process of firms with (high) innovation potential. Panel A begins with all firms newly founded in Norway between 2004 and 2017, from which we remove financial services and real estate firms, newly formed subsidiaries of established companies, holding company structures, and firms in non-innovative industries. Panel B describes the process for identifying the sub-sample of firms that have a high propensity to engage in innovation based on ex ante observable characteristics. Thus, we flag firms based on three alternative characteristics measured at year-end of their year of founding: founded with an English-language name, located in one of the country's four innovation hubs, and having at least one board member who lives far from the city in which the company is located.

Panel A: Full Sample	Firms	% of (A)
Firms (C-corps) founded in 2004–2017	321,548	
- Financial services and real estate firms	-143,496	
- Subsidiaries of established companies	-19,499	
- Holding structures	-6,275	
- Transaction data not matched	-27,930	
- Non-innovative industry	-45,152	
Newly established firms in potentially innovative industries: (A)	**79,196**	100.00%

Panel B: Ex Ante Innovation Flags	Firms	% of (A)
English name	26,452	33.40%
Located in an innovation hub (Oslo, Bergen, Stavanger, Trondheim)	23,887	30.16%
At least one board member who lives far from the firm	14,148	17.86%
At least one ex ante innovation flag:	46,121	58.24%

Table A2: Distance of External Investors

Firm-Years	External Investor Only			Informal × External Investors			T-test	
	N	p50	mean	N	p50	mean	b	se
N informal investors per firm	69,305	0.00	0.00	5,936	1.00	1.36	-1.36***	0.00
N external investors per firm	69,305	1.00	2.62	5,936	2.00	6.84	-4.23***	0.13
Average distance of external investors	69,305	8.92	68.59	5,936	19.25	94.61	-26.02***	2.26

Table A3: Financing from the Same Investors: Instrumental Variables

Table A3 replicates Table 7 Panel A, but restricts the external-only financed firms to startups, in which their external investors are informal investors in other firms in our sample. Column (1) corresponds to Column (4), Column (2) to Columns (5)–(6), while Column (3) to Column (7). The dependent variable in Columns (1)–(3) is $Informal\ (1/0)$, a dummy variable taking the value of one if the firm has at least one informal investor. The main independent variable of interest, $Ln\ (Mean\ distance)$, is our instrument, which measures the average geographical distance between the startup's headquarters location and its individual investors residual addresses. The dependent variables in Columns (4)–(7) are proxies for firm's risk-taking in year t as in Table 6. Control variables as in Table 6, calendar year by industry, firm age by industry and region fixed effects are included in all stages and specifications. A constant term is estimated but suppressed for brevity. Standard errors are clustered at firm level and are reported in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1% level, respectively.

	First-Stage Estimates			Second-Stage Estimates			
				Return on Assets	Intangibles/ Total Assets	Total Patent Applications	1-yr Revenue Growth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Informal (1/0)				2.442***	-0.654***	-0.853***	-4.444***
				(0.548)	(0.135)	(0.253)	(1.468)
Ln (Mean distance)	-0.013***	-0.013***	-0.013***				
	(0.002)	(0.002)	(0.002)				
Observations	17,901	17,901	13,341	17,901	17,901	17,901	13,341
R-squared	12.3 %	12.5 %	14.6 %	36.5 %	-71.7 %	-19.8 %	5.5 %
F-statistic				59.6	58.0	58.0	45.3
Mean of dependent variable				-0.32	0.06	0.05	0.91

Table A4: Inheritance as Instrumental Variable

Table A4 replicates Table 7 Panel C (informal $\times$ external-financed vs. external-financed firms), but uses the inheritance as an instrumental variable. Column (1) corresponds to Column (4), Column (2) to Columns (5)–(6), while Column (3) to Column (7). The dependent variable in Columns (1)–(3) is $Informal$ $(1/0)$, a dummy variable taking the value of one if the firm has at least one informal investor. The main independent variable of interest, $Inheritance$ $(1/0)$, is our instrument, which is the dummy variable whether the investor receives an inheritance in up to three years before making the investment. The dependent variables in Columns (4)–(7) are proxies for firm's risk-taking in year t as in Table 6. Control variables as in Table 6, calendar year by industry, firm age by industry and region fixed effects are included in all stages and specifications. A constant term is estimated but suppressed for brevity. Standard errors are clustered at firm level and are reported in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1% level, respectively.

	First-Stage Estimates			Second-Stage Estimates			
				Return on Assets	Intangibles/ Total Assets	Total Patent Applications	1-yr Revenue Growth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Informal (1/0)				-4.531***	0.486***	0.483	4.595
				(1.069)	(0.160)	(0.331)	(3.303)
Inheritance (1/0)	0.060***	0.059***	0.052***				
	(0.012)	(0.012)	(0.013)				
Observations	18,463	18,463	12,869	18,463	18,463	18,463	12,869
R-squared	8.6 %	8.7 %	8.4 %				
F-statistic				25.4	24.9	24.9	14.9
Mean of dependent variable				-0.50	0.07	0.04	1.62

Chapter 3

The Consequences of Customer Concentration When Competition Hits

The Consequences of Customer Concentration When Competition Hits*

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Abstract

I examine how customer concentration affects supplier firms' operating performance in competitive markets using large, industry-level tariff cuts as shocks to their product market competition. These shocks increase the risk of customers switching to foreign suppliers and intensify the risks associated with having a concentrated customer base. Tariff cuts enhance major customers' bargaining power vis-à-vis their suppliers. In addition, in the event of experiencing reduced demand from major customers, the relationship-specific investments commonly associated with major customer relationships make it costly for suppliers to re-deploy their assets to alternative uses. I find evidence that higher customer concentration ex-ante leads to lower asset turnover, reduced profitability, and increased costs related to acquiring new customers following tariff cuts. I also provide evidence that suppliers' financial flexibility mitigates these effects.

Keywords: Customer concentration, product market competition, operating performance.
JEL codes: L25, M41, L10, G30.

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1 Introduction

Publicly traded firms in the U.S. commonly depend on a few major customers for a large fraction of their total sales, leading to what is called customer concentration. There is a growing body of literature that looks at the effects of customer concentration, including a series of studies of the link between customer concentration and suppliers' operating performance (Cohen and Li, 2020; Hui et al., 2019; Irvine et al., 2016; Patatoukas, 2012). These studies argue for both risks and rewards of having major customers and point to a complex and dynamic relationship between customer concentration and operating performance. As drivers of this relationship, the main focus is on different aspects of the bilateral trade relationship between a supplier and its major customer(s), while putting little emphasis on product market interactions. In this study, I argue for product market competition as a determinant of how customer concentration relates to suppliers' operating performance, because it could intensify the key risk dimensions of customer concentration [1]. My analysis provides new evidence on the effects of customer concentration by examining whether it represents an impediment to firm performance as firms experience a shock to their product market competition.

Extant literature argues that customer concentration is inherently risky for firms. The low sales diversification of firms with major customers implies that declining demand from a single customer can lead to significant losses (Banerjee et al., 2008; Hertzel et al., 2008). In addition, major customers are often associated with a high degree of customer-specific investments, which exacerbates this risk. While specific investments are essential to facilitate exchange between major trade partners (Banerjee et al., 2008; Cen, Dasgupta, and Sen, 2016; Irvine et al., 2016), they also come with risk, the essence of which lies in their low value outside of the relationship. As another dimension of customer concentration risk, the literature emphasizes customers' strong bargaining power. To the extent that customer concentration reflects high customer power, it should be negatively related to suppliers' operating performance, if major customers bargain for and enforce favorable contract terms at the expense of their dependent suppliers. The evidence in recent studies of the customer concentration-firm performance relationship (Cohen and Li, 2020; Hui et al., 2019; Irvine et al., 2016;

[1] My main focus is on major corporate customers. Prior studies outline differences between major corporate and major government customers suggesting that corporate customers most closely adhere to predictions about the effects of customer concentration in my empirical setting. See for example Chen et al. (2022); C. Liu et al. (2021); Cohen and Li (2020) and Banerjee et al. (2008). It is argued that government customers, relative to corporate customers, represent a more stable source of demand because their high creditworthiness make them less likely to default or go bankrupt and because their purchases are typically governed by longer term contracts and not solely driven by profit motives. Also, government customers are more concerned for the public and may prefer to trade with domestic firms.

Patatoukas, 2012) provide mixed evidence with regards to whether the negative effects implied by this view dominate potential efficiency gains associated with customer concentration.

Existing studies support the idea that that firms' product market environment matters for the effects of customer concentration and that product market competition can intensify its key risk dimensions. For example, C. Liu et al. (2021) argue that customers' relative bargaining power can be influenced by the intensity of competition in the product market of their supplier and show that intensified competition from foreign rivals cause suppliers to adjust their CEO option compensation to accommodate their major customers. Further substantiating this view, Martin and Otto (2023) show that lower import tariffs in upstream industries affect corporate investment in downstream industries, arguing that upstream tariff reductions reduce costs, leading downstream firms to invest more, an effect that is driven by downstream firms with greater bargaining power. In addition, a broader literature finds differential effects of customer concentration depending on the product market position and competitive environment of the supplier firm, see for example Chen et al. (2022) and Campello and Gao, 2017. To the best of my knowledge, no study examines suppliers' product market competition as a determinant of the relationship between their customer concentration and operating performance.

To study whether customer concentration represents an impediment to firm performance as the supplier experiences an exogenous shock to product market competition, inspired by C. Liu et al. (2021), I use import tariff cuts in suppliers' industries to generate exogenous variation in the intensity of customer-supplier relationships. The idea is that reductions in import tariffs intensifies competition in suppliers' industries by making it less costly for customers to purchase from foreign suppliers. This improves the relative bargaining power of customers vis-a-vis their suppliers and leads to a higher likelihood of a supplier losing an existing customer. In addition, the high degree of relationship-specific investments and product customization commonly associated with major customer relationships (Banerjee et al., 2008) represents a risk for suppliers in the setting of tariff cuts. Such investments may carry little value outside of the relationship setting and give rise to assets that are customer specific, making them costly to re-deploy to alternative uses. Thus, the empirical setting of tariff cuts is closely related to predictions in the literature about why customer concentration is inherently risky for firms and why it might impede firm performance.

As extant literature argues for the use of large tariff reductions as a source of exogenous variation in competitive pressure, see for example de Bodt et al. (2023), C. Liu et al. (2021), Frésard and Valta (2016), Valta (2012) and Fresard (2010), tariff cuts presents an opportunity for gathering causal evidence on the effects of customer concentration. Rather than being randomly determined, customer concentration is determined simultaneously with other firm-level outcomes. This, in addition to unobserved heterogeneity in customer-supplier relationships, poses a challenge to identification of any effects of customer concentration. While identification concerns have been addressed in various ways, the inability of prior studies to rule them out represents a limitation of research to date. Furthermore, the main empirical tests in prior studies of the customer concentration-performance relationship are not designed to capture within firm variation in firm performance caused by customer concentration [2]. This may be explained by there being too little within firm variation in customer concentration to exploit, as explained by Chen et al. (2022), precluding the use of firm fixed effects in regressions that estimate the relationship between customer concentration and firm performance in a panel data setting. Utilizing import tariff cuts, my analysis evaluates within-firm variation in operating performance, without explicitly relying on within firm variation in customer concentration.

Because product market competition induced by tariff cuts affect firms' strategic product market behavior (e.g., de Bodt et al., 2023; Frésard and Valta, 2016), whether firms engage in major customer relationships could itself represent strategic responses to import tariff cuts that are determined simultaneously with operating performance. Therefore, I differentiate between firms' based on their ex-ante level of customer concentration and examine how it relates to firm performance following tariff reductions. To obtain shocks to suppliers' product market that are relatively unanticipated, I follow de Bodt et al. (2023) and use only the first significant tariff cut experienced by each industry. Furthermore, not all industries experience large import tariff reductions, and for those that do, large tariff cuts in different industries are staggered across time. This empirical setting facilitates the use of difference-in-difference analysis, which I carry out through a stacked difference-in-difference approach.

In the setting of import tariff cuts in suppliers' industries, there are several reasons why customer concentration could negatively affect suppliers' operating performance. First, major customers may use the increase in bargaining power induced by tariff cuts to bargain for more favorable terms of trade. Higher customer concentration implies that a larger share of suppliers' overall business will be subject to a new, less profitable bargaining equilibrium, where major customers are able

[2] The studies I refer to are studies focused on the relationship between customer concentration and firms' opearting performance, see Patatoukas (2012), Irvine et al. (2016), Hui et al., 2019 and Cohen and Li (2020). However, one notable exception is Cohen and Li (2020), who provide some empirical tests that rely on within firm variation in customer concentration and firm performance through the inclusion of supplier firm-fixed effects in panel data regressions.

to capture more of the gains from the relationships. I predict that this results in lower operating profitability for suppliers with higher customer concentration [3].

Next, provided that tariff cuts result in lower demand from existing customers, the close association between customer concentration and relationship-specific investments may imply a negative effect of customer concentration on firm performance. Due to the specific nature of their assets, suppliers with higher customer concentration may experience greater difficulties, and higher costs, related to switching to new customers and redeploying their assets to alternative uses. I predict this to result in in lower revenues per unit of assets in place for suppliers with higher customer concentration. Furthermore, I predict this to be accompanied by an increase in investments related to establishing and maintaining new customer relationships [4]. I further predict the negative effect on revenues and increase in expenses to negatively impact operating profitability.

Finally, specific assets can arise because of a high degree of product customization in the context of major customer relationships (Banerjee et al., 2008). As a result, in the event of experiencing reduced demand from existing major customers, suppliers could experience greater difficulties related to converting excess inventories, of specific goods and inputs, into sales. This implies reduced turnover of inventories [5].

Substantiating these predictions, prior studies show that efficiency gains accrue to firms with major customers that are achieved by higher asset utilization, improved working capital management yielding faster cash conversion cycles and inventory turnover, and lower SG&A expenses (Irvine et al., 2016; Patatoukas, 2012). Thus, if tariff cuts cause disruptions to major customer relationships, we should expect a negative impact on these dimensions of firm performance following tariff cuts for suppliers with a higher concentration of sales to major customers ex-ante.

Consistent with my predictions, I find that firms' ex-ante level of customer concentration is negatively related to asset turnover and operating profitability following tariff cuts. The effect on operating profitability persists when controlling for sales growth, which facilitates the interpretation that increased customer bargaining power yield less profitable major customer relationships for

[3]Throughout my empirical analysis, I measure operating profitability as income before depreciation scaled by total assets.

[4]Following Irvine et al. (2016), in my empirical analysis, I proxy for such investments using selling, general and administrative (SG&A) expenses, which are scaled by total revenues.

[5]In my empirical analysis, I examine firms' days inventory outstanding, a working capital management ratio that measures the number of days that a company holds inventory before turning it into sales. I employ a measure of this used in related literature (Patatoukas, 2012), defined as the ratio of total inventories to cost of goods sold multiplied by 365.

suppliers. I also find that customer concentration is positively related to SG&A expenses as a proportion of revenues and days inventory outstanding following large tariff reductions. This is consistent with customer concentration resulting in higher expenses related to establishing new customer relationships and with excess inventory being more difficult to turn into sales.

Further tests provide support for the effects of customer concentration around tariff reductions being driven by product market competition and for customers' switching costs and suppliers' specific assets as underlying channels. First, the effects are more pronounced among firms in industries with more concentrated sales prior to tariff reductions. Using industry sales concentration as a proxy for competitive pressure, this supports that the effects are driven by intensified competition, as tariff cuts arguably represent larger shocks to competition in more concentrated industries. Next, the effects are pronounced among firms in non-durable goods industries, but not among producers of durable goods. Arguably, firms in durable goods industries produce goods that are more customized to the specific needs of their customers, which makes it more costly for customers to switch suppliers (Banerjee et al., 2008). Thus, for industries of non-durable, more standardized goods, import tariff reductions likely represents a more salient driver of switching costs, implying that the effects should be more pronounced in these industries. Pointing to the role of relationship-specific investments, I show that the effects are concentrated among suppliers with greater research & development (R&D) intensity prior to tariff cuts [6]. In the context of major customer relationships, R&D expenses commonly serve as a proxy for relationship-specific investments, see for example Campello and Gao (2017), Kale and Shahrur (2007) and Chen et al. (2022). Thus, to the extent that it is more costly for firms with relationship specific assets to redeploy their assets when experiencing reduced demand from existing customers following tariff cuts, we should expect the effects to be more pronounced among more R&D intense firms.

If costs related to re-deployment of customer-specific assets and finding new customers drive to the negative association between customer concentration and firm performance following tariff cuts, we should expect this to be less pronounced for firms with greater financial flexibility. To this end, I examine whether the observed effects of customer concentration around tariff cuts varies with firm-level proxies for firms' financial flexibility, including cash holdings, profitability and financial leverage. Based on these proxies, I find that the effects are more pronounced among firms with lower financial flexibility, suggesting that customer concentration represents more of an

[6] I proxy for R&D intensity by firms' R&D expenses as a proportion of total assets.

impediment to these firms [7].

While my main focus is major corporate customers, I examine the effects of concentration of sales to major government customers. As argued by C. Liu et al. (2021), we may expect firms with major government customers to be less sensitive to import tariff reductions because large government customers prefer to trade with domestic firms. While I find some evidence that government customer concentration is also negatively related to asset turnover following tariff reductions, I find no effects of major government customer concentration when considering the other dimensions of firm performance. Taken together with my previous findings, I view this as supportive of my main predictions about the effects of customer concentration around tariff cuts, to which corporate customers more closely adhere.

This paper relates to existing studies of the relationship between customer concentration and suppliers' operating performance (Cohen and Li, 2020; Hui et al., 2019; Irvine et al., 2016; Patatoukas, 2012). I contribute to this literature by focusing on product market competition as a determinant of this relationship and, by utilizing exogenous shocks to suppliers' product market competition, I provide new evidence on a specific setting where customer concentration represents an impediment to firm performance. With further regards to suppliers' operating performance, I also relate to Cen, Dasgupta, and Sen (2016), who also relate major customers to suppliers' performance around external operating environment shocks [8]. More broadly, I contribute to a large and growing literature on the role of customers as important stakeholders in firms. This literature shows that customer base structure can influence various firm policies and financial market outcomes, including firms' loan contract terms and cost of both debt and equity financing (Campello and Gao, 2017; Cen, Dasgupta, Elkamhi, and Pungaliya, 2016; Dhaliwal et al., 2016), capital structure (Banerjee et al., 2008; Kale and Shahrur, 2007), ability to raise external funding and financial constraints (Itzkowitz, 2015; L. X. Liu et al., 2018), cash holdings (Itzkowitz, 2013) accounting policies (Hui et al., 2012), earnings management (Raman and Shahrur, 2008), innovation (Chu et al., 2019), corporate misconduct (Chen et al., 2023) and tax strategies (Cen et al., 2017). I also relate to a broader literature using large tariff cuts as a source of exogenous variation in competitive pressure, including Fresard (2010), Valta (2012), Frésard and Valta (2016), C. Liu et al. (2021) and

[7] Related to these results, Itzkowitz (2013) provide evidence that firms with major customers hold more cash, arguing that this is a precautionary measure against the operating risk induced by customer concentration.

[8] They focus on the influence of takeover protection on the quality of customer-supplier relationships and utilize the enactment of business combination laws as exogenous variation in takeover protection faced by supplier firms. It is argued that takeover protection improves the incentives of major customers to commit to relationships with suppliers, leading to more profitable customer-supplier relationships.

de Bodt et al. (2023).

The rest of the paper is organized as follows. Section 2 discusses background literature and hypotheses, section 3 describes data and empirical methodology, section 4 discusses the empirical results and section 5 concludes.

2 Background and hypotheses

In this section, I discuss different dimensions of customer concentration risk, recent evidence on the relationship between customer concentration and suppliers' operating performance and hypotheses about the effects of customer concentration in the context of import tariff cuts in suppliers' industries.

2.1 Customer concentration risk

Extant literature argues that major customer relationships are inherently risky. Given the low sales diversification of firms with major customers, the loss of a single customer, for example because the customer decides to switch supplier or because of customer bankruptcy, can lead to significant losses (Banerjee et al., 2008; Hertzel et al., 2008; Kolay et al., 2016). In addition to large, abrupt reductions in cash flow and costs related to replacing the customer, firms are extra exposed to the loss of a customer when investments specific to the customer relationship have been made, that result in relationship-specific assets. The literature highlights the importance of relationship-specific investments to facilitate exchange between trade partners and to create high quality trade relationships (e.g. Banerjee et al., 2008; Johnson et al., 2015; Cen, Dasgupta, and Sen, 2016; Irvine et al., 2016; Harford et al., 2019). At the same time, a feature of such investments is that they lose some, potentially all, of their value if relationships between trade partners are broken. Thus, while facilitating exchange between firms, specific investments in important trade relationships also exacerbates the financial exposure of one firm to another, in ways that can cause large costs in the event that trade relationships come to an end. In line with this view, financial distress of important customers can lead to significant value reductions in supplier firms, as suggested by Titman (1984) and shown by Hertzel et al. (2008). Furthermore, Kale and Shahrur (2007) and Banerjee et al. (2008) find that both customers and suppliers in bilateral relationships maintain lower leverage as a precaution against the loss of value in relationship-specific assets should one of the two trade partners become financially distressed.

As explained by Banerjee et al. (2008), in the context of major customer relationships, the firm's assets are likely to be specific to its major customer. Moreover, a key aspect of such bilateral relationships is that the product being produced is more likely to be unique, customized to the customer, and hence require specific investments. Such investments represent a source of risk, the essence of which lies in their low value outside of the relationship and the potential high costs required to redeploy specific assets to alternative uses. Therefore, especially for suppliers of major customers, potentially resulting in a high proportion of relationship specific assets, the risk of reduced demand from existing customers is a key concern.

Another feature of major customer relationships, that underscores central predictions about trade partners' gains from such relationships, concerns the relative bargaining power of customers and suppliers. With reference to early work (Galbraith, 1952; Porter, 1974; Scherer, 1970), Patatoukas (2012) explains that major customers often place orders around which the production and investment of suppliers with concentrated customer bases become organized. Because a shift in this practice can impose prompt and heavy losses, the threat or even the fear of sanctions is enough to provide customers with considerable bargaining power over transaction prices and trade credit terms. This view is supported by early industry-level studies, e.g. Lustgarten (1975), finding that measures of downstream bargaining power are associated with lower upstream gross margins. While this view is maintained in recent studies of the relationship between customer concentration and suppliers' operating performance (Cohen and Li, 2020; Hui et al., 2019; Irvine et al., 2016; Patatoukas, 2012), the evidence with regards whether the negative effects it implies dominate potential efficiency gains from customer concentration is mixed.

2.2 Recent evidence on customer concentration and firm performance

Patatoukas (2012) shows that customer concentration relates positively to various dimensions of firm performance and offers the interpretation that efficiency gains, realized through close collaboration between suppliers and customers, accrue to firms with a concentrated customer base. Efficiency gains are reflected in improved asset utilization and higher profitability. Important sources of such gains are improved working capital management, relating to trade credit and inventory management, and lower selling, general and administrative expenses for firms with higher customer concentration.

Irvine et al. (2016) provide evidence that suppliers' profitability improves over the life-cycle of the major customer relationship, arguing that significant investments required to establish and maintain the major customer relationship leads to poor performance at its initial stages. However, as the relationship matures, required relationship-specific investments decline and the firm becomes able to realize significant benefits from the relationship.

Hui et al. (2019) focus on testing two hypotheses regarding the effects of major customer concentration on firm profitability; the collaboration hypothesis, under which both the supplier and major customer obtain benefits from the relationship and; the competition hypothesis, under which the major customer benefit at the expense of the supplier firm. In favor of the competition hypothesis, and pointing to the importance of relative bargaining power, it is shown that customer concentration is negatively associated with suppliers' profitability and positively associated with major customers' profitability and that these effects weaken as suppliers' relative power grows.

Cohen and Li (2020) focus on differentiating between major corporate and government customers and argue that concentration of sales to major corporate customers can negatively affect suppliers' profitability because it induces greater uncertainty of future demand, leading to sub-optimal investment decisions. Taken together, existing studies point to a complex and dynamic relationship between customer concentration and suppliers' operating performance.

2.3 Customer concentration risk and import tariff cuts

Existing studies imply that, instead of focusing on *whether* customer concentration is an impediment to firm performance, we may rather ask *when* it is. Against this backdrop, I examine whether customer concentration represents an impediment to firm performance by focusing on a setting where, arguably, the key risks associated with customer concentration are intensified. Specifically, inspired by C. Liu et al. (2021), I exploit import tariff cuts in U.S. manufacturing industries as a source of exogenous variation in the intensity of customer-supplier relationships. The idea is that import tariff cuts in the supplier's industry lowers the costs of the supplier's customers of switching their source of supply to foreign competitors of the supplier. This increases the risk of the supplier experiencing reduced demand from existing customers and serves to raise customers' relative bargaining power by intensifying supplier industry competition.

In this setting, there several reasons why customer concentration could have a negative effect on supplier firm performance. First, if major customers use the increase in bargaining power induced by tariff cuts to bargain for more favorable terms of trade, for example relating to prices or trade credit terms, this could negatively affect suppliers' operating performance, as more of the gains from the relationship are captured by major customers. In other words, higher customer concentration implies that a larger share of suppliers' overall business will be subject to a new, less profitable bargaining equilibrium. I hypothesize that this manifests in lower operating profitability for suppliers with higher customer concentration, in line with the findings if Hui et al. (2019).

Next, provided that tariff cuts results in lower demand from existing customers, the close association between customer concentration and relationship-specific investments implies that firms with higher customer concentration will experience greater difficulties, and higher costs, related to switching to new customers and redeploying their assets to alternative uses. Due to the specific nature of their assets, suppliers with major customers face a heightened risk, as reduced demand from these customers may be harder to replace, as opposed to firms with a more diversified customer base, whose assets are more applicable to a broader set of customers. I hypothesize that this manifests in lower revenues per unit of assets in place, referred to as asset turnover, for suppliers with higher customer concentration. Furthermore, I hypothesize this to be accompanied by an increase in investments related to establishing and maintaining new customer relationships. I further predict reduced asset utilization and higher costs related to establishing new customer relationships to have a negative impact on overall operating profitability.

Finally, specific assets can arise because of a high degree of product customization in the context of major customer relationships (Banerjee et al., 2008). As a result, in the event of experiencing reduced demand from existing major customers, suppliers could experience greater difficulties related to converting excess inventories, of specific goods and inputs, into sales. I hypothesize that this manifests as a positive relationship between customer concentration and inventories outstanding following tariff cuts.

3 Data and empirical methodology

3.1 Data

Firm-year financials

I obtain annual firm level financial data from the CRSP-Compustat-Merged (CCM) database. I select firms in manufacturing industries, defined by primary SIC codes 2000-3999, because the tariff data I use includes manufacturing firms. I retain fiscal years 1977-2019 because sales to major customers is observable starting in fiscal year 1977 and because the tariff data covers the period until 2017, leaving me with two years of firm-year financial data after the last observed tariff data. The customer and tariff data is discussed greater in detail in the following sections. In the CCM data, I also require non-missing values of sales, assets, firm age, operating profitability, sales growth, book leverage and market-to-book value of firms' assets, this to be able to control for a minimum of factors that likely correlate with operational performance and firms' level of customer concentration and that also could be affected by import tariff reductions. These requirements yields a starting point of 85,469 firm-year observation from the CCM data. Based on this sample, Figure 1 plots the number of firms each year over the 1977-2019 period.

Firm-level customer data

The Statement of Financial Accouniting Standards No.14 (SFAS No. 14) of the Financial Accounting Standards Board (FASB) requires that firms report information for segments that represent 10% or more of consolidated sales, for fiscal years ending after 1977. This includes disclosure of sales to principal buyers, if the revenue generated from sales to a particular buyer exceeds 10% of the revenue of the firm, or if the firm considers the sales to a buyer to be important to its business. Prior to 1997, firms were required to disclose the name of such customers. In 1997, the FASB issued SFAS No. 131, revising SFAS No. 14 such that firms are permitted to optionally report customer names. Customers, their names when available and revenue from each customers is collected in the Compustat Segment files. I extract firm-level customer information from the Compustat Segment files for the 1977-2019 period.

The Compustat segment files are at the supplier-year-customer level. To measure firms' sales to major corporate customers, in the Compustat Segment files, I retain firms' corporate customers, as identified by the entry "COMPANY" on the customer type variable ($ctype$) in the data. The data includes a source date variable, indicating when the data was sourced, from which I infer which fiscal year the customer sales information belongs to. Specifically, for customer data sourced in the months June through December, the fiscal year is defined as the year of the data year, while for months January through May, the fiscal year is set to the year prior to the year of the source date. Based on suppliers' gvkey and fiscal year I merge in firms' annual sales from the CCM data, which allows me to compute the fraction of total sales in a given fiscal year each entry in the customer data corresponds to. I measure firms total customer concentration in a given year by aggregating all entries of fraction of sales to customers within a given year. Next, the data on firms annual fraction of total sales to major corporate customers is merged with the annual CCM sample and the customer concentration measure is set to 0 in firm-years without any sales to major customers.

In addition to the number of firms in my CCM sample, Figure 1 shows the number and fraction of firms with any major corporate customer each year over the 1977-2019 period. For firm-years with any reported sales to major corporate customers, Figure 2 shows firms' average and median fraction of sales to major corporate customers.

I also measures firms' sales to major government customers. To do this, I follow the same procedure as for corporate customers, but based on retaining observations with the entries "GOVDOM", "GOVFRN", "GOVLOC" and "GOVSTATE" in the customer type variable ($ctype$).

Import tariff data

I start out with import tariff data for the period 1974-2017. This data is based on the data used in Frésard and Valta (2016), which is made available on the website of Phillip Valta (www.valta.ch) and covers the 1974-2005 period, and the data used in Schott (2008), for the 2006-2017 period. Because the tariff data is only available for manufacturing industries, as defined by the four digit SIC code range 2000-3999, I focus my analysis on these industries. The raw tariff data covers 514 unique manufacturing industries over the period from 1974 to 2017. To identify significant tariff reductions at the industry-year-level, I first follow the procedure of Frésard and Valta (2016), which involves defining significant tariff cuts as year-by-year reductions in the annually recorded tariff rate that is at least three times larger than the average change in tariff rate within a given industry over the sample period. Next, I restrict my focus to the first significant tariff cut within each industry only. This restriction, which follows recent work by de Bodt et al. (2023) and leaves me with 376 significant tariff cuts that occur in the period between 1975 and 2012, meaning no industry had its first significant tariff cut after 2012. The restriction to industries' first significant tariff cuts is imposed to capture tariff cuts that were relative unanticipated by firms [9]. Due to not all industries in the tariff data applying to firms in my CCM sample described above, as well as various steps taken to construct a stacked regression sample, my empirical analysis will not be based on the full set of 376 tariff cuts. The sample formation is described in greater detail in the following.

3.2 Empirical methodology

I analyze whether firms' level of major customer concentration impedes firm performance following significant tariff cuts. I note the possibility that, as a cause of intensified product market competition

[9] de Bodt et al. (2023) focus on tariff cuts over 1975-2005 period and identifies 324 such tariff cuts. I confirm my sampling methodology by identifying 324 tariff cuts when restricting my tariff data sample period to end in 2005.

following tariff cuts, firms may end up with major customer relationship and that this may coincide with changes to firm performance caused by intensified competition. Thus, relating contemporaneous measures of firm performance and customer concentration in the event of a shock to competition does not facilitate the right interpretation. Rather, I focus on firms' dependency on sales to major customers ex-ante, in the years before they experience tariff cuts, and examine how this relates to their performance following tariff cuts. Specifically, I define firms' level of customer concentration by their maximum fraction of sales to major customers over the two years preceding the year of the tariff cut in their industry.

Due to the customer data being available from the fiscal year 1977, lagged firm-year observations of customer concentration starts in fiscal year 1978. Thus, from the sample of 376 industry-level tariff cuts identified in the raw tariff data, I drop tariff cuts occurring before 1978, leaving me with 233 tariff cuts that are uniquely defined at the industry-year level. Merging these tariff cuts with my Compustat sample and requiring firms to be in the sample in the year of the tariff cut as well as one year prior and one year after the year of the tariff cut leaves me with 793 treated firms in 67 unique industries. Of these firms, 292 firms belonging to 54 unique industries, reported any sales to major corporate customers in the two years preceding the year of the tariff cut.

Stacked difference-in-differences approach

I define unique treatment events by the year of tariff cuts, leaving me with 22 unique treatment years. Furthermore, I restrict my analysis to a maximum window of 2 years on both sides of the year of any tariff cut. Since the first year with information about firms lagged level of customer concentration is in 1978, the event period is 4 years for the 1978 event and 5 years for all other 21 event years, resulting in a total of 109 event years.

The industry-level tariff cuts are staggered in time, allowing me to adopt a difference in difference approach. Analysing staggered exogenous shocks is more appealing than analyzing a single shock as any single shock may be affected by confounding factors simultaneously affecting the dependent and independent variables of interest (Bertrand and Mullainathan, 2003; Roberts and Whited, 2013). Recent literature suggests that, in the presence of staggered treatment events with heterogeneous treatment effects, the standard regression approach used for staggered difference-in-difference analysis, regressions with two-way fixed effects, is likely to generate biased results when units treated earlier in the sample are used as controls for units currently being treated (Baker et al., 2022; Goodman-Bacon, 2021). In light of the potential problems of the staggered difference-in-difference design, I instead estimate a stacked difference-in-difference specification.

I create a stacked sample in the following steps. First, I group treated firms by the 22 different event years with tariff shocks. To illustrate, sic industries 2271, 3531, 3555, 3652 and 3661 all experienced their first large tariff reduction in 1983 and, thus, all firms in these industries represent the treated firms in the 1983 cohort. Moreover, since I only focus on industries' first large tariff cut, firms in these industries will not be treated firms in any other cohort, which is defined by year of tariff cut. Next, I choose control firms for cohort c, representing any of the 22 event years, those firms that are in industries never treated during the sample period or those firms that are treated first in years greater than $c+2$ (i.e., treated more than 2 years later than the event year of any given cohort c). As with the treated firms, for a control firm to be included I require the firm to, at a minimum, be in the CCM sample in year $t-1$, year t and year $t+1$, and include in the sample year $t-2$ and $t+2$ whenever available in the CCM sample. This procedure creates 22 cohort-specific datasets with treated and control firms ensuring that control firms are either never-treated or not-yet treated, avoiding comparison of treated firms to already-treated firms. To form the regression sample, I stack all cohort specific datasets together to form a stacked sample. The stacked sample contains duplicates observations at the firm-year level, as a result of the same firm serving as a control firm in multiple if the 22 cohorts, but no such duplicates at the firm-year-cohort level. This approach allows me to maximize the number of control observations while avoiding comparison of treated firms to already-treated firms and firms that are to be treated within the selected event window of any given cohort.

The main difference-in-difference regression specification employed in the analysis is defined by the following equation:

$$\begin{aligned} Y_{i,t,c} = \alpha + \beta_1 Post\ cut_{i,t,c} + \beta_2 CC_{i,c} \\ +\ \beta_3 Post\ cut_{i,t,c} \times CC_{i,c} \\ +\ \beta_4 X_{i,t,c} \\ +\ \gamma_{i,c}\ +\ \lambda_{t,c} + \varepsilon_{i,t,c} \end{aligned} \tag{1}$$

In Equation 1, i, t and c denotes firm, fiscal year and cohort, respectively. $Y_{i,t,c}$ represents various firm-fiscal year level outcome variables. $Post\ cut_{i,t,c}$ is an indicator variable that takes the value of one if the firm's industry s has experienced a tariff cut in or prior to year t, and zero otherwise. $CC_{i,c}$ is the maximum level of customer concentration for firm i over the two years preceding the year of the tariff cut of the firm's cohort c. $Post\ cut_{i,t,c} \times CC_{i,c}$ is the interaction of $Post\ cut_{i,t,c}$ and $CC_{i,c}$. $X_{i,t,c}$ represents a vector of firm-fiscal year level control variables that likely correlate with firms' operational performance and level of customer concentration and that could be affected by import tariff reductions, including the natural logarithm of firm age, the natural logarithm of total assets, one year sales growth, market-to-book value of assets and book leverage. $gamma_{i,c}$ represents firm-cohort fixed effects and $lambda_{t,c}$ represents year-cohort fixed effects. Note, the specific fixed effects subsumes the individual term $CC_{i,c}$ when estimating the regression. Standard errors are clustered at the firm level.

Multiple samples approach

In light of differences between prior studies of the effects of major customers, I carry out empirical tests in three separate samples, referred to as the full sample, the customer concentration sample and the matched sample.

The $full\ sample$ includes all firms, irrespective of having any sales to major customers in the period leading up to the import tariff reduction of their cohort. This sample includes all 739 unique treated firms and 5,120 unique control firms identified in the sample construction procedure described above. Firms without sales to major customers are included with share of sales to major customers set to 0, thereby facilitating tests of the effect of customer concentration on the extensive margin, i.e. comparing firms with any reported major customer to firms with no reported major customer, as well as comparison of firms with varying levels of customer concentration while including firms with no concentration of sales to major customers. This sample construction procedure aligns closely with that of L. X. Liu et al. (2018) and Chen et al. (2022), although these studies differ significantly in key aspects that has to do with how they use the major customer sales data, identification strategy and the time period they study.

The $customer\ concentration\ sample$ includes firms with any sales to major customer leading up to the import tariff reduction of their cohort. This sample includes all the 292 unique treated firms with any sales to major customers and 3,278 unique control firms with any sales to major customers. This sample facilitates comparison of firms with varying levels of sales concentration to major customers. Relative to the full sample, this sample arguably facilitates comparison of more similar firms, reducing the concern that observed effects of customer concentration around import tariff reductions are driven by other differences between firms that correlate with customer concentration and that are not captured by the control variables included in the regressions. Inclusion of only firms with any sales to major customers prior to the tariff reductions aligns more closely with prior accounting studies of the effects of customer concentration on firm performance, see for example Patatoukas (2012).

As argued by C. Liu et al. (2021), an advantage of using repeat experiments over a time period of several decades, is that treatment effects are estimated based on different groups of firms in different time periods, thereby reducing concerns that the effects are driven by a particular group of firms in particular industries in a specific time period. However, one concern is that policy makers consider various industry conditions before imposing import tariff reductions. In addition, some firms, e.g., larger firms, may be able to lobby for desired trade policies. This presents risks relating to the randomness of the experimental setting I utilize and that treated firms systematically differ from untreated firms. By controlling for firm size, sales growth, leverage and market to book ratio I arguably reduce this concern. However, I would ideally be able to compare a firm as it experiences a tariff reduction to the same firm in the same time period had it not been hit by by a tariff reduction.

To get closer to this setting, I perform a matched sample approach based on propensity score matching, which involves matching each treated firm in the customer concentration sample with a set of similar control firms based on observable firm-characteristics, all measured prior to the import tariff reduction. The characteristics on which firms are matched include operating profitability, asset turnover, maximum share of sales to major corporate customers over the two year period prior to the tariff reduction, the natural logarithm of firm age, the natural logarithm of total assets, sales growth, book leverage and market to book value, research and development (R&D) expenses scaled by total assets and the concentration of firm-level sales in firms' SIC4 industry. The aim of the matched sample approach is to reduce the number of control firms to a set of control firms that are not significantly different from the treated firms on the mentioned characteristics. Thus, this approach facilitates comparison of firms that, prior to the tariff cut, are similar with respect to the share of sales accounted for by major customers, as well as along other dimensions. Arguably, this allows me to better isolate the effect if import tariff reductions, which serves as a source of exogenous variation in the intensity of customer-supplier relationships.

Using the customer concentration sample and including only firm-years one year prior to the import tariff reduction (year $t-1$), I estimate the probability that a firm experiences an import tariff reduction bu running a logit regression where the dependent variable is an indicator value taking the value of one for treated firms and zero for control firms and where the explanatory variables include the above mentioned matching characteristics. Selection of matched firms based on observable characteristics on year before the event aligns with the matching procedure used by Frésard and Valta (2016). Next, I construct a matched sample using nearest neighbor matching based on the propensity scores obtained from the logit model. Specifically, each treated firm-year observation is matched with its five closest untreated control firm-years based on propensity scores. To ensure similarity of treated and control firms, while at the same time ensuring that each of the 292 treated firms is matched with at least one control firm, I impose the restriction that the maximum value of of the difference in propensity scores between the treated and control firm years is 0.025 in absolute value. The $matched\ sample$ is based on the customer concentration sample and still includes all the 292 unique treated firms and 906 unique control firms.

Table 1 reports descriptive statistics for all firms, and separately for treated and control firms, separately for the full sample (Panel A) and the customer concentration sample (Panel B). T-tests of the difference in means of treated and controls firms are also reported. Each variable is measured in the year prior to the import tariff reduction (year $t-1$), except $Max\ share\ of\ sales\ to\ customers$, which reports the firm-level maximum fraction of sales to major customers over the two years preceding the tariff reduction (year $t-1$ and $t-2$). I focus on firm characteristics prior to the import tariff reduction only, to facilitate simple assessment of whether treated and control firms differ prior to the tariff event of their cohort. As seen by the number of observations, N, the number of treated firms corresponds to the number of unique treated firms in each regression sample. However, when looking at the number of control firm observations, it exceeds the number of unique control firms mentioned for each sample above. This is a result of the stacked-sample procedure, which is based on creating a cohort of firms for a every single treatment event, while allowing the same firm to serve as a control firm in multiple cohorts. This implies that, considering the full sample in Panel A or the customer concentration sample in Panel B, which only includes firm-year observations in the year prior to the tariff reduction of each cohort, while there are no firm-year-cohort duplicates, a single firm may appear multiple times, as a result of serving as a control firm in multiple cohorts.

From Panel A, we see that the fraction of firm that report the presence of a major corporate customer is 0.45. The t-test in suggest that that treated and control firms differ along several dimensions, including SG&A expenses, days inventory, R&D intensity, industry concentration and market share. Relative to the group of treated firms, there is also a greater fraction of firms with any reported major corporate customer among control firms.

Moving to Panel B we see that, relative to the full sample, the customer concentration sample features firms that, on average, are smaller and younger. Also, the customer concentration firms display lower operating profitability, higher growth in sales and higher market-to-book ratios. These observations are in line with the idea that younger and smaller firms are more likely to have major customers, growing faster and have greater growth potential. The firms in this sample all reported any sales to major customers in the two-year period leading up to the tariff reduction of their cohort, and, on average, the maximum share of sales to major customers over this period is 0.37 for both treated and control firms. Based on the t-tests, treated and control firms appear to be more similar in the customer concentration sample, relative to the full sample. However, control and treated firms are still significantly different when considering SG&A expenses, days inventory, R&D intensity and industry concentration.

The apparent differences between treated and control firms in the full sample and customer concentration sample warrants the construction of the matched sample, for which descriptive statistics are presented in Table 2 [10]. Based on the t-tests, treated and control firms in the matched sample do, on average, not differ on any of the reported statistics, with the exception of days inventory.

4 Empirical analysis

4.1 Customer concentration and firm performance around tariff cuts

In this section, I examine the relationship between supplier firms' ex-ante level of customer concentration and their firm performance following large import tariff cuts in suppliers' industries.

Table 3 presents the results from estimating Equation 1 with asset turnover as the dependent variable. The variable $Post\ cut$ takes value 1 for treated firms in the year of experiencing an import tariff reduction and the two years thereafter. For all other firm-years the variable takes value 0. Columns (1)–(4) is based on the full sample and in columns (1)–(2) the main explanatory variable of interest is an indicator variable for whether firms reported any sales to major customer in the two year period prior to the tariff cut of their cohort, $Major\ customer\ (1/0)$. In columns (3)–(8), this indicator is replaced by a the continuous measure of firms' maximum level of customer concentration over the two year period prior to the tariff cut of the firms' cohort, CC. Columns

[10] In contrast to the full sample and the customer concentration sample, the matched sample does include some firm-year-cohort duplicates among the control firm observations, this as a result of allowing the same control firm to serve as control for multiple treated firms within the same cohort. The number of unique control firm-years is 1,234, while the number of unique control firms is 906.

(5)–(6) is based on the customer concentration sample, while columns (7)–(8) is based on the matched sample. These samples include only firms with any customer concentration prior to the tariff reduction of their cohort, hence the only relevant major customer measure is the level of customer concentration.

Across all columns of Table 3, as judged from the coefficient estimate for $Post\ cut$, we see that firms experiencing import tariff cuts, relative to firms that do not, have higher asset turnover, consistent with the idea that competition has a disciplining effect on firms, manifesting in improved asset utilization. To illustrate the magnitude of this effect, the coefficient of 0.049 in column (4), suggests that following import tariff reductions, treated firms with no sales to major customers experience an increase in asset turnover of 3.8%, when seen relative to full sample mean of asset turnover of 1.26 in the year before import tariff reductions. However, of my main interest is the interaction of $Post\ cut$ and the measures of customer concentration. Column (1)–(2) suggests that the development of asset turnover around tariff reductions does not significantly differ between firms depending on whether they simply have a major customer. However, across all remaining columns, the coefficient on the interaction between $Post\ cut$ and CC is significantly negative, suggesting that the level of concentration of sales to major customers, is negatively related to asset turnover following large tariff reductions. Considering the full sample and the specification with all control variables in Column (4), a fraction of sales to major customers of 0.25, which represents the 75th percentile value, prior to the tariff cut of their cohort, is associated with asset turnover that is lower by 0.035, thereby significantly reducing the positive effect indicated by $Post\ cut$. Considering the customer concentration sample and the specification in Column (6), firms with a fraction of sales of 0.53, which represents the 75th percentile value in this sample, is associated with asset turnover that is lower by 0.098, suggesting in an overall negative effect on asset turnover when comparing it to the $Post\ cut$ coefficient of 0.075. If instead basing the interpretation on standard deviation changes, a one standard deviation change in CC of 0.26, which refers to the the standard deviation in the customer concentration sample, is associated with with a moderating effect on asset turnover of -0.047.

Table 4 presents the results from estimating Equation 1 with operating profitability as the dependent variable. Resembling the results for asset turnover, across all columns in Table 4, we see a positive relationship between tariff cuts and operating profitability, indicative of a disciplining effect of competition on firms operating performance. To illustrate the magnitude of this result, the coefficient of 0.014 in column (4), suggests that following import tariff reductions, treated firms with no sales to major customers experience an increase in operating profitability of around 14%, when seen relative to full sample mean of profitability of 0.10 in the year before import tariff reductions. Columns (1)–(2) show that the development of operating profitability around tariff reductions does not significantly differ between firms depending on whether they simply have a major customer. However, as shown in columns (3)–(8), the coefficient on the interaction between $Post\ cut$ and CC is significantly negative, suggesting that higher level of concentration of sales to major customers, is negatively related to operating profitability following tariff reductions. Considering the full sample and the specification with all control variables in Column (4), a fraction of sales to major customers of 0.25, which represents the 75th percentile value, prior to the tariff cut of their cohort, is associated with operating profitability that is lower by 0.013, thereby effectively cancelling out the positive effect indicated by $Post\ cut$. Considering the customer concentration sample and the specification in Column (6), firms with a fraction of sales to major customers of 0.53, which represents the 75th percentile value in this sample, is associated with operating profitability that is lower by 0.037, suggesting an overall negative effect on operating profitability when comparing it to the $Post\ cut$ coefficient of 0.027. If instead basing the interpretation on standard deviation changes, a one standard deviation change in CC of 0.26, is associated with with a moderating effect on operating profitability of -0.018.

Taken together, these results in Table 3 and Table 4 suggest that firms ex-ante level of customer concentration is negatively related to asset turnover and profitability following tariff reductions. Furthermore, due to a positive effect of tariff cuts on these dimensions of firm performance, the overall effect on asset turnover is negative for firms with customer concentration above a threshold. Overall, the results are consistent with the idea that customer concentration is associated with relationship specific assets that are harder to deploy to alternative uses, in order to generate new sources of revenues, as firms experience reduced demand from existing customers following import tariff reductions. The negative effect on operating performance could be a direct result of the negative effect on sales. In addition, because the negative effect persists when controlling for sales growth, the results support the idea that customers use their increased bargaining power at expense of their dependent suppliers.

To look for evidence that firms with higher levels of customer concentration ex-ante incur larger costs related to re-deployment of relationship-specific assets, I examine the relationship between customer concentration and firms' selling and general administrative (SG&A) expenses around tariff reductions. The idea is that firms who's existing assets to a large degree are specific to their existing customers, will have to incur larger expenses related to establishing new customer relationships, in the event of experiencing reduced demand from existing customers following tariff cuts. Following (Irvine et al., 2016), I use (SG&A) expenses scaled by total sales to proxy for investments related to acquiring and maintaining new customer relationships and Table 5 presents the results from estimating Equation 1 with this proxy as the dependent variable. The main effect of import tariff reductions, as judged by the $Post\ cut$ coefficient, is negative. When seen together with the results for asset turnover and operating profitability, this is in line with the view that firms become more disciplined in their operations through cost reductions following intensified competition. However, our main coefficient of interest, the interaction between $Post\ cut$ and CC, suggest that customer concentration bears a positive relationship to SG&A expenses as a fraction of sales following tariff reductions. Considering the customer concentration sample and the specification in Column (6), firms with a fraction of sales of 0.53, which represents the 75th percentile value in this sample, is associated with SG&A expenses that are higher by 0.099, suggesting in an overall positive effect on SG&A expenses when comparing it to the $Post\ cut$ coefficient of -0.068.

To look for evidence for the prediction that firms with higher levels of customer concentration ex-ante experience greater difficulties of converting inventories, of specific goods and inputs that are commonly associated with major customer relationships, to sales, I examine the relationship between customer concentration and the time firms use to convert inventories into sales, proxied by the ratio of total inventories to costs of goods sold multiplied by 365. Table 6 presents the results from estimating Equation 1 with this proxy as the dependent variable. Columns (3)–(8) point to a negative effect of tariff cuts on days inventory, as judged by the $Post\ cut$ coefficient, further supporting the view that firms become more disciplined in their operations following intensified competition. However, our main coefficient of interest, the interaction between $Post\ cut$ and CC, suggest that customer concentration bears a positive relationship to days inventory following tariff reductions. Considering the customer concentration sample and the specification in Column (6), firms with a fraction of sales of 0.53, which represents the 75th percentile value in this sample, is associated with days inventory that are higher by 28.665, suggesting in an overall positive effect on days inventory when comparing it to the $Post\ cut$ coefficient of -17.438.

Taken together, the results in Table 5 and Table 6 results support my predictions that firms with higher levels of customer concentration ex-ante incur larger expenses related to establishing new customer relationships and greater difficulties of converting excess inventories into sales, in the event of experiencing reduced demand from existing customers following tariff cuts.

At this point, a shortcoming of my analysis that is important to highlight is the lack of concrete evidence that suppliers' experience reduced demand from existing customers following tariff cuts.

4.2 The timing of effects around tariff cuts

To explore whether the observed effects of customer concentration are indeed driven by import tariff reductions, I next examine, in greater detail, the timing of effects around import tariff reductions. I estimate a modified version of the regression specification in Equation 1, defined by the following equation:

$$
\begin{aligned}
Y_{i,t,c} = \alpha &+ \beta_1 Treated_{i,c} \times Reltime_{t,c} \\
&+ \ \beta_2 Treated_{i,c} \times Reltime_{t,c} \times CC_{i,c} \\
&+ \ \beta_3 X_{i,t,c} \\
&+ \ \gamma_{i,c} \ + \ \lambda_{t,c} + \varepsilon_{i,t,c}
\end{aligned} \tag{2}
$$

In Equation 2, i, t and c denotes firm, fiscal year and cohort, respectively. $Y_{i,t,c}$ represents various firm-fiscal year level outcome variables. $Treated_{i,c}$ is an indicator variable that takes the value of one for treated firms in cohort c and zero otherwise. $Reltime_{t,c}$ is a categorical variable taking separate values for each year of cohort c, measuring the time relative to the year of the cohort's import tariff reduction. $CC_{i,c}$ is the maximum level of customer concentration for firm i over the two years preceding the year of the tariff cut of the firm's cohort c. $Treated_{i,c} \times Reltime_{t,c}$ is the interaction of $Treated_{i,c}$ and $Reltime_{t,c}$. $Treated_{i,c} \times Reltime_{t,c} \times CC_{i,c}$ is the triple interaction of $Treated_{i,c}$, $Reltime_{t,c}$ and $CC_{i,c}$. $X_{i,t,c}$ is a vector of the same firm-fiscal year level control variables as previously defined for Equation 1. $gamma_{i,c}$ and $lambda_{t,c}$ denote firm-cohort and year-cohort fixed effects, respectively. For brevity, I leave out of Equation 2 the individual terms $Treated_{i,c}$, $CC_{i,c}$ and $Reltime_{t,c}$, and the interaction of $Treated_{i,c}$ and $CC_{i,c}$ which are all subsumed by the fixed effects included in the equation. Standard errors are clustered at the firm level.

Table 7 reports results from estimating Equation 2 in each of the three regression samples for each of the four dependent variables, asset turnover, operating profitability, SG&A expenses scaled by sales and days inventory. First, highlighting a potential concern, when looking at When looking at Column (1), (4) and (9) we see significant coefficients for the $Treated$ coefficient one year prior to the tariff reduction. Moreover, Column (1) additionally shows a significant coefficient for $Treated \times CC$. This poses the concern that treated firms and their control counterparts do not follow similar trends with respect to asset turnover and days inventory prior to the tariff reduction, thereby violating the parallel trends assumption of the difference-in-difference setting. However, such effects are not evident in any of the remaining columns and, notably, not for any of the dependent variables in the regressions carried out in the customer concentration sample. This leads me to believe that this sample features the most appropriate sample for comparison of treated and control firms.

Focusing on the customer concentration sample, as judged by the coefficient coefficient estimates for $Treated \times Reltime$ and $Treated \times Reltime \times CC$, we see that both the effects of tariff cuts on firm performance and the moderating effects of customer concentration are mainly pronounced in the year of the tariff cuts ($Reltime$ is 0) and/or the following years. Moreover, the effects of customer concentration on asset turnover and profitability generally strengthens over the years following tariff cuts. Arguably, following tariff cuts, it may take some time for major customers to switch to foreign suppliers and for firms to adjust to the new bargaining equilibrium, and therefore for effects to materialize. Overall, I view the results in Table 7 as supportive of using large import tariff cuts as exogenous shocks to competition and the intensity of customer-supplier relationships.

4.3 Cross-sectional heterogeneity tests

In this section, I perform tests that make use of variation in several characteristics of supplier firms and the industries they operate in to provide support for the mechanisms behind the observed relationship between customer concentration and firm performance around tariff reductions. Specifically, I examine whether the effect of customer concentration on firm performance varies with proxies for the ex-ante intensity of competition in firms' industry, customers' cost of switching suppliers, relationship-specific investments, firms overall financial flexibility and firm age. To this end, I estimate the baseline difference-in-difference specification defined by Equation 1 separately for sub-samples of firms constructed based on these dimensions of heterogeneity, allowing me to examine whether they matter for the extent to which customer concentration represents an impediment to firm performance. These tests are reported in Table 8, which presents regressions for the different measures of firm performance in four separate panels, asset turnover in Panel A, operating profitability in Panel B, SG&A expenses in Panel C and days inventory in Panel D.

Industry concentration

As argued by C. Liu et al. (2021), if intensified competition drives the observed relationship between customer concentration and firm performance around tariff reductions, we can expect the impact of import tariff reductions to be stronger for firms that operate in more concentrated industries prior to the shock. The reasoning is that suppliers in more concentrated industries, where competition is arguably less intense, stand to experience a greater shock competition from foreign suppliers following import tariff reductions, relative to suppliers in less concentrated industries, where competition is arguably more intense ex-ante.

I define samples of firms operating in high concentration industries and low concentration industries, based on the sales concentration in firms' four digit SIC industry in the year prior to the tariff reduction and with high and low concentration being defined by above and below median sales concentration, respectively. I then estimate the difference-in-difference specification defined by Equation 1 separately for sub-samples of firms in high and low concentration industries. The results are reported in Column (1) and Column (2) of Table 8. Considering asset turnover in Panel A, operating profitability in Panel B and SG&A expenses in Panel C, the results show that both the main effect of tariff reductions and the moderating effect of customer concentration is only pronounced among firms in high-concentration industries. This supports that the observed relationship between tariff cuts, customer concentration and firm performance is driven by intensified competition from foreign rivals induced by import tariff reductions. However, considering the effects on days inventory in Panel D does not indicate significant differences between the two subsamples.

Customers' switchig costs

An important concern related to having a concentrated customer base is that a major customer may switch to other suppliers, resulting in abrupt reductions in sales for the dependent supplier. Therefore, strong reliance on major customers is especially risky when the customer can switch suppliers at a low cost. As argued above, import tariff reductions in the supplier's industry represents a decrease in customers' costs related to switching to foreign suppliers. This increases the risk that the supplier experiences reduced demand from existing customers and increases major customers' relative bargaining power. Thus, if customers' switching cost is an underlying driver of the negative performance effects I observe, I expect the relationship between customer concentration and firm performance around tariff reductions to be more pronounced when import tariff cuts likely represents a more salient driver of customers' switching costs.

To examine this, I make use of two proxies for customers' switching costs. The first proxy is based on whether the supplier is a producer of durable versus non-durable goods, with producers of durable goods being defined by the firm having SIC industry code 3499-3999. Firms in durable goods industries arguably produce goods that are more customized to the specific needs of their customers, which makes it more costly for customers to switch between suppliers (Banerjee et al., 2008). This implies that, for industries of non-durable, more standardized goods, reductions in import tariffs likely represent a more direct driver of customers' costs of switching to foreign suppliers, implying that the effects of customer concentration following tariff cuts should be more pronounced in these industries. As an alternative proxy for customers switching costs, I follow Chen et al. (2022) and Dhaliwal et al., 2016 and use supplier market share, defined as the fraction of four-digit SIC industry sales accounted for by the individual firm in the year before the tariff reduction. The idea is that, the lower the supplier's market share, the more alternative suppliers that customers could potentially purchase from, and the lower the switching costs. This implies that, we may expect any effects of customer concentration following tariff cuts to be more pronounced for suppliers with higher market shares ex-ante, as a result of tariff reductions representing a more significant decrease in the switching costs for customers of these suppliers.

Column (3) and Column (4) of Table 8 is based on firms in durable goods and non-durable goods industries, respectively. Considering any measure of firm performance, the results show that both the main effect of tariff reductions and the moderating effect of customer concentration is only pronounced among firms in non-durable goods industries. I consider this supportive of the idea that customers' switching costs is a determinant of the effects of customer concentration as suppliers experience intensified competition.

Column (5) and Column (6) of Table 8, include firms with high and low market shares, respectively. Using this proxy for customers' switching costs, results are not as consistent. First, in line with my prediction, considering operating profitability in Panel B, we see that the effect of customer concentration is more pronounced among firms with high market shares, that is, among firms for which import tariff reductions likely represents a larger shock to customers' switching costs. However, when considering both asset turnover in Panel A and SG&A expenses in Panel C, the effects of customer concentration on firm performance around tariff reductions is concentrated among firms with lower ex-ante market shares. This potentially speaks against that the effects are driven by firms for which import tariff reductions represent a larger decrease in customers' switching costs. These results facilitate the interpretation that customer concentration represents more of an impediment to firm performance follow tariff reductions among firms who's customers have lower switching costs ex-ante, or alternatively, among firms with lower ex-ante bargaining power vis-a-vis their customers.

Relationship-specific investments

Relationships with major customers are commonly associated with relationship specific investments. Such investments are risky because they offer little value outside the relationship setting (Banerjee et al., 2008; Titman and Wessels, 1988) and suppliers that have relationship specific assets face greater costs related to re-deploying their assets should an existing customer relationship be terminated. In addition, firms with more relationship-specific assets face the risk of ex-post opportunistic behavior by customers with strong bargaining power. Thus, in the setting of large tariff cuts, which induces a reduction in customers' switching costs, thereby increasing the risk that customers switch suppliers and customers relative bargaining power, I hypothesize that the negative effect of customer concentration on firm performance should be more pronounced for suppliers that have made more customer-specific investments.

Following Chen et al. (2022), Raman and Shahrur (2008) and Kale and Shahrur (2007), I proxy for relationship-specific investments with research and development (R&D) expenses scaled by total assets. The idea behind this proxy is that firms with greater R&D-intensity tend to produce more customized products for their customers and that unique products require more relationship-specific investments. Table 8 Columns (7)–(8), presents regression results for firms with high and low R&D intensity, defined by having above or below median R&D intensity in the year prior to the tariff reduction, respectively. The results support the idea that the effects of customer concentration following tariff reductions is concentrated among firms with more relationship-specific investments, as, considering any dimensions of firm performance, the effects of customer concentration is only pronounced in the High R&D intensity sample.

Financial flexibility

Fresard (2010) shows that financial flexibility is important for firms ability to gain market shares at the expense of their industry rivals and documents a causal impact of cash holdings on product market performance using import tariff cuts as exogenous variation in competition. As argued above, it may be more costly for firms with high customer concentration to redeploy their existing assets to generate new sources of revenue, should they experience reduced demand form existing customers following tariff cuts. If this is the case, I expect firms with greater financial flexibility to be better equipped to mitigate negative effects of customer concentration, e.g. because of having greater investment capacity. To examine this line of reasoning I estimate the regression specification defined by Equation 1 separately for sub-samples of firms with high and low financial flexibility. As proxies for firms' financial flexibility I rely on cash holdings, profitability and book leverage, all measured in the year prior to the import tariff reduction of a given cohort. Firms are defined as having high or low financial flexibility based on having above or below median values on these proxies, respectively.

In Table 8, considering asset turnover (Panel A) and profitability (Panel B) it appears that the negative effects of customer concentration following tariff cuts are only pronounced among firms with low cash holdings, low profitability and low book leverage. This is considered supportive of the idea that customer concentration represents more of an impediment to firm performance for firms with lower financial flexibility. When it comes to SG&A expenses (Panel C), the positive effect of customer concentration is also more pronounced for firms with lower leverage and lower profitability. At the same time, comparing firms with high and low cash holdings reveals that the effect on SG&A expenses is more pronounced for firms with higher cash reserves. This is not necessarily an inconsistent result, as it facilitates the interpretation that firms with higher cash holdings have greater flexibility with regards to increasing expenses. When it comes to the effects of customer concentration on days inventory following tariff cuts in Panel D, the results do not indicate significant differences between subsamples of firms based on the various proxies for financial flexibility.

Firm age

Prior work highlights the importance of relationship specific investments and commitment by major trade partners to create high quality trade relationships (e.g. Banerjee et al., 2008; Johnson et al., 2015; Cen, Dasgupta, and Sen, 2016; Irvine et al., 2016; Harford et al., 2019). Irvine et al. (2016) studies the development of firm performance over the life-cycle of major customer relationships, and argues that value creation from such relationship increase over time. It is argued that the early phases of major customer relationships is associated with significant operating risk for the supplier firm, as establishing and maintaining relationships with major customers requires large fixed investments. However, as the relationship matures, costs related to such investments decline, enabling firms to increasingly realize gains from the operating efficiencies associated with major customer relationships (Patatoukas, 2012). This points to a dynamic nature of major customer relationships, where relationships develop and increase in value over time. Consistent with this view, prior work on the certification effects of trade relationships with major customers (Cen, Dasgupta, Elkamhi, and Pungaliya, 2016), emphasize relationship length as an underlying driver of implicit certification effects. Taken together, this implies that more mature relationships are more costly for trade partners to end and that less mature relationships are less costly for major customers to switch out of. Importantly, to the extent that relationship-specific investments are made at the early stages of the relationship, the supplier is still exposed to the risks associated with such investments. This implies that, if the negative effects associated with customer concentration around tariff reductions are driven by reduced commitment to the relationship by major customers, we should expect suppliers in less mature relationships to be more exposed to the negative effects of import tariff cuts.

To examine this line of reasoning, I proxy for the length of the relationship between a supplier and its major customers using firm age in the year prior to the tariff reduction. Next, I estimate the regression specification defined by Equation 1 separately for sub-samples of old and young firms, in Column (15) and Column (16) of Table 8, respectively, with old and young being defined as above and below the median firm age, respectively. Consistent with my prediction, considering all dimensions of firm performance, the results indicate that the effects of customer concentration following tariff cuts are more pronounced among young firms.

4.4 Concentration of sales to major government customers

Prior studies highlight differences in the implications of major customer relationships, depending on whether the supplier is trading with major corporate customers or major government customers (e.g. Chen et al. (2022); C. Liu et al., 2021; Cohen and Li, 2020 and Banerjee et al., 2008). Government customers differ from corporate customers in several respects. In particular, they likely represent a more stable source of demand for their suppliers, as their high creditworthiness make them less likely to default or go bankrupt and because their purchases are typically governed by longer term contracts and not solely driven by profit motives. Furthermore, government customers are more concerned for the public and may prefer to trade with domestic firms. Thus, compared to major corporate customers, major government customers represent a more stable source of revenues and carry less of the risks commonly associated with major customer relationships. Moreover, this implies that, in general, and following tariff cuts, major government customers, relative to major corporate customers, are less likely to switch to foreign suppliers.

I expect firms with major government customers, relative to firms with major corporate customers, to be less sensitive to import tariff reductions. Any evidence that the observed relationship between customer concentration and firm performance around tariff reductions is less pronounced when considering government customer concentration, would be considered consistent with customers switching costs and bargaining power as underlying channels of the observed relationships between corporate customer concentration and various dimensions of firm performance around tariff cuts.

Table 9 presents the results from estimating the regression defined by Equation 1, now with CC representing firms' concentration of sales to major government customers. Overall, there is little evidence of a relationship between major government customer concentration and firm performance around tariff cuts.

5 Conclusion

In this study, I provide new evidence on the effects of customer concentration by examining its relationship to supplier firms' operating performance as they experience an exogenous shock to their product market competition. Focusing on product market competition as a determinant of this relationship is motivated by its influence on the key risk dimensions associated with having a concentrated customer base.

I utilize large import tariff cuts in suppliers' industries to generate exogenous variation in the intensity of customer-supplier relationships. The idea is that tariff cuts intensify competition in suppliers' industries by making it less costly for customers to purchase from foreign suppliers. This improves the relative bargaining power of customers vis-à-vis their suppliers and leads to a higher likelihood of suppliers losing an existing customer. In addition, in this setting, the high degree of relationship-specific investments and product customization commonly associated with major customer relationships represents a risk for suppliers. Such investments may carry little value outside of the relationship setting and give rise to assets that are customer-specific and costly to re-deploy to alternative uses, in the event of experiencing reduced demand from existing customers.

I find that firms' ex-ante level of customer concentration is negatively related to asset turnover and operating profitability following tariff cuts. These effects persist when controlling for sales growth, facilitating the interpretation that increased customer bargaining power yield less profitable major customer relationships for suppliers. I also find that customer concentration is positively related to proxies for investments related to establishing new customer relationships and the speed at which firms convert their inventories into sales. This is consistent with customer concentration resulting in higher expenses related to establishing new customer relationships and with excess inventories, of specific goods and inputs, being more difficult to convert into sales. Taken together, my findings point to a specific setting where customer concentration represents an impediment to firm performance, namely when competition hits.

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Figure 1: **Firms with sales to major corporate customers**

Figure 1 shows the total number of firms in the CCM firm-year sample defined in Section 3.1 and the fraction of these firms that reported any sales to major corporate customers.

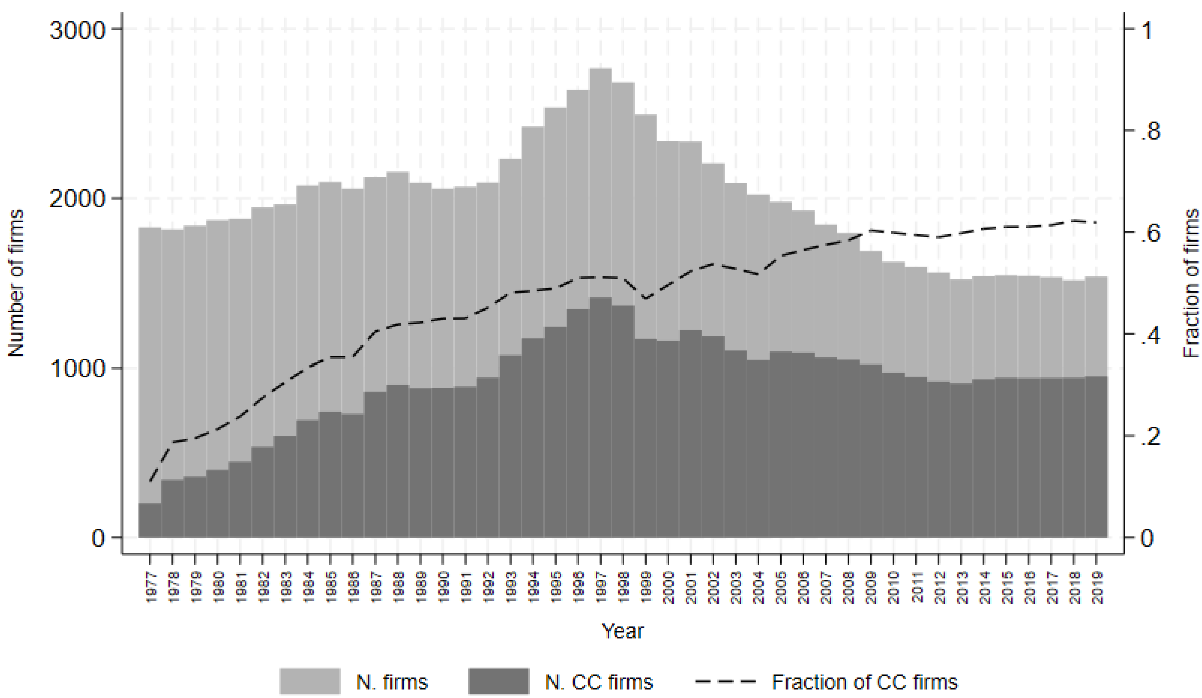

Figure 2: **Development of sales to major corporate customers**

Figure 2 shows the mean and median value of fraction of total sales to major corporate customers for firm-years, in the CCM firm-year sample defined in Section 3.1, with any reported sales to major corporate customers.

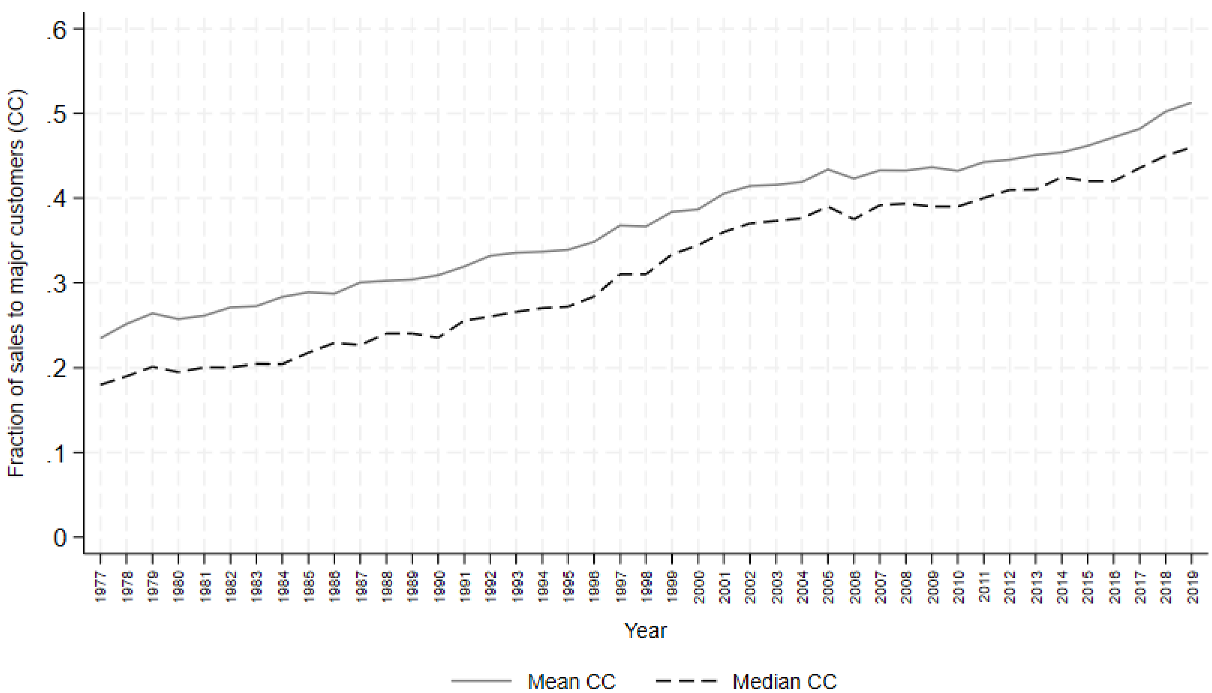

Table 1: Firm characteristics prior to tariff reductions

Table 1 presents descriptive statistics of firms in the year prior to the import tariff cut of their cohort, separately for the full sample (Panel A) and the customer concentration sample (Panel B) defined in Section 3.2. $Sales$ refers to total sales, while $Assets$ refers to book value of total assets. $Asset\ turnover$ is sales scaled by assets, $Profitability$ is operating income before depreciation scaled by assets, $SG\&A/Sales$ is selling, general and administrative (SG&A) expenses scaled by sales, $Days\ inventory$ is the ratio of total inventories multiplied by 365 to costs of goods sold, $Sales\ growth$ is one year sales growth, $Book\ leverage$ is book leverage scaled by total assets, $Market\ to\ book\ ratio$ is market value of assets scaled by book value of assets, $Cash/Assets$ is cash holdings scaled by assets, $R\&D/Assets$ is research and development (R&D) expenses scaled by assets, $Sales\ based\ industry\ concentration$ is the Herfindahl–Hirschman Index (HHI) of firm-level sales in firms' primary four-digit SIC industry, $Market\ share$ is the fraction of sales in firms' primary four-digit SIC industry accounted for by the firm, $Any\ major\ corporate\ customer$ $(1/0)$ is an indicator taking value one for firms with any reported sales to major corporate customers over the two years prior to the tariff reduction of firms' cohort and $Max\ share\ of\ sales\ to\ corporate\ customers$ is the maximum reported fraction of sales to major corporate customers over the same two-year period. $Any\ major\ government\ customer$ $(1/0)$ and $Max\ share\ of\ sales\ to\ government\ customers$ are quivalent measures based on sales to major government customers.

	All Firms						Control Firms			Treated Firms				T-test		
	N	Mean	SD	p25	p50	p75	N	Mean	p50	N	Mean	p50	Difference	SE	t	p
Panel A: Full sample																
Sales	33,620	978.10	2783.00	26.18	111.20	507.60	32,881	977.20	111.90	739	1,016.00	75.28	-38.75	103.53	-0.37	0.71
Assets	33,620	976.60	3057.00	24.29	88.62	412.10	32,881	976.60	89.27	739	976.60	60.39	0.02	113.73	0.00	1.00
Firm age	33,620	15.90	11.91	6.00	12.00	24.00	32,881	15.91	12.00	739	15.33	13.00	0.58	0.44	1.32	0.19
Asset turnover	33,620	1.26	0.60	0.87	1.23	1.61	32,881	1.26	1.23	739	1.29	1.22	-0.02	0.02	-1.08	0.28
Profitability	33,620	0.10	0.18	0.06	0.13	0.19	32,881	0.10	0.13	739	0.09	0.13	0.01	0.01	1.72	0.09
SG&A/Sales	33,620	0.27	0.28	0.13	0.21	0.33	32,881	0.27	0.21	739	0.31	0.24	-0.04	0.01	-3.69	0.00
Days inventory	33,620	109.50	81.13	56.73	91.89	141.90	32,881	109.30	91.61	739	120.40	104.20	-11.13	3.02	-3.69	0.00
Sales growth	33,620	0.17	0.42	-0.01	0.10	0.24	32,881	0.17	0.10	739	0.18	0.12	0.00	0.02	-0.27	0.79
Book leverage	33,620	0.22	0.18	0.07	0.20	0.33	32,881	0.22	0.20	739	0.21	0.19	0.01	0.01	1.47	0.14
Market to book ratio	33,620	1.55	1.53	0.72	1.03	1.68	32,881	1.55	1.03	739	1.55	1.05	-0.01	0.06	-0.09	0.93
Cash/Assets	33,620	0.15	0.18	0.02	0.07	0.20	32,881	0.15	0.07	739	0.14	0.07	0.01	0.01	0.82	0.41
R&D expenses/Assets	33,620	0.05	0.09	0.00	0.02	0.06	32,881	0.05	0.02	739	0.06	0.03	-0.01	0.00	-2.86	0.00
Sales based industry concentration	33,620	0.27	0.18	0.14	0.22	0.34	32,881	0.27	0.22	739	0.29	0.26	-0.02	0.01	-3.23	0.00
Market share	33,620	0.09	0.16	0.00	0.02	0.09	32,881	0.09	0.02	739	0.07	0.01	0.02	0.01	2.93	0.00
Any major corporate customer (1/0)	33,620	0.45	0.50	0.00	0.00	1.00	32,881	0.45	0.00	739	0.41	0.00	0.04	0.02	2.12	0.03
Max share of sales to corporate customers	33,620	0.16	0.25	0.00	0.00	0.25	32,881	0.16	0.00	739	0.15	0.00	0.01	0.01	1.42	0.16
Any major government customer (1/0)	33,620	0.14	0.35	0.00	0.00	0.00	32,881	0.14	0.00	739	0.17	0.00	-0.03	0.01	-2.26	0.02
Max share of sales to government customers	33,620	0.04	0.15	0.00	0.00	0.00	32,881	0.04	0.00	739	0.04	0.00	0.00	0.01	0.65	0.52
Panel B: Customer concentration sample																
Sales	14,336	457.30	1259.00	18.41	69.04	262.80	14,044	460.00	69.81	292	324.60	36.55	135.42	74.44	1.82	0.07
Assets	14,336	446.50	1329.00	18.94	59.77	227.60	14,044	449.30	60.68	292	311.10	37.77	138.24	78.56	1.76	0.08
Firm age	14,336	13.70	11.32	5.00	10.00	19.00	14,044	13.73	10.00	292	12.53	9.00	1.20	0.67	1.79	0.07
Asset turnover	14,336	1.22	0.61	0.80	1.20	1.60	14,044	1.22	1.20	292	1.20	1.19	0.03	0.04	0.77	0.44
Profitability	14,336	0.07	0.20	0.04	0.12	0.18	14,044	0.07	0.12	292	0.06	0.10	0.02	0.01	1.31	0.19
SG&A/Sales	14,336	0.29	0.34	0.12	0.21	0.34	14,044	0.29	0.21	292	0.33	0.25	-0.04	0.02	-2.03	0.04
Days inventory	14,336	109.70	84.81	54.75	90.77	142.30	14,044	109.20	90.43	292	131.50	111.00	-22.24	5.01	-4.44	0.00
Sales growth	14,336	0.20	0.49	-0.02	0.10	0.29	14,044	0.20	0.10	292	0.16	0.11	0.04	0.03	1.38	0.17
Book leverage	14,336	0.21	0.19	0.04	0.18	0.33	14,044	0.21	0.18	292	0.20	0.18	0.01	0.01	1.26	0.21
Market to book ratio	14,336	1.77	1.80	0.77	1.13	1.94	14,044	1.76	1.12	292	1.87	1.33	-0.11	0.11	-1.00	0.32
Cash/Assets	14,336	0.18	0.21	0.02	0.09	0.26	14,044	0.18	0.09	292	0.18	0.09	0.00	0.01	-0.38	0.71
R&D expenses/Assets	14,336	0.06	0.10	0.00	0.02	0.08	14,044	0.06	0.02	292	0.08	0.05	-0.01	0.01	-2.20	0.03
Sales based industry concentration	14,336	0.26	0.18	0.14	0.20	0.33	14,044	0.26	0.20	292	0.31	0.29	-0.06	0.01	-5.58	0.00
Market share	14,336	0.06	0.13	0.00	0.01	0.04	14,044	0.06	0.01	292	0.04	0.00	0.01	0.01	1.73	0.08
Any major corporate customer (1/0)	14,336	1.00	0.00	1.00	1.00	1.00	14,044	1.00	1.00	292	1.00	1.00	0.00	0.00	.	.
Max share of sales to corporate customers	14,336	0.37	0.26	0.16	0.31	0.53	14,044	0.37	0.31	292	0.37	0.32	0.00	0.02	0.21	0.83
Any major government customer (1/0)	14,336	0.15	0.36	0.00	0.00	0.00	14,044	0.15	0.00	292	0.21	0.00	-0.07	0.02	-3.12	0.00
Max share of sales to government customers	14,336	0.05	0.16	0.00	0.00	0.00	14,044	0.05	0.00	292	0.06	0.00	-0.02	0.01	-1.94	0.05

Table 2: Matched sample firm characteristics prior to tariff reductions

Table 2 presents descriptive statistics of firms in the year prior to the import tariff cut of their cohort, for the matched sample defined in Section 3.2. $Sales$ refers to total sales, while $Assets$ refers to book value of total assets. $Asset\ turnover$ is sales scaled by assets, $Profitability$ is operating income before depreciation scaled by assets, $SG\&A/Sales$ is selling, general and administrative (SG&A) expenses scaled by sales, $Days\ inventory$ is the ratio of total inventories multiplied by 365 to costs of goods sold, $Sales\ growth$ is one year sales growth, $Book\ leverage$ is book leverage scaled by total assets, $Market\ to\ book\ ratio$ is market value of assets scaled by book value of assets, $Cash/Assets$ is cash holdings scaled by assets, $R\&D/Assets$ is research and development (R&D) expenses scaled by assets, $Sales\ based\ industry\ concentration$ is the Herfindahl–Hirschman Index (HHI) of firm-level sales in firms' primary four-digit SIC industry, $Market\ share$ is the fraction of sales in firms' primary four-digit SIC industry accounted for by the firm, $Any\ major\ corporate\ customer$ $(1/0)$ is an indicator taking value one for firms with any reported sales to major corporate customers over the two years prior to the tariff reduction of firms' cohort and $Max\ share\ of\ sales\ to\ corporate\ customers$ is the maximum reported fraction of sales to major corporate customers over the same two-year period. $Any\ major\ government\ customer$ $(1/0)$ and $Max\ share\ of\ sales\ to\ government\ customers$ are quivalent measures based on sales to major government customers.

	All Firms						Control Firms			Treated Firms				T-test		
	N	Mean	SD	p25	p50	p75	N	Mean	p50	N	Mean	p50	Difference	SE	t	p
Sales	1,748	270.20	938.00	11.19	34.43	126.10	1,456	259.30	34.26	292	324.60	36.55	-65.25	60.14	-1.08	0.28
Assets	1,748	263.90	1026.00	11.83	32.12	101.80	1,456	254.40	31.66	292	311.10	37.77	-56.65	65.76	-0.86	0.39
Firm age	1,748	12.89	10.42	5.00	9.00	19.00	1,456	12.96	9.00	292	12.53	9.00	0.43	0.67	0.65	0.52
Asset turnover	1,748	1.22	0.58	0.83	1.21	1.55	1,456	1.22	1.22	292	1.20	1.19	0.02	0.04	0.60	0.55
Profitability	1,748	0.07	0.21	0.02	0.12	0.19	1,456	0.07	0.12	292	0.06	0.10	0.01	0.01	0.59	0.55
SG&A/Sales	1,748	0.31	0.34	0.14	0.23	0.37	1,456	0.31	0.23	292	0.33	0.25	-0.02	0.02	-1.10	0.27
Days inventory	1,748	121.30	94.68	59.46	99.69	159.20	1,456	119.30	97.50	292	131.50	111.00	-12.15	6.07	-2.00	0.05
Sales growth	1,748	0.18	0.46	-0.03	0.10	0.29	1,456	0.19	0.10	292	0.16	0.11	0.02	0.03	0.77	0.44
Book leverage	1,748	0.19	0.18	0.03	0.15	0.30	1,456	0.19	0.15	292	0.20	0.18	-0.01	0.01	-0.95	0.34
Market to book ratio	1,748	1.95	1.99	0.80	1.23	2.24	1,456	1.97	1.22	292	1.87	1.33	0.10	0.13	0.77	0.44
Cash/Assets	1,748	0.18	0.21	0.02	0.09	0.27	1,456	0.18	0.10	292	0.18	0.09	0.00	0.01	0.08	0.93
R&D expenses/Assets	1,748	0.08	0.11	0.00	0.03	0.10	1,456	0.08	0.03	292	0.08	0.05	0.00	0.01	-0.01	0.99
Sales based industry concentration	1,748	0.31	0.19	0.15	0.27	0.42	1,456	0.31	0.26	292	0.31	0.29	-0.01	0.01	-0.48	0.63
Market share	1,748	0.05	0.13	0.00	0.00	0.03	1,456	0.05	0.01	292	0.04	0.00	0.01	0.01	0.99	0.32
Any major corporate customer (1/0)	1,748	1.00	0.00	1.00	1.00	1.00	1,456	1.00	1.00	292	1.00	1.00	0.00	0.00	.	.
Max share of sales to corporate customers	1,748	0.37	0.25	0.15	0.32	0.53	1,456	0.37	0.32	292	0.37	0.32	0.00	0.02	0.17	0.86
Any major government customer (1/0)	1,748	0.18	0.38	0.00	0.00	0.00	1,456	0.17	0.00	292	0.21	0.00	-0.04	0.02	-1.59	0.11
Max share of sales to government customers	1,748	0.05	0.17	0.00	0.00	0.00	1,456	0.05	0.00	292	0.06	0.00	-0.01	0.01	-1.06	0.29

Table 3: Customer concentration and asset turnover

Table 3 reports stacked difference-in-difference estimate from estimating the regression model defined by Equation 1. Regressions are carried out in the three different samples defined in Section 3.2. Columns (1)–(4) reports results based on the $full\ sample$, while Columns (5)–(6) are based on the $customer\ concentration\ sample$ and Columns (7)–(8) are based on the $Matched\ sample$. The dependent variable is $Asset\ turnover\ (AT)$, measured as total revenues scaled by total assets. $Post\ cut$ is an indicator variable that takes value one if the firm's industry has experienced a tariff cut and zero otherwise. $Major\ customer\ (1/0)$ is an indicator variable taking value one for firms who reported any major customer over the two year period prior to the tariff reduction of the firm's cohort and zero otherwise. CC is the firm's maximum level of customer concentration over the two year period prior to the tariff reduction of the firm's cohort. $Ln\ (Firm\ age)$ is the natural logarithm of firm age, $Ln\ (Assets)$ is the natural logarithm of total assets, $Sales\ growth$ is one year sales growth, $Book\ leverage$ is book leverage scaled by total assets and $Market\ to\ book\ ratio$ is market value of assets scaled by book value of assets. Standard errors are clustered at the firm level and reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Full sample				CC sample		Matched sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post cut	0.043***	0.043***	0.051***	0.049***	0.084***	0.075***	0.100***	0.091***
	(0.013)	(0.012)	(0.011)	(0.011)	(0.028)	(0.028)	(0.030)	(0.030)
Post cut x Major customer (1/0)	-0.025	-0.035*						
	(0.021)	(0.021)						
Post cut x CC			-0.125**	-0.138***	-0.182**	-0.184**	-0.187***	-0.189***
			(0.049)	(0.048)	(0.073)	(0.072)	(0.071)	(0.071)
Ln (Firm age)	0.212***	0.281***	0.212***	0.281***	0.242***	0.323***	0.371***	0.493***
	(0.015)	(0.016)	(0.015)	(0.016)	(0.022)	(0.023)	(0.054)	(0.056)
Ln (Assets)	-0.261***	-0.288***	-0.261***	-0.288***	-0.272***	-0.299***	-0.285***	-0.327***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.010)	(0.022)	(0.022)
Sales growth		0.146***		0.146***		0.137***		0.156***
		(0.005)		(0.005)		(0.006)		(0.014)
Book leverage		-0.217***		-0.217***		-0.193***		-0.183***
		(0.021)		(0.021)		(0.029)		(0.063)
Market to book ratio		0.002		0.002		0.003		0.001
		(0.002)		(0.002)		(0.003)		(0.005)
Observations	161,101	161,101	161,101	161,101	68,798	68,798	8,380	8,380
Adjusted R-squared	87.1 %	88.0 %	87.1 %	88.0 %	86.1 %	87.0 %	84.6 %	85.9 %
Firm*Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year*Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Customer concentration and operating profitability

Table 4 reports stacked difference-in-difference estimate from estimating the regression model defined by Equation 1. Regressions are carried out in the three different samples defined in Section 3.2. Columns (1)–(4) reports results based on the $full\ sample$, while Columns (5)–(6) are based on the $customer\ concentration\ sample$ and Columns (7)–(8) are based on the $Matched\ sample$. The dependent variable is $Profitability$, measured as operating income before depreciation scaled by total assets. $Post\ cut$ is an indicator variable that takes value one if the firm's industry has experienced a tariff cut and zero otherwise. $Major\ customer$ $(1/0)$ is an indicator variable taking value one for firms who reported any major customer over the two year period prior to the tariff reduction of the firm's cohort and zero otherwise. CC is the firm's maximum level of customer concentration over the two year period prior to the tariff reduction of the firm's cohort. Ln $(Firm\ age)$ is the natural logarithm of firm age, Ln $(Assets)$ is the natural logarithm of total assets, $Sales\ growth$ is one year sales growth, $Book\ leverage$ is book leverage scaled by total assets and $Market\ to\ book\ ratio$ is market value of assets scaled by book value of assets. Standard errors are clustered at the firm level and reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Full sample				CC sample		Matched sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post cut	0.011**	0.011**	0.015***	0.014***	0.036***	0.027**	0.041***	0.030**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.013)	(0.013)	(0.014)	(0.013)
Post cut x Major customer (1/0)	-0.003	-0.010						
	(0.009)	(0.009)						
Post cut x CC			-0.041*	-0.051**	-0.073**	-0.070**	-0.078**	-0.071**
			(0.023)	(0.022)	(0.035)	(0.035)	(0.035)	(0.035)
Ln (Firm age)	-0.025***	0.012*	-0.025***	0.012*	-0.027***	0.023**	-0.020	0.053**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.010)	(0.009)	(0.028)	(0.025)
Ln (Assets)	0.062***	0.058***	0.062***	0.058***	0.081***	0.072***	0.097***	0.078***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)	(0.011)	(0.011)
Sales growth		0.062***		0.062***		0.071***		0.081***
		(0.002)		(0.002)		(0.003)		(0.007)
Book leverage		-0.234***		-0.234***		-0.252***		-0.281***
		(0.008)		(0.008)		(0.012)		(0.029)
Market to book ratio		0.008***		0.008***		0.007***		0.003
		(0.001)		(0.001)		(0.001)		(0.003)
Observations	161,101	161,101	161,101	161,101	68,798	68,798	8,380	8,380
Adjusted R-squared	73.7 %	77.0 %	73.7 %	77.0 %	71.2 %	75.2 %	69.8 %	74.1 %
Firm*Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year*Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Customer concentration and SG&A expenses

Table 5 reports stacked difference-in-difference estimate from estimating the regression model defined by Equation 1. Regressions are carried out in the three different samples defined in Section 3.2. Columns (1)–(4) reports results based on the $full\ sample$, while Columns (5)–(6) are based on the $customer\ concentration\ sample$ and Columns (7)–(8) are based on the $Matched\ sample$. The dependent variable is $SG\&A/Sales$ (SGA), measured as selling, general and administrative expenses scaled by total revenues. $Post\ cut$ is an indicator variable that takes value one if the firm's industry has experienced a tariff cut and zero otherwise. $Major\ customer$ $(1/0)$ is an indicator variable taking value one for firms who reported any major customer over the two year period prior to the tariff reduction of the firm's cohort and zero otherwise. CC is the firm's maximum level of customer concentration over the two year period prior to the tariff reduction of the firm's cohort. Ln $(Firm\ age)$ is the natural logarithm of firm age, Ln $(Assets)$ is the natural logarithm of total assets, $Sales\ growth$ is one year sales growth, $Book\ leverage$ is book leverage scaled by total assets and $Market\ to\ book\ ratio$ is market value of assets scaled by book value of assets. Standard errors are clustered at the firm level and reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Full sample				CC sample		Matched sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post cut	-0.006	-0.006	-0.017**	-0.017**	-0.071***	-0.068***	-0.076***	-0.070***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.022)	(0.022)	(0.022)	(0.021)
Post cut x Major customer (1/0)	0.001	0.004						
	(0.013)	(0.013)						
Post cut x CC			0.080**	0.085**	0.183***	0.186***	0.166**	0.162**
			(0.038)	(0.038)	(0.070)	(0.070)	(0.065)	(0.064)
Ln (Firm age)	-0.012	-0.035***	-0.012	-0.035***	-0.023	-0.062***	0.035	-0.026
	(0.012)	(0.012)	(0.012)	(0.012)	(0.017)	(0.017)	(0.053)	(0.053)
Ln (Assets)	-0.042***	-0.033***	-0.042***	-0.033***	-0.054***	-0.039***	-0.059***	-0.036*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.019)	(0.019)
Sales growth		-0.047***		-0.047***		-0.068***		-0.081***
		(0.005)		(0.005)		(0.006)		(0.015)
Book leverage		0.054***		0.054***		0.044**		0.117**
		(0.013)		(0.013)		(0.022)		(0.047)
Market to book ratio		-0.003		-0.003		-0.002		0.005
		(0.002)		(0.002)		(0.002)		(0.006)
Observations	161,101	161,101	161,101	161,101	68,798	68,798	8,380	8,380
Adjusted R-squared	74.7 %	75.1 %	74.7 %	75.1 %	71.8 %	72.5 %	72.2 %	73.1 %
Firm*Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year*Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Customer concentration and days inventory

Table 6 reports stacked difference-in-difference estimate from estimating the regression model defined by Equation 1. Regressions are carried out in the three different samples defined in Section 3.2. Columns (1)–(4) reports results based on the $full\ sample$, while Columns (5)–(6) are based on the $customer\ concentration\ sample$ and Columns (7)–(8) are based on the $Matched\ sample$. The dependent variable is $Days\ inventory\ (DINV)$, measured as the ratio of total inventories to cost of goods sold multiplied by 365. $Post\ cut$ is an indicator variable that takes value one if the firm's industry has experienced a tariff cut and zero otherwise. $Major\ customer\ (1/0)$ is an indicator variable taking value one for firms who reported any major customer over the two year period prior to the tariff reduction of the firm's cohort and zero otherwise. CC is the firm's maximum level of customer concentration over the two year period prior to the tariff reduction of the firm's cohort. $Ln\ (Firm\ age)$ is the natural logarithm of firm age, $Ln\ (Assets)$ is the natural logarithm of total assets, $Sales\ growth$ is one year sales growth, $Book\ leverage$ is book leverage scaled by total assets and $Market\ to\ book\ ratio$ is market value of assets scaled by book value of assets. Standard errors are clustered at the firm level and reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Full sample				CC sample		Matched sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post cut	-1.373	-1.388	-4.393**	-4.279**	-18.043***	-17.438***	-16.873**	-15.153**
	(2.068)	(2.073)	(2.017)	(2.016)	(6.234)	(6.211)	(6.578)	(6.560)
Post cut x Major customer (1/0)	2.774	3.394						
	(3.843)	(3.835)						
Post cut x CC			28.480***	29.335***	54.137***	54.085***	51.579***	49.902***
			(10.100)	(10.043)	(16.788)	(16.709)	(16.478)	(16.218)
Ln (Firm age)	-8.200***	-11.813***	-8.312***	-11.927***	-10.501***	-14.801***	-5.418	-15.021*
	(2.339)	(2.383)	(2.338)	(2.382)	(3.212)	(3.260)	(8.316)	(8.700)
Ln (Assets)	18.056***	18.893***	18.057***	18.892***	16.901***	18.141***	15.944***	19.143***
	(1.171)	(1.174)	(1.170)	(1.174)	(1.513)	(1.508)	(4.086)	(4.025)
Sales growth		-6.716***		-6.718***		-6.939***		-11.731***
		(0.934)		(0.933)		(1.186)		(2.588)
Book leverage		18.744***		18.751***		14.355***		36.991***
		(3.214)		(3.213)		(4.710)		(12.942)
Market to book ratio		-0.468		-0.472		-0.273		0.877
		(0.389)		(0.389)		(0.475)		(1.065)
Observations	161,101	161,101	161,101	161,101	68,798	68,798	8,380	8,380
Adjusted R-squared	79.4 %	79.6 %	79.4 %	79.6 %	76.8 %	77.0 %	76.1 %	76.5 %
Firm*Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year*Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Timing of effects around tariff reductions

Table 7 reports stacked difference-in-difference estimate from estimating the regression model defined by Equation 2. Regressions are carried out in the three different samples defined in Section 3.2. Columns (1)–(3) reports results based on the $full\ sample$, while Columns (4)–(6) are based on the $customer\ concentration\ sample$ and Columns (7)–(9) are based on the $Matched\ sample$. The dependent variable is $Asset\ turnver\ (AT)$ in Column (1), (5) and (9), $Profitability$ in Column (2), (6) and (10), $SG\&A/Sales\ (SGA)$ in Column (3), (7) and (11) and $Days\ inventory\ (DINV)$ in Column (4), (8) and (12). $Treated$ is an indicator variable that takes value one for the treated firms in the cohort and zero otherwise. $Reltime$ is a categorical variable taking separate values for each year of the cohort, indicating the number of year relative to the import tariff reduction of the cohort. CC is the firm's maximum level of customer concentration over the two year period prior to the tariff reduction of the firm's cohort. The full set of control variables used in Table 3 is included in all Columns. Standard errors are clustered at the firm level and reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Full sample				CC sample				Matched sample			
Dependent variable:	AT	Profitability	SGA	DINV	AT	Profitability	SGA	DINV	AT	Profitability	SGA	DINV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated x Reltime (-1)	0.033***	-0.001	-0.006	-4.187**	0.038	-0.002	-0.031	-2.435	0.064**	0.005	-0.041	-5.948
	(0.011)	(0.004)	(0.007)	(2.037)	(0.030)	(0.013)	(0.031)	(6.137)	(0.032)	(0.014)	(0.033)	(6.473)
Treated x Reltime (0)	0.050***	0.004	-0.010	-6.005**	0.092**	0.018	-0.083**	-16.161*	0.115***	0.022	-0.082**	-15.663*
	(0.013)	(0.005)	(0.010)	(2.741)	(0.037)	(0.016)	(0.035)	(8.952)	(0.039)	(0.018)	(0.037)	(9.235)
Treated x Reltime (1)	0.074***	0.016***	-0.023***	-5.115*	0.124***	0.031*	-0.085***	-19.634**	0.161***	0.042**	-0.081**	-16.488*
	(0.015)	(0.005)	(0.009)	(2.698)	(0.042)	(0.017)	(0.033)	(8.844)	(0.046)	(0.020)	(0.035)	(9.308)
Treated x Reltime (2)	0.087***	0.020***	-0.025**	-7.563**	0.110**	0.028	-0.078**	-13.856	0.133***	0.034	-0.075*	-15.356*
	(0.017)	(0.007)	(0.011)	(3.055)	(0.045)	(0.018)	(0.038)	(8.449)	(0.050)	(0.021)	(0.039)	(9.263)
Treated x Reltime (-1) x CC	-0.119**	-0.011	0.048	17.446	-0.130	-0.007	0.095	12.881	-0.149	-0.034	0.111	14.509
	(0.061)	(0.020)	(0.051)	(12.101)	(0.093)	(0.030)	(0.102)	(19.095)	(0.092)	(0.036)	(0.109)	(19.333)
Treated x Reltime (0) x CC	-0.153**	-0.034	0.101*	37.005**	-0.231**	-0.057	0.241**	55.987**	-0.239**	-0.071	0.205*	51.746*
	(0.074)	(0.030)	(0.058)	(16.492)	(0.111)	(0.047)	(0.111)	(27.473)	(0.112)	(0.052)	(0.118)	(27.759)
Treated x Reltime (1) x CC	-0.230***	-0.030	0.102*	37.981**	-0.321***	-0.054	0.221**	64.332**	-0.348***	-0.086	0.160	55.018**
	(0.081)	(0.031)	(0.059)	(16.367)	(0.121)	(0.047)	(0.105)	(26.465)	(0.124)	(0.054)	(0.110)	(26.223)
Treated x Reltime (2) x CC	-0.283***	-0.093***	0.129**	33.401**	-0.326***	-0.108**	0.226*	43.782**	-0.309**	-0.111**	0.195	45.223*
	(0.078)	(0.033)	(0.065)	(13.974)	(0.115)	(0.049)	(0.125)	(22.066)	(0.124)	(0.056)	(0.127)	(23.733)
Observations	161,101	161,101	161,101	161,101	68,798	68,798	68,798	68,798	8,380	8,380	8,380	8,380
Adjusted R-squared	88.0 %	77.0 %	75.1 %	79.6 %	87.0 %	75.2 %	72.5 %	77.0 %	85.9 %	74.1 %	73.1 %	76.5 %
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year*Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Exploring cross-sectional heterogeneity

Table 8 reports OLS estimates from the regression model defined by Equation 1. The underlying sample is the customer concentration sample, as defined in Section 3.2, but regressions are carried out in sub samples of firms based on various industry and firm level characteristics. The dependent variable is $Asset\ turnover$ in Panel A, $Profitability$ in Panel B and $SGA/Sales$ in Panel C and $Days\ inventory$ in Panel D. Columns (1)–(2) are based on firms in SIC4 industries with high and low concentration of firm level sales in the year prior to the tariff reduction, respectively. Columns (3)–(4) are based on firms in durable goods versus non-durable goods industries, respectively. Columns (5)–(6) are based on firms with high and low market share in the year prior to the tariff reduction, respectively, with market share being defined as the fraction of total SIC4 industry sales accounted for by a firm. Columns (7)–(8) are based on firms with high and low R&D intensity in the year prior to the tariff reduction, respectively, with R&D intensity being defined as R&D expenses scaled by total assets. Columns (9)–(10) are based on firms with high and low cash holdings in the year prior to the tariff reduction, respectively, with cash holdings defined as cash scaled by total assets. Columns (11)–(12) are based on firms with high and low profitability in the year prior to the tariff reduction, respectively, with profitability defined as operating income before depreciation scaled by total assets. Columns (13)–(14) are based on firms with high and low book leverage in the year prior to the tariff reduction, respectively, with book leverage defined as total debt scaled by total assets. Columns (15)–(16) are based on old and young firms, respectively, with firm age being measured in the year prior to the tariff reduction. High (Old) and Low (Young) refers to above and below the median value in the distribution of all firms in the year prior to the tariff reduction, respectively. The full set of control variables used in Table 3, Firm*Cohort and Year*Cohort fixed effects are included in all regressions. Standard errors are clustered at the firm level and reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Industry concentration		Industry type		Market share		R&D intensity		Cash holdings		Profitability		Book Leverage		Firm age	
	High	Low	DG	Non-DG	High	Low	High	Low	High	Low	High	Low	High	Low	Old	Young
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: Dependent variable is Asset turnover																
Post cut	0.078**	0.069	0.034	0.137**	0.069**	0.085**	0.097***	-0.007	0.057	0.101***	0.060*	0.081*	0.111**	0.048	0.067**	0.086*
	(0.035)	(0.044)	(0.032)	(0.053)	(0.032)	(0.042)	(0.034)	(0.044)	(0.042)	(0.036)	(0.033)	(0.042)	(0.053)	(0.035)	(0.031)	(0.046)
Post cut x CC	-0.208**	-0.033	-0.051	-0.400***	-0.145	-0.215**	-0.267***	0.119	-0.149	-0.279***	-0.107	-0.230**	-0.245	-0.149**	-0.154*	-0.214**
	(0.083)	(0.150)	(0.077)	(0.144)	(0.103)	(0.096)	(0.082)	(0.137)	(0.098)	(0.101)	(0.085)	(0.103)	(0.170)	(0.072)	(0.090)	(0.105)
Observations	28,467	16,717	27,887	16,558	33,536	24,984	28,300	30,216	30,207	30,651	31,348	33,551	32,016	34,386	29,676	33,722
Adjusted R-squared	85.6 %	88.4 %	82.1 %	90.4 %	88.6 %	85.3 %	85.6 %	87.1 %	86.6 %	85.8 %	88.4 %	85.7 %	86.5 %	87.3 %	88.5 %	85.6 %
Panel B: Dependent variable is Profitability																
Post cut	0.034**	-0.001	0.010	0.056***	0.020	0.043**	0.043**	-0.001	0.031	0.026*	0.007	0.047**	0.003	0.034**	0.006	0.046**
	(0.016)	(0.018)	(0.015)	(0.020)	(0.012)	(0.020)	(0.017)	(0.013)	(0.021)	(0.014)	(0.011)	(0.020)	(0.024)	(0.016)	(0.011)	(0.022)
Post cut x CC	-0.095**	0.034	0.012	-0.203***	-0.103**	-0.083*	-0.092**	-0.002	-0.074	-0.074**	-0.019	-0.122**	0.030	-0.108***	-0.011	-0.111**
	(0.040)	(0.060)	(0.040)	(0.057)	(0.046)	(0.047)	(0.041)	(0.045)	(0.050)	(0.037)	(0.029)	(0.052)	(0.079)	(0.035)	(0.033)	(0.052)
Observations	28,467	16,717	27,887	16,558	33,536	24,984	28,300	30,216	30,207	30,651	31,348	33,551	32,016	34,386	29,676	33,722
Adjusted R-squared	75.7 %	77.3 %	70.0 %	80.6 %	66.9 %	75.3 %	75.4 %	65.9 %	76.7 %	68.5 %	56.9 %	73.0 %	71.7 %	77.6 %	74.6 %	74.2 %
Panel C: Dependent variable is SG&A/Sales																
Post cut	-0.082***	-0.014	-0.037*	-0.114***	-0.036	-0.102***	-0.098***	0.009	-0.105***	-0.020	-0.008	-0.120***	-0.074**	-0.058**	-0.018	-0.099***
	(0.027)	(0.019)	(0.020)	(0.041)	(0.027)	(0.034)	(0.029)	(0.007)	(0.035)	(0.016)	(0.008)	(0.039)	(0.036)	(0.026)	(0.011)	(0.038)
Post cut x CC	0.218***	0.029	0.024	0.482***	0.175	0.226**	0.241***	0.000	0.279***	0.038	0.035	0.304***	0.165	0.190**	0.002	0.298***
	(0.081)	(0.031)	(0.042)	(0.166)	(0.131)	(0.089)	(0.086)	(0.024)	(0.105)	(0.029)	(0.023)	(0.112)	(0.103)	(0.091)	(0.024)	(0.109)
Observations	28,467	16,717	27,887	16,558	33,536	24,984	28,300	30,216	30,207	30,651	31,348	33,551	32,016	34,386	29,676	33,722
Adjusted R-squared	77.2 %	70.8 %	76.1 %	68.9 %	80.9 %	69.4 %	69.6 %	75.5 %	70.6 %	75.8 %	80.7 %	70.2 %	71.2 %	72.1 %	73.6 %	70.2 %
Panel D: Dependent variable is Days inventory																
Post cut	-18.285**	-16.963**	-8.331	-32.719***	-16.893*	-19.062**	-22.299***	-0.217	-23.530**	-10.692	-11.811*	-21.464**	-22.292**	-13.380*	-15.097**	-16.799*
	(7.801)	(7.620)	(6.728)	(12.389)	(8.831)	(8.961)	(8.202)	(5.198)	(9.989)	(6.686)	(6.920)	(9.842)	(9.750)	(7.936)	(7.037)	(9.717)
Post cut x CC	53.530***	60.240***	25.969	105.409***	63.628**	51.820**	65.910***	1.727	62.601**	41.283**	36.251**	66.103***	65.093**	46.154**	33.779*	63.163***
	(19.643)	(20.172)	(18.368)	(29.398)	(30.732)	(20.864)	(20.184)	(13.044)	(24.449)	(16.860)	(18.347)	(24.488)	(25.740)	(21.229)	(17.374)	(24.370)
Observations	28,467	16,717	27,887	16,558	33,536	24,984	28,300	30,216	30,207	30,651	31,348	33,551	32,016	34,386	29,676	33,722
Adjusted R-squared	78.4 %	74.5 %	75.2 %	77.8 %	84.6 %	71.9 %	72.6 %	83.3 %	73.8 %	82.3 %	83.9 %	72.7 %	78.7 %	75.4 %	81.3 %	73.2 %

Table 9: Government customer concentration and firm performance

Table 9 reports stacked difference-in-difference estimate from estimating the regression model defined by Equation 1. Regressions are carried out in two different samples. Columns (1)–(8) reports results based on the $full\ \ sample$ defined defined in Section 3.2, while Columns (9)–(16) are based on the $Government\ customer\ concentration\ sample$ defined in Section 4.4. The dependent variable is $Asset\ turnover\ (AT)$ in Columns (1)–(2) and (9)–(10), $Profitability$ in Columns (3)–(4) and (11)–(12), $SG\&A/Sales\ (SGA)$ in Columns (5)–(6) and (13)–(14) and $Days\ inventory\ (DINV)$ in Columns (7)–(8) and (15)–(16). $Post\ cut$ is an indicator variable that takes value one if the firm's industry has experienced a tariff cut and zero otherwise. CC is the firm's maximum level of government customer concentration over the two years prior to the year of the tariff cut of the firm's cohort. $Ln\ (Firm\ age)$ is the natural logarithm of firm age, $Ln\ (Assets)$ is the natural logarithm of total assets, $Sales\ growth$ is one year sales growth, $Book\ leverage$ is book leverage scaled by total assets and $Market\ to\ book\ ratio$ is market value of assets scaled by book value of assets. Standard errors are clustered at the firm level and reported in parentheses. One, two and three asterisks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Full sample								GC sample							
	AT		Profitability		SGA		DINV		AT		Profitability		SGA		DINV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Post cut	0.039***	0.035***	0.010**	0.008**	-0.005	-0.004	-0.738	-0.530	-0.000	-0.006	0.010	0.009	-0.011	-0.010	5.734	5.447
	(0.011)	(0.011)	(0.004)	(0.004)	(0.007)	(0.007)	(1.921)	(1.917)	(0.040)	(0.035)	(0.015)	(0.012)	(0.011)	(0.010)	(5.304)	(5.335)
Post cut x CC	-0.149*	-0.162**	-0.029	-0.038	-0.015	-0.010	12.728	13.503	-0.092	-0.096	-0.044	-0.049	-0.017	-0.016	-6.991	-5.021
	(0.085)	(0.081)	(0.042)	(0.039)	(0.029)	(0.029)	(11.121)	(11.045)	(0.117)	(0.102)	(0.056)	(0.050)	(0.031)	(0.030)	(12.775)	(12.439)
Ln (Firm age)	0.212***	0.281***	-0.025***	0.011*	-0.012	-0.035***	-8.169***	-11.776***	0.227***	0.312***	-0.028	0.010	0.059***	0.039**	4.751	-1.653
	(0.015)	(0.016)	(0.006)	(0.006)	(0.012)	(0.012)	(2.339)	(2.383)	(0.048)	(0.052)	(0.020)	(0.018)	(0.019)	(0.018)	(7.509)	(7.573)
Ln (Assets)	-0.261***	-0.288***	0.062***	0.058***	-0.042***	-0.033***	18.054***	18.891***	-0.295***	-0.329***	0.041***	0.035***	-0.032***	-0.022**	22.085***	23.726***
	(0.008)	(0.008)	(0.003)	(0.003)	(0.005)	(0.005)	(1.171)	(1.174)	(0.023)	(0.024)	(0.008)	(0.009)	(0.009)	(0.009)	(2.951)	(3.098)
Sales growth		0.146***		0.062***		-0.047***		-6.715***		0.265***		0.094***		-0.069***		-14.989***
		(0.005)		(0.002)		(0.005)		(0.934)		(0.018)		(0.007)		(0.010)		(2.970)
Book leverage		-0.217***		-0.234***		0.054***		18.730***		-0.352***		-0.236***		0.074***		9.463
		(0.021)		(0.008)		(0.013)		(3.213)		(0.054)		(0.020)		(0.019)		(8.397)
Market to book ratio		0.002		0.008***		-0.003		-0.469		-0.005		0.008***		0.004		-2.399**
		(0.002)		(0.001)		(0.002)		(0.389)		(0.007)		(0.003)		(0.005)		(1.146)
Observations	161,101	161,101	161,101	161,101	161,101	161,101	161,101	161,101	14,137	14,137	14,137	14,137	14,137	14,137	14,137	14,137
Adjusted R-squared	87.1 %	88.0 %	73.7 %	77.0 %	74.7 %	75.1 %	79.4 %	79.6 %	82.5 %	84.9 %	67.8 %	73.1 %	78.6 %	79.8 %	81.9 %	82.2 %
Firm*Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year*Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes