The Better Angels of our Nature?*

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Abstract

This paper studies the investment behavior of angel investors in private and public markets. Their angel investment returns in innovative firms are highly skewed and exhibit pronounced performance persistence that is unlikely to be driven by contemporaneous exposure to economy-wide shocks. Investor fixed effects absorb approximately 45% of the total variation in returns, indicating that accounting for persistent individual differences is critical for understanding this market. We find evidence that some angel investors have access to better deal flow than other investors, such that, even if they choose randomly, they are choosing from a set of potential investments with better ex ante returns than those associated with the deals available to other investors. When comparing angel investors' returns in the public market, a market where all investors face more or less the same ex ante distribution of investments, we find evidence of better due diligence skills for some of them.

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

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1 Introduction

Angel investors are an 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 done 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 their investment portfolios like? Are some angels persistently better than others?

These questions are important not simply because they inform our understanding of household finance and of the connections between angel investment and later-stage investment from institutional VCs. 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] The emergence of online crowdfunding platforms also raises important questions about the nature of the angel investment market.

To study these questions, we draw on detailed administrative and tax records from Norway. Our data include equity transactions by individuals into privately held and 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 the performance of

[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, Howell, Mezzanotti, Wang, and Xu (2023) for a detailed description of such programs. Norway, the setting of our study, has begun to allow personal taxpayers to generate income tax deductions based on their investments in startup companies. See https://www.skatteetaten.no/person/skatt/hjelp-til-riktig-skatt/aksjer-og-verdipapirer/om/skatteinsentivordningen/ for more information.

angel investors in other asset classes. Multiple investments by the same investors allow us to analyze performance persistence among angel investors and to uncover the importance of (unobserved) differences between angel investors in explaining variation in investment performance.

For our purposes, an angel investor is an individual who makes an investment in a high-innovation-potential firm but who is not a part of that firm's founding team. We identify all such individuals in Norway between 2004 and 2017. Our definition hinges critically on constructing an ex ante measure of expected innovative potential based on characteristics observable at the time of firm founding, potentially before the firm has realized its innovative potential. For this, we build on Kisseleva, Mjøs, and Robinson (2023). Their methodology, which is inspired by the Startup Cartography Project, described in Andrews, Fazio, Guzman, Yupeng Liu, and Stern (2022), defines four indicators for high innovation propensity.[3] A potentially innovative firm is one satisfying at least two of these four criteria.

We differentiate between several angel investor types. First, we separate whether angels invest in only a single or in multiple firms. This differentiation connects our definition of an angel investor more closely to that in Bach, Baghai, Strömberg, and Warg (2022). Second, we differentiate among angel investors by their wealth level, which connects our angel definition to the US definition of the accredited angel investor and, thus, to Lindsey and Stein (2020) and Denes, Howell, Mezzanotti, Wang, and Xu (2023). Finally, we differentiate between—in the general management sense—sophisticated and nonsophisticated angel investors.

How do their angel investments perform? To answer this, we document the distribution of realized returns to angel investments. Even if the average returns are approximately

[3]The indicators are a firm's having an English-language company name, being located near the largest university cities, having at least one geographically distant board member, and not being in an industry regarded as not innovative.

twice the invested amounts, most of the money is lost in nearly half of the investments, and only investments above the 75^{th} return percentile pay back at least the invested money. These results align with the survey findings from the UK in Mason and Harrison (2002). Similarly to what Cochrane (2005) and Korteweg and Sorensen (2010) find in their analyses of VC risk and return, our results underscore the importance of accounting for the pronounced skewness of the observed distribution of early-stage returns in analyzing returns to angel investing. This finding echoes the large literature on the firm dynamics of newly established firms (e.g., Hurst and Pugsley, 2011; Haltiwanger, Jarmin, and Miranda, 2013; Adelino, Ma, and Robinson, 2017).

Our cross-sectional analyses provide evidence that angel investors vary systematically in their average angel investment performance and that unobserved differences across investors and their firm selection lie behind the observed variation in performance. In particular, investor fixed effects explain approximately 45% of the total variation in angel investment performance—far more than any other observable factor. Inspired by prior literature on performance persistence among private equity (PE) firms (Kaplan and Schoar, 2005; Korteweg and Sorensen, 2017; Nanda, Samila, and Sorenson, 2020), we document pronounced performance persistence for the angel investors in our sample. The returns in the previous angel investment are strong predictors of the performance in the current investment, regardless of angel type. Our point estimates are lower than the estimates of PE fund performance persistence found in Kaplan and Schoar (2005), suggesting that performance persistence is less pronounced in angel investing than in institutional investing.

Why do some angel investors perform better than others? A first potential explanation is that some angels have a better social network (Hochberg, Ljungqvist, and Lu, 2007). Startup investment opportunities are generally not available to all investors, and angel investors are exposed to different investment opportunities depending on their network. This implies that some angels perform better than others as a result of facing a better proprietary deal flow. Another advantage of a better social network could be—in the absence of any other scope for value-adding activities in this early-stage market—greater opportunities for the angel investor to help the firm secure follow-up financing from other investors.

To explore these ideas, we construct two different measures of angel investor performance. The first, straightforward, measure is $TVPI$, an investor's average realized total value to paid-in capital in all her angel investments. The second measure is the investor-specific conditional mean return from angel investments, which we obtain from recovering angel investor fixed effects from the regression on the cross-sectional variation in angel returns. Based on these two performance measures (each separately), we group angel investors into performance quintiles and find evidence that better-performing angels are better connected to the wider investor community of early-stage investors, which, in turn, enables them to bring on board other investors and secure more firm financing, yielding a more dispersed ownership structure. We further observe that top-performing angels tend to invest in firms that also obtain VC financing. We do not observe any statistically significant association between angel performance and follow-up VC investments, suggesting that the social network among VC investors is essential for angels to be exposed to a better deal flow but that it does not help attract further VC financing.

An alternative explanation for why some angel investors may outperform others is that they may simply have better skills in selecting investments (Bach, Baghai, Strömberg, and Warg, 2022). To test this explanation, we turn to the public market, a liquid market that every investor has access to at low cost and where every investor shares the same set of investment opportunities and thus has the same deal flow. Furthermore, individual investors acquiring a small share of a public company are unlikely to be able to affect the firm itself, and a finding that angel investors make good direct investments in publicly traded stocks would be consistent with the interpretation that they are also better at screening and selecting private investments.

Indeed, a key difference between our work and earlier work in this area is that as we are able to observe the performance of angel investors' investments over time in both public and private investments. We find that better-performing angels on average also do better in the public market. We show that a 10% increase in investors' average realized TVPI from angel investments is associated with a 0.15-basis-point higher daily return. Further analyses confirm that better angels are simply better investors and have, thus, better selection skills, as even after we account for angel investors' risk preferences, angel investment performance has a positive and statistically significantly relationship with public performance. The difference across angel types is smaller when we analyze risk-unadjusted public returns, indicating that risk-taking plays a role in explaining the differences among angel types.

Taken together, our results are informative for policymakers trying to encourage investments in startups by individuals. To the extent that our findings reveal characteristics of the pool of potential investors who might react to such policies, our results point to the importance of considering whether any given policy design will serve to benefit mainly people who are already well off and whether it will push individuals with low investment ability into excessively risky savings portfolios.

Our findings contribute to a burgeoning literature on angel investment, including Mason and Harrison (2002), Kerr, Lerner, and Schoar (2011), Lerner, Schoar, Sokolinski, and Wilson (2018), Denes, Howell, Mezzanotti, Wang, and Xu (2023), Lindsey and Stein (2020) and Wong (2002). That literature highlights the importance of exposure to angel investors for the subsequent success of the firms in question. Our work adds to this literature by illustrating the fact that some angels appear to possess better investment skills than others.

In this regard, we also add to the literature on performance persistence in PE investing. Important papers here are Kaplan and Schoar (2005), Korteweg and Sorensen (2017), Braun, Jenkinson, and Stoff (2017), and Nanda, Samila, and Sorenson (2020). The fact that we find even stronger persistence than is documented elsewhere highlights the importance of networks for individual investors and what insiders refer to as "proprietary deal flow"—i.e., access to investment opportunities that others do not have. In this regard, our paper is also related to Hellmann and Thiele (2015) and Hellmann, Schure, and Vo (2021), who study the relation between the angel and VC markets.

Finally, our paper adds to a large literature documenting the returns to PE investing. Papers in this area include Hamilton (2000), Moskowitz and Vissing-Jø rgensen (2002), Korteweg and Sorensen (2010), and Harris, Jenkinson, and Kaplan (2014). In contrast to these studies, our paper concentrates on noninstitutionalized private capital in the early-stage market.

The paper is structured as follows. Section 2 describes our data and sample construction. Section 3 describes the returns to angel investing. Section 4 evaluates whether some angels are systematically better than others. Section 5 disentangles possible explanations behind angel performance, and Section 6 concludes.

2 Data and Sample Construction

2.1 Data Sources

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 Hvide and Jones, 2018; Fagereng, Mogstad, and Rønning, 2021; 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 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. Thus, 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

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, and holding structures. To recognize high innovation potential to target a sample of firms potentially seeking early-stage equity financing, we follow the spirit of the Startup Cartography Project (Andrews, Fazio, Guzman, Yupeng Liu, and Stern, 2022; Guzman and Stern, 2015, 2020) and its application to the Norwegian business context in Kisseleva, Mjøs, and Robinson (2023). 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. Although any one flag may yield false negatives and false positives, by developing a series of flags to be applied together, our goal is to produce a robust measure of future innovation potential based on observable firm characteristics.

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 a firm operates in an innovative industry. The final 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 any two flags can be applied to it. This criterion yields a sample of 51,243 firms and contains 87% of all the firms that receive any VC funding in our data.[4]

Out of the entire pool of HIP firms, 17,678 HIP firms are financed by at least one angel investor. 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 exclude individuals who are closely related to the firm founders.[5] Given that there is no "official " definition of an angel investor, we keep our definition as broad as possible to remain agnostic regarding which definition is appropriate in which setting. Our final sample covers 42,826 angel investors and 78,217 angel investments. Fifty percent of these investments are fully or partially realized by the end of our sample period.

3 Returns to Angel Investing

Table 1 presents the distribution of realized returns to angel investments over our sample period. We measure realized returns as total value to paid-in capital, a measure commonly used in the PE literature that we compute as the realization (sales or liquidation) amount divided by the purchase amount of the realized shares.

[4]Kisseleva, Mjøs, and Robinson (2023) 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 than average 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.

[5]We define these informal investors following Baik, Karlsen, and Kisseleva (2023). These are individual investors who either a) share a last name with a founder or b) live on the same street (and thus have the same zipcode and street name) as the founder (or both).

We report return distributions in Table 1, which shows that returns to angel investing are highly skewed. Though the average returns are approximately twice the invested amounts, nearly half of the investments lose most of the money (median TVPI 0.24), and only investments above the 75^{th} percentile pay back at least the invested money. This results align with the previous survey findings from the UK in Mason and Harrison (2002). Only the top 10% of angel investments generate an investment multiple of more than three.

Insert Table 1 here.

We differentiate whether angels invest in only a single firm (69% of returns) or multiple firms (31% of returns) during our sample period. This distinction connects our definition of an angel investor more closely to that in Bach, Baghai, Strömberg, and Warg (2022). We also differentiate among angel investors by wealth level, which aligns our definition of an angel with the US definition of an accredited angel investor and, thus, with that in Lindsey and Stein (2020) and Denes, Howell, Mezzanotti, Wang, and Xu (2023). Specifically, we compute the average wealth of each investor over our sample period and define angels as wealthy if their average wealth level is above the median for all angel investors. Finally, we differentiate sophisticated and nonsophisticated angel investors. We define a sophisticated angel is an individual who, by the time of her first angel investment, has made at least one direct investment in a public stock, has held a board position in a company other than the one she is investing in, and who is older than the median angel investor in the year of the first angel investment.

In addition, our data allow us to observe whether the shares are purchased in financing rounds (85% of all purchases) or in secondary trades (from existing investors). This relative split between the purchasing categories is similar across all angel investor types, as is the number of return realizations per investor for shares bought in secondary trades. For the angel types as classified above, we observe on average 1.3 return realizations of shares purchased in financing rounds by single-firm angel investors and 2.6 by multifirm angels, slightly less than the number that we observe for wealthy multifirm angels.

Wealthy multifirm investors have the highest returns (with an average TVPI of 2.46 from purchases in financing rounds and TVPI of 2.14 in secondary purchases), and they lose less money in their secondary trades (median TVPI of 0.78 and 75^{th} percentile TVPI of 1.34). In contrast, sophisticated investors have the lowest returns (an average TVPI of 1.46 in purchases in financing rounds and TVPI of 1.47 in secondary purchases). Thus, our intuitive, general management–related definition of sophistication is not necessarily correlated with higher returns from angel investing. Angels who invest in only one firm earn on average 83% from providing equity in financing rounds and 56% from purchasing shares in secondary trades.

With an exception of sophisticated investors, angel investors earn a higher average $TVPI$ from equity purchases in financing rounds than from secondary purchases, which might be due to their different pricing mechanisms. While equity pricing in financing rounds is negotiated between the firm itself and (potential) shareholders, secondary pricing is set between the seller and the buyer independently. As argued in Nadauld, Sensoy, Vorkink, and Weisbach (2019), the seller's liquidity needs may play a role in her willingness to trade and set the price. This also explains why the skewness is more pronounced in secondary trades than in financing rounds.

4 Are Some Angels Better than Others?

4.1 Cross-Sectional Variation in Angel Returns

This section investigates whether angel investors systematically differ in their investment performance and whether unobserved heterogeneity across investors plays a crucial role for explaining it. To explore the systematic cross-sectional variation in returns to angel investing, we estimate the following regression model:

$$\begin{aligned} TVPI_{i,j,t,s} = {} & \alpha + \beta_1 Angel\ Type_j + \beta_2 Investor\ Age_{j,t} + \beta_3 Male_j + \beta_4 Ownership_{i,j,t} \\ & + \beta_5 Board\ Seat_{i,j,t} + \beta_6 Secondary_{i,j,t} + \beta_7 Holding\ Period_{i,j,t,s} \\ & + \gamma_{i,j,t,s} + \delta_j + \varepsilon_{i,j,t,s} \end{aligned} \tag{1}$$

The dependent variable, $TVPI_{i,j,t,s}$, is the natural logarithm (+1) of $TVPI$, with $TVPI$ computed as the realization (through sale or liquidation of shares) amount in year s divided by the purchase amount of the realized shares in year t. The dependent variable is winsorized at the 1^{th} and 99^{th} percentiles. $Angel\ Type_j$ is a set of dummy variables taking value one for different types of angel investors as introduced in Table 1: single-firm, multifirm, wealthy, multifirm and wealthy and sophisticated angels. The omitted category in all estimations is the single-firm angel. $Investor\ Age_{i,t}$ is the natural logarithm of the investor's age at the time of investment. $Male_i$ is the dummy variable taking the value of one for male investors. $Ownership_{i,j,t}$ is the natural logarithm of the ownership stake of the investment. $Board\ Seat_{i,j,t}$ is a dummy variable taking the value of one if the angel investor receives a board seat at the time of investment. $Secondary_{i,j,t}$ is a dummy variable taking value of one if the investor buys shares in a secondary trade. $Holding\ Period_{i,j,t,s}$ is the natural logarithm of the holding period of the investment measured in days. $\gamma_{i,j,t,s}$ is purchase and realization calendar year and firm age (at the time of investment) fixed effects, and δ_j is the investor fixed effect. Standard errors are clustered at the firm level.

Table 2 shows the cross-sectional variation in angel investment returns by angel investor type. Column (1) shows that our differentiation among angel investor types significantly explains the variation in angel returns. In particular, multifirm and wealthy angels generate approximately 11% higher returns than single-firm angels, while sophisticated investors generate 15% lower returns. This result indicates that relevant investor performance ability stems from the angel investment experience and wealth management rather than from investor's more general management capabilities. This result is robust to the inclusion of calendar year, firm age and industry fixed effects (Column (2)) and of controls for observable investor and investment characteristics (Column (3)). Angel investors who both have angel investment experience and are wealthy generate on average an almost 20% higher return than single-firm angels. When we introduce investor fixed effects in Column (4), the adjusted R^2 increases from 4.7% (without the investor fixed effects in Column (3)) to 50.9%. This increase is evidence of large unobserved heterogeneity across investors, which plays a crucial role in explaining the returns from angel investing.

Insert Table 2 here.

In our final specification in Column (5), we replace the investor fixed effects with firm fixed effects; i.e., we study only the variation in returns between different angel investors within the same firm. The coefficients on the multifirm and/or wealthy investor type dummies are no longer significant. This implies that, once invested in the same firm, they earn the same return as single-firm angels. Sophisticated angels still perform 2.2% worse than all other angel investors in the same firm, confirming that having general management capabilities and public capital market knowledge does not help investors write better contractual terms or execute more favorable share realizations. However, the adjusted R^2 increases further from 4.7% to 62.1%, indicating that, in general, different types of angels invest in fundamentally different types of firms, resulting in different returns.

Overall, Table 2 provides suggestive evidence that angel investors vary systematically in their average angel investment performance and that unobserved differences across investors and their firm selection lie behind the observed variation in performance.

4.2 Persistence in Angels' Performance

To analyze performance persistence in angel investing, we turn to the investor–firm-level analysis and aggregate multiple realizations and investments made by an angel investor in the same firm to one observation. The implicit assumption is that the conditions for share realizations through sales or liquidation are already fixed in contractual terms at the time of the investment. In the spirit of Kaplan and Schoar (2005), we extend the basic specification of Equation 1 to include the lagged performance of the previous investment (in a different firm) as a right-hand-side variable. We then estimate the following ordinary least squares (OLS) model:

$$TVPI_{i,j,t} = \alpha + \beta_1 TVPI_{k \neq i,j,z<t} + Controls_{i,j,t} + \gamma_{i,j,t} + \varepsilon_{i,j,t} \tag{2}$$

The dependent variable, $TVPI_{i,j,t}$, is the natural logarithm (+1) of the $TVPI$ of an investment made by investor j in firm i at time t, with $TVPI$ being computed as the weighted (by purchase amount of realized shares) average $TVPI$ of all realizations by the investor in the firm. $TVPI_{k \neq i,j,z<t}$ is the natural logarithm (+1) of the $TVPI$ that investor j earned on a prior investment in another firm k at date z, with $z < t$. We include controls (results untabulated) for the investor and investment characteristics shown in Equation 1.

Standard errors are clustered at the firm level. $\gamma_{i,j,t}$ is fixed effects for the calendar year of share purchase and firm age at the time of the investment. Standard errors are clustered at the firm level.

Both Kaplan and Schoar (2005) and Korteweg and Sorensen (2017) raise the concern of spurious persistence, which—in their PE fund setting—may arise from the partial overlap of consecutive funds managed by the same PE fund manager. They argue that partially overlapping funds are exposed to the same market conditions during the overlapping period. This may induce a positive correlation in the performance of subsequent overlapping funds, showing up as spurious persistence in an AR(1) model. In contrast to the fund performance setting, our setting is advantageous in the sense that we can track the exact timing of investments by each individual investor in each individual firm. We address the concern related to exposure to common market conditions by controlling for the calendar year of share purchase of each individual investment.

Table 3 provides evidence of performance persistence in angel investing. In particular, the return from the current angel investment is positively and statistically significantly correlated with the return from the prior angel investment in a different firm. The coefficient estimates in Columns (1)–(3) range between 0.131 (without controls or fixed effects) and 0.115 (with controls and fixed effects), implying that a 1% increase in lagged investment $TVPI$ is associated with approximately 0.12% higher $TVPI$ on the subsequent investment. These point estimates are lower than the PE fund performance persistence found in Kaplan and Schoar (2005), suggesting that the performance persistence of angel investors is less pronounced than that of institutional PE investors. This could be due to angels' investment portfolio consisting of fewer firms or simply to their lacking the same degree of exposure to expertise as VCs. In Column (4), we introduce the second lagged investment return, which yields a higher and statistically significant coefficient estimate of 0.198 for the most recent investment performance, while the $TVPI$ on the second lagged investment itself is not significantly related to current investment performance. This indicates that performance persistence in angel investing is a rather short-term phenomenon.

Insert Table 3 here.

To investigate performance persistence across different angel investor types, Table 4 replicates Table 3 Column (3) for the subsamples of angel types. Because we study performance persistence based on angel investments in different firms, all investors included in this analysis are angel investors in multiple firms, and we differentiate only along the wealth and sophistication dimensions within this group. The split on wealth suggests stronger persistence among less wealthy angel investors, with coefficient estimates of 0.09% for high-wealth angels vs. 0.22% for low-wealth angels. Low-wealth investors' performance persistence may be driven by their undertaking a more diligent process in angel investing. The study closest to ours, Bach, Baghai, Strömberg, and Warg (2022), points out the relevance of socioeconomic background and generational wealth for the likelihood of becoming an angel investor. If wealth increases the likelihood of becoming an angel investor because it "makes it easier" to bear long-term, illiquid, lumpy investments in risky assets or to prioritize the nonpecuniary benefits of investing in startups, we pose the idea that less wealthy investors become angel investors, to a larger extent than is the case for wealthier investors, based on their experience making successful investments. Moreover, if less wealthy individuals are more financially constrained, they may need to pass a higher bar before making high-risk investments in startups. Moreover, because of greater financial constraints, we conjecture that less wealthy individuals make angel investments based on nonpecuniary motives less often than do their wealthier counterparts.

We do not observe large difference between sophisticated and nonsophisticated investors, with their persistence rates similar to the average persistence rate among all angel investors (Table 3), which may suggest that general management capabilities and experience from investing in public stock markets are not significantly related to angel investors' performance persistence.

Insert Table 4 here.

4.3 Persistence in Firms' Performance

While realized investment returns represent a sharp measure of investment performance at the level of the individual investor, a potential drawback is that this measure does not cover unrealized investments in our analyses. The share of such investments by the end of our sample period is approximately 50%. To take them into account, we switch to a firm-level approach and analyze the persistence in firm exit outcomes of all firms in which an angel investor has invested. To do so, we track all sample firms from their establishment 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). Firms that are independently operating by the end of the period are not categorized. To proxy for angels' investment performance, we rely on the first exit event.

We run a logit estimation of the following firm-level model:

$$Outcome_{i,j,t} = \alpha + \beta_1 Outcome_{k \neq i,j,z<t} + Controls_{i,j,t} + \gamma_{i,j,t} + \varepsilon_{i,j,t} \quad (3)$$

The dependent variable, $Outcome_{i,j,t}$, is a dummy variable representing the exit outcome (success or failure) of firm i, with t referring to investor j's investment sequence. $Outcome_{k \neq i,j,z<t}$ is a dummy variable representing the exit outcome of the firm k in which investor j invested before, in $z < t$. We include controls (results untabulated) for the investor and investment characteristics shown in Equation 1. $\gamma_{i,j,t}$ is investment (calendar) year and firm founding year fixed effects. Standard errors are clustered at the firm level.

Table 5 documents strong firm-level performance persistence and thus investors' ability to repeatedly select good or bad firms. In Columns (1)–(4), we analyze the persistence of success (the firm's being acquired, merged or IPO'ed), while in Columns (5)–(8), we analyze the persistence of failure (firm bankruptcy or liquidation). We find that past investments in successful firms are succeeded by current investments in successful firms; investors in previously successful firms have 1.91 (without controls or fixed effects) to 1.50 (with controls and fixed effects) times the odds of investing in a successful firm again. The odds of investing in a failing firm again are a bit lower; investors in previously failed firms have 1.63 (without controls or fixed effects) to 1.34 (with controls and fixed effects) times the odds of investing in another firm that ultimately fails. Given the high rate of failure of early-stage firms, it is more likely that an investor learns from some previous investments' failure than successes before making new investments. Investors' being better informed is consistent with the lower selection persistence for failing firms.

Insert Table 5 here.

To explore the drivers of the firm-level performance persistence, we examine whether the sequential correlation of investment success or failure differs among different angel types or with the angel's investment strategy. We make three predictions. First, if the performance persistence differs by angel investor type, as defined by level of wealth and sophistication, it would support the view that performance persistence is related to investor selection ability rather than simply resulting from luck. Wealth and sophistication are assumed to be permanent proxies of investor attributes and are likely to partially explain firm selection ability. Second, if performance persistence is more pronounced for sequential investments that are closer in time, it would support the idea that exposure to common market conditions gives rise to the observed performance persistence and that persistence in investors' performance attenuates over time. We define two investments as being made close in time if the number of days between the first and the second investments is less than or equal to the median number of days between sequential investments by the same investor. Third, if performance persistence is more pronounced for sequential investments in different firms but in the same industry, it would support the conjecture that specific industry investment experience gives rise to the observed performance persistence. It may also point to industry specialization by angel investors as a factor that induces persistence in investment performance. We employ two different industry classifications: one broad 10-industry classification and one narrow two-digit classification.[6]

Table 6 replicates Table 5 Column (3), whereas Panel A investigates persistence in firm success and Panel B in firm failure. All investors here are multifirm angels, so that we differentiate only along the wealth and sophistication dimensions within this group. Wealthy angel investors have 1.45 times the odds of investing again in a successful firm, compared to 1.66 times the odds for low-wealth angel investors. However, the persistence of low-wealth investors in selecting failing firms is almost as high, at 1.57 times the odds of investing again, compared to 1.28 for wealthy angel investors. This indicates that wealthy angel investors—in addition to realizing higher returns from each individual investment, as shown in Table 2—select failing firms again less frequently than do low-wealth investors. The observation that low-wealth investors have very similar persistence irrespective of the first investment being in a successful or failing firm could also indicate a lower skill of learning from past experiences.

Insert Table 6 here.

Sophisticated investors have 1.59 times the odds of investing in a new successful firm,

[6]The broad 10-industry classification is the variable that we use for industry fixed effects.

just slightly higher than the odds of nonsophisticated investors. The persistence in selecting failing firms is also marginally higher for the former group than for the latter, which confirms our results and interpretation at the investor–firm level that general management capabilities and experience from investing in public stock markets are not significantly related to angel investors' performance persistence.

Investments made close in time have 1.68 (1.33) times the odds of becoming a success (failure) again, compared to 1.40 (1.36) times the odds if more time between investments goes by. These odds indicate that common market conditions support investment persistence, which is more pronounced in sequential investments in successful firms. The lower and similar persistence coefficients on investments that are distant in time, regardless of success or failure, also support this interpretation.

Industry focus matters significantly for persistence in sequential firm selections. Using a broader industry definition, we find that an angel with a previous investment in a successful firm has 1.79 times the odds of investing in a new successful firm in the same industry. In comparison to the odds of a subsequent successful investment, the odds are 1.40 times for failing firms, implying that angel investors with industry knowledge have better capabilities in selecting successes and avoiding failures. The magnitude of the results is amplified if we consider industries narrowly defined. In this case, an angel with a previous investment in a successful (failing) firm has 3.50 (2.51) times the odds of investing in a new successful (failing) firm in the same narrowly defined industry. At the same time, we observe neither large nor statistically significant persistence for investments in different industries. This indicates that any industry focus helps investors select successful firms (consistent with the findings of Fulghieri and Sevilir, 2009, for VC portfolios), but also that persistence is affected by industry-specific market conditions.

5 Why are Some Angels Better than Others?

5.1 Social Network

Why do some angel investors perform better than others? A first potential explanation is that some angels have a better social network (Hochberg, Ljungqvist, and Lu, 2007). In contrast to public stocks, not all startup investment opportunities are generally available to all investors, and angel investors are exposed to different investment opportunities depending on their network. This implies that some angels perform better than others as a result of their facing a better proprietary deal flow.

Another advantage of a better social network could be that—in the absence of any other scope for value-adding activities in this early-stage market—a wider network offers greater opportunities for the angel investor to help the firm secure follow-up financing from other investors. To explore these ideas, we analyze whether better-performing angel investors tend to invest in firms that raise more financing from other investors, both in total and as follow-up financing after the angel investor first invested in the firm. We hypothesize that this is the case for investors who are better connected to the wider investor community, including other angel investors and VC investors.

We construct two different measures of each angel investor's performance. The first, straightforward measure is an investor's average realized $TVPI$ in all her angel investments. The second measure is the investor-specific conditional mean return from angel investments, which we obtain from recovering angel investor fixed effects from the regression in Equation 1 and as shown in Table 2 Column (4). This measure allows us to measure an angel investor's performance while controlling for the timing of her investments and for the other observable investor and investment characteristics included in the cross-sectional fixed effects regression. This approach allows us to have a performance measure that is more closely tied to individual investor traits. Based on these two performance measures (each separately), we group angel investors into performance quintiles.

We run an OLS estimation of the following regression model:

$$Financing_{i,t} = \alpha + \beta_1 Performance\,Quintile_j + \beta_2 Total\ Equity_{i,j} + \gamma_{i,j,t} + \varepsilon_{i,j,t} \quad (4)$$

The dependent variable, $Financing_{i,t}$, is the firm–investment year variable representing total firm financing excluding that of the respective angel investor. Based on the measures of angel investment performance described above, we group angels into angel investor performance quintiles, with the highest quintile representing investors with the highest average $TVPI$. $Performance\ quintile_j$ is a set of dummy variables for each performance quintile, either using the angel investor's $TVPI$ or her recovered fixed effect. $Total\ Equity_{i,j}$ is the total equity amount provided by angel investor j to firm i. $\gamma_{i,j,t}$ is investment calendar year, firm founding year and industry fixed effects.

Tables 7 and 8 suggest that, similarly to VC investors, better-performing angels have a better investor network. Table 7 Column (1) shows that firms selected by the best 20% (40%) of angel investors raise 38% (20%) more total equity than the firms that worse-performing angels invest in. Once we replace the angel performance measure $TVPI$ by the angel's conditional mean return (Column (2)), the effect becomes gradually visible and statistically significant even at the lower quintiles, whereas the magnitude of the effect increases to 95% for the top-performing angel investors. The results remain robust, albeit of a slightly lower magnitude, if we consider only follow-up financing (in/after the year of the first investment by the respective angel investor) in Columns (3) and (4). Our findings support our prediction that better-performing angels are better connected to the wider investor community of early-stage investors, which can, in turn, enable them to bring on board other investors. Columns (5) and (6) replace the dependent variable with the ratio of equity provided by the respective angel investor to total equity provided to the firm from any investor, i.e., an indicator of the angel investor's ownership relative to that of other investors. The results consistently confirm that better-performing angel investors provide a lower share of the total equity. This implies that the firms that better angels invest in are able to receive more financing from other investors, yielding a more dispersed ownership structure.

Insert Table 7 here.

Previous literature suggests that angel financing precedes VC funding and represents a complementary source of capital in the market for early-stage finance (in particular, Hellmann and Thiele, 2015; Hellmann, Schure, and Vo, 2021). To further test our prediction on the importance of social networks among early-stage investors, we analyze whether better angel investors invest in the same firms as VCs, identifying angel investors' connection to the most prominent source of early-stage capital for growth-oriented startups. To do so, we replicate Table 7 but replace the dependent variables with VC financing only.

The results in Table 8 suggest that top-performing angels tend to invest in firms that also obtain VC financing. In particular, the logit estimates in Columns (1)–(2) provide evidence that angels in the top performance quintile, relative to those in the lowest quintile, have 1.72 (Column (1)) to 1.88 (Column (2)) times the odds of investing in a firm in which a VC investor also invests. In addition, Columns (3)–(4) show that, conditional on a firm's drawing a VC investment, VC investors invest equity amounts that are more than 50% (Column (3)) and over 70% (Column (4)) larger in the firms that top-performing angels invest in than in the firms with the worst-performing angels. This suggests that the best angel investor invests not only in the best firms as selected by VCs but also in the firms attracting the highest amounts of venture funding.

Insert Table 8 here.

The magnitude of the effect attenuates and becomes statistically insignificant if we consider only follow-up VC investments in/after the year of the first investment by the respective angel investor in Columns (5)–(6). This result is consistent with the explanation that angels' social network among VC investors is essential for their exposure to a better deal flow but does not help firms attract further VC financing, which confirms the small scope and possibilities for angel investors to add value to their portfolio firms.

5.2 Selection Skills

Some angel investors may outperform others because they simply have better skills in selecting investments (Bach, Baghai, Strömberg, and Warg, 2022). To test this explanation, we turn to the public market, which is a liquid market that every investor has access to at low cost and where every investor shares the same set of investment opportunities and thus has the same deal flow. Furthermore, because individual investors acquiring a small share of a public company are unlikely to be able to affect the firm itself, a finding of better public investment performance among better-performing angels would align with the interpretation that these investors are better at screening and selecting investments overall.

We analyze the relationship between angels' investment performance and their returns to direct investments in public stocks listed on the Oslo Børs stock exchange by estimating the following OLS regression model:

$$\begin{aligned} Return_{i,j,t,s} = \alpha + \beta_1 Angel\ Performance_j + \beta_2 Angel\ Type_j + \\ \beta_3 Angel\ Performance_j * Angel\ Type_j +\ Controls_{j,t} + \varepsilon_{i,j,t} \end{aligned} \tag{5}$$

The dependent variable, $Return_{i,j,t,s}$, is the market-adjusted daily return earned by investor j on an investment in public stock i made at date t and realized at date s. The market-adjusted return is computed as the daily stock return over the angel's investment period less the daily return of the Oslo Børs Benchmark Index (OSEBX)[7] over the same period. For investments not yet realized by the end of our sample period, we calculate paper gains or losses based on quoted stock prices, with s being the latest observable date in our sample period with a quoted stock price.[8] The dependent variable is winsorized at the 1^{th} and 99^{th} percentiles. $Performance_j$ represents one of the two investor-level measures of angel investment performance described in the previous section; however, instead of using quintiles, we use the continuous performance measures. $Angel\ Type_j$ is a set of dummy variables for different types of angel investors as defined above (single-firm, multifirm, wealthy, multifirm and wealthy and sophisticated angels).[9] The omitted category in all estimations is the single-firm angel. $Performance_j * Angel\ Type_j$ is the interaction term between these two variables. We include controls (results untabulated) for the investor and investment characteristics shown in Equation 1.

Table 9 provides evidence that better-performing angels on average also do better in the public market: the coefficient estimate of 0.015 in Column (1) implies that a 10% increase in investors' average realized TVPI from angel investments is associated with a 0.15-basis-point higher daily return (0.56% annualized). The performance measure based on investor fixed effects in Column (7) is not in logarithmic form and yields a slightly different but consistent interpretation: the coefficient estimate of 0.021 implies that a one-standard-deviation increase in the investor-specific conditional mean return from angel investments is associated with an increase of 1.6-basis-point (6.0% annualized) higher daily return, given

[7]https://live.euronext.com/en/markets/oslo/equities-by-index/osebx

[8]Approximately 6% of public investments are left unrealized by the end of our sample period.

[9]Forty-three percent of the public stock investments in our sample are carried out by multifirm angels. Close to 90% of the public stock investments in our sample are carried out by angel investors defined as high-wealth angels. Approximately 40% of the public stock investments in our sample are made by angel investors who are defined as high wealth and who make angel investments in multiple firms. Forty-six percent of the public stock investments in our sample are carried out by angels that meet our definition of sophisticated.

the performance mean of -0.03 and standard deviation of 0.77.

Insert Table 9 here.

How does the effect of angel performance on public market performance differ between angel types? Column (2) compares multifirm to single-firm angel investors. It shows that the angel investment performance for multifirm investors is associated twice as strongly with public market investment performance as it is for the whole sample, with a coefficient of 0.033, which translates to an increase in daily return of 0.33 basis points (1.21% annualized) for every 10% increase in angel performance. While the angel performance of single-firm angels is not correlated with their public performance and multifirm angels do just as well in the public market as single-firm angels, the entire performance effect is driven by the effect of angel performance among multifirm angels rather than single-firm angels. Column (7) with its positive and statistically significant interaction effect (coefficient 0.104) confirms that angel performance is more strongly correlated with the public performance for multifirm angels than for single-firm angels. Specifically, a one-standard-deviation increase in angel performance of multifirm angels is associated with a 6-basis-point higher daily return (24.5% annualized).[10]

Although wealthy investors have a 23.5-basis-point (135.55% annualized) higher public market return than low-wealth angels (Column (3)), their angel investment performance is more weakly (less positively) associated with their public market performance (with a statistically significant interaction coefficient of -0.085). This negative effect offsets the positive main effect of angel performance of low-wealth angels (with a statistically significant coefficient of 0.085), resulting in a lack of correlation between angel and public performance for wealthy angels. These results are confirmed when we incorporate investor fixed effects in

[10]To estimate the magnitude of the effect, we add up the main and interaction performance coefficients to 0.078 and multiply by the standard deviation of 0.77.

Column (8), where the negative interaction effect of -0.071 effectively cancels out the main positive effect of 0.078.

Angel investors who both are wealthy and invest in multiple startups earn a 4-basis-point higher daily return (15.72% annualized) than angel investors who do not meet either of the criteria (Column (4)). However, the angel performance of the first is associated with their public performance to the same extent as for the latter group of angels, with a statistically insignificant interaction coefficient of 0.012 and a positive, statistically significant main effect of 0.01 basis points (0.04% annualized).

When we proxy angel performance by the investor-specific conditional mean return in Column (9), we observe a different pattern, given the difference in the underlying nature of our two proxies. When we control for the various observable investor and investment characteristics, the recovered investor fixed effect absorbs all unobservable time-invariant investor characteristics and is more closely tied to individual investor traits, such as selection skills. In particular, the angel performance of investors who are either low wealth or invested in a single firm is not correlated with their public performance. However, the angel investment performance of multifirm and wealthy investors is associated three times as strongly with the public market investment performance as it is for the whole sample in Column (6). The positive and statistically significant coefficient estimate of 0.062 implies that a one-standard-deviation increase in angel performance is associated with a 4.7-basis-point higher daily public return (19% on an annualized basis).

Sophisticated angel investors in Column (5) have a 7.3-basis-point (31% annualized) lower daily market return than angel investors without general management skills. In addition, their angel performance is associated with their public performance to the same extent as for the other angel types, with a statistically insignificant interaction coefficient of -0.009. These results are broadly confirmed by the estimates in Column (10).

The analyses in Table 9 do not account for angel investors' risk-taking behavior. Thus, in the next step, we evaluate the public investment performance relative to investors' risk preferences. To examine this question, we replicate Table 9 using the investment-level Sharpe ratio[11] as the dependent variable. The Sharpe ratio represents a public market risk-adjusted investment return. Table 10 strengthens our finding that better angels are better investors, as even after we account for the risk preferences of angel investors, angel investment performance has a positive and statistically significantly relationship with public performance. In particular, a 10% increase in investors' average realized TVPI from angel investments is associated with an increase in the investment Sharpe ratio of approximately 0.001, which corresponds to a 1.4% increase over the sample mean Sharpe ratio of 0.07 (based on daily returns and standard deviations). This also roughly holds for single-firm, multifirm, sophisticated and nonsophisticated angels, while the effect is three to four times larger for low-wealth angels (with a statistically significant coefficient of 0.038 in Column (3)) and only approximately half of the average effect for wealthy angels (based on adding the performance coefficient and interaction term coefficient to 0.005 in Column (3)). In Column (4), multifirm and wealthy angels display a combined coefficient of 0.004, relative to 0.013 for angels not fulfilling either of the criteria. This corresponds to increases of 0.5% and 1.9% over the mean Sharpe ratio, respectively, when we consider a 10% increase in the performance measure. Thus, the differences across angel types are smaller than those found when we analyze the risk-unadjusted public returns, indicating that risk-taking plays a role in explaining differences among the angel types.

Insert Table 10 here.

[11]The Sharpe ratio is calculated as the daily return of a public stock less the average daily risk-free rate, divided by the standard deviation of that stock return.

6 Conclusion

The better angels that echo through English literature, from Shakespeare's *Othello* to the writings of Abraham Lincoln, are of course references to the better temperaments of the human spirit. Nevertheless, applied to early-stage investing in innovative startups, the phrase encourages us to ask whether some angel investors possess traits that make them systematically better than others.

This question would be impossible to answer without highly detailed investment-level time-series data linked back to individual investors in private companies. We assemble such data 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.

We find that there are indeed better angels among us in the early-stage capital market. Investor fixed effects absorb approximately 45% of the total variation in returns, indicating that persistent individual differences are critical for understanding this market. Concomitantly, there is strong performance persistence across investments made by the same investor. One explanation for this is that some angel investors have access to better deal flows than others, such that even if they choose randomly, they are choosing from a set of potential investments with better ex ante returns than those associated with the deals available to other investors. Another explanation is that some angel investors possess better due diligence skills, such that some angel investors are pickier than others even though all investors face more or less the same ex ante distribution of investments. Distinguishing between these explanations is important for guiding policy and is an important question for future research.

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Table 1: Distribution of Angels' Returns

Table 1 reports the distribution of realized returns to angel investments over our sample period. We measure realized returns as *total value to paid-in capital (TVPI)*, which we compute as the realization (through sales or liquidation) amount divided by the purchase amount of the realized shares. We report return distributions both for the total pool of realized angel returns and separately by angel investor type. First, we separate whether angels invest in only a single firm or multiple firms during our sample period. Second, we separate wealthy (above-median wealth) angel investors. Finally, we identify sophisticated angel investors. We define a sophisticated angel is an individual who, by the time of her first angel investment, has made at least one direct investment in a public stock, who has held any company board position, and who is older than the median angel investor. We differentiate between primary share purchases in financing rounds and in secondary trades from existing investors.

		N per	TVPI									
	N	Angel	Mean	SD	Skew.	p10	p25	p50	p75	p90	p95	p99
All transactions	41,530	1.8	1.97	5.98	5.31	0.00	0.00	0.24	1.03	3.63	9.07	43.51
Purchase in a financing round	35,306	1.5	2.01	6.11	5.24	0.00	0.00	0.27	1.02	3.67	9.35	43.51
Secondary purchase	6,224	2.0	1.74	5.22	5.73	0.00	0.00	0.11	1.15	3.33	7.90	31.04
Single-firm angels												
Purchase in a financing round	24,682	1.3	1.83	5.68	5.56	0.00	0.00	0.30	1.00	3.12	7.65	38.17
Secondary purchase	4,173	2.0	1.56	4.91	6.00	0.00	0.00	0.09	1.01	3.00	7.13	28.84
Multifirm angels												
Purchase in a financing round	10,624	2.6	2.41	6.99	4.64	0.00	0.00	0.21	1.14	4.88	11.98	43.51
Secondary purchase	2,051	2.1	2.11	5.76	5.27	0.00	0.00	0.72	1.36	4.00	9.15	40.00
Wealthy angels												
Purchase in a financing round	20,406	1.8	2.26	6.72	4.83	0.00	0.00	0.34	1.06	4.00	11.67	43.51
Secondary purchase	4,262	2.2	2.01	5.86	5.24	0.00	0.00	0.25	1.24	3.76	8.99	40.86
Multifirm and wealthy angels												
Purchase in a financing round	8,212	2.7	2.46	7.21	4.58	0.00	0.00	0.21	1.14	4.55	12.00	43.51
Secondary purchase	1,733	2.2	2.14	5.89	5.17	0.00	0.00	0.78	1.34	3.69	9.15	40.86
Sophisticated angels												
Purchase in a financing round	5,114	2.0	1.46	5.03	6.73	0.00	0.00	0.13	1.00	2.34	5.00	37.16
Secondary purchase	950	2.1	1.47	4.37	6.52	0.00	0.00	0.37	1.19	2.45	4.81	24.56

Table 2: Cross-Sectional Variation in Angels' Returns

Table 2 reports OLS estimates from running the regression model as shown in Equation 1. The dependent variable is the natural logarithm (+1) of $TVPI$, computed as the realization (through sales or liquidation) amount divided by the purchase amount of the realized shares and winsorized at the 1^{th} and 99^{th} percentiles. We differentiate between the following types of angel investors: single-firm, multifirm, wealthy, multifirm and wealthy and sophisticated angels. The omitted category in all estimations is the single-firm angel. $Ln(Investor\ Age)$ is the natural logarithm of the investor's age at the time of investment. $Male$ is a dummy variable taking the value of one for male investors. $Ln(Ownership)$ is the natural logarithm of the ownership stake of the investment. *Board Seat* is a dummy variable taking the value of one if the angel investor receives a board seat at the time of investment. *Secondary purchase* is a dummy variable taking the value of 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. 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.

	(1)	(2)	(3)	(4)	(5)
Multifirm angel (1/0)	0.113**	0.103**	0.102**		-0.008
	(0.048)	(0.043)	(0.042)		(0.021)
Wealthy angel (1/0)	0.111***	0.142***	0.162***		0.015
	(0.024)	(0.020)	(0.020)		(0.012)
Multifirm and wealthy angel (1/0)	-0.049	-0.061	-0.067*		-0.012
	(0.042)	(0.040)	(0.039)		(0.024)
Sophisticated angel (1/0)	-0.152***	-0.144***	-0.104***		-0.022*
	(0.029)	(0.023)	(0.021)		(0.012)
Investor characteristics					
Log (Investor age)			-0.189***	-1.084	-0.034*
			(0.031)	(0.783)	(0.019)
Male (1/0)			0.009		
			(0.024)		
Investment characteristics					
Log (Ownership)			-0.005	0.039***	0.042***
			(0.009)	(0.015)	(0.011)
Secondary purchase (1/0)			0.007	-0.050*	-0.044*
			(0.054)	(0.025)	(0.024)
Log (Holding period)			-0.120***	0.017	0.050*
			(0.020)	(0.041)	(0.028)
Board seat (1/0)			0.016	0.048	0.029*
			(0.024)	(0.052)	(0.017)
Observations	40,985	40,985	40,985	26,248	35,395
Adjusted R-squared	0.8%	4.0%	4.7%	50.9%	62.1%
Calendar year FE	NO	YES	YES	YES	YES
Investment firm age FE	NO	YES	YES	YES	YES
Industry FE	NO	YES	YES	YES	YES
Investor FE	NO	NO	NO	YES	NO
Firm FE	NO	NO	NO	NO	YES

Table 3: Persistence in Angel Performance

Table 3 reports OLS estimates from running the regression model as shown in Equation 2. The dependent variable is the natural logarithm (+1) of the investor–firm-level $TVPI$, computed as the realization (through sale or liquidation of shares) amount divided by the purchase amount of all realized shares in that firm. For investments with multiple realizations, $TVPI$ is computed as the weighted (by purchase amount of the realized shares) average of all realizations by the investor in the firm. $TVPI_{i-1}$ and $TVPI_{i-2}$ are the natural logarithm (+1) of $TVPI$ realized in the first and second lagged angel investments in different firms by the same angel investor, with the investment sequence defined by the date of the first investment in each firm. $Ln(Investor\ Age)$ is the natural logarithm of the investor's age at the time of investment. $Male$ is a dummy variable taking the value of one for male investors. $Ln(Ownership)$ is the natural logarithm of the ownership stake of the investment. *Board Seat* is a dummy variable taking the value of one if the angel investor receives a board seat at the time 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.

	(1)	(2)	(3)	(4)
$TVPI_{i-1}$	0.131***	0.118***	0.115***	0.198**
	(0.033)	(0.031)	(0.031)	(0.077)
$TVPI_{i-2}$				-0.023
				(0.049)
Investor characteristics				
Ln (Investor age)			-0.170*	-0.518***
			(0.089)	(0.168)
Male (1/0)			0.104*	-0.204
			(0.060)	(0.212)
Investment characteristics				
Ln (Ownership)			-0.172	-0.009
			(0.161)	(0.263)
Board seat (1/0)			0.098**	0.110
			(0.046)	(0.086)
Observations	2,521	2,521	2,521	560
Adjusted R-squared	2.0%	5.4%	5.8%	7.9%
Calendar year FE	NO	YES	YES	YES
Firm age at investment FE	NO	YES	YES	YES
Industry FE	NO	YES	YES	YES

Table 4: Does Persistence Vary by Angel Type?

Table 4 replicates Table 3 Column (3) for the subsamples of angel investor types. The dependent variable is the natural logarithm (+1) of the investor–firm-level $TVPI$, computed as the realization (through sale or liquidation of shares) amount divided by the purchase amount of all realized shares in that firm. For investments with multiple realizations, $TVPI$ is computed as the weighted (by purchase amount of the realized shares) average of all realizations by the investor in the firm. $TVPI_{i-1}$ is the natural logarithm (+1) of $TVPI$ realized in the first lagged angel investment in a different firm by the same angel investor, with the investment sequence defined by the date of the first investment in each firm. We in controls (results untabulated) for the investor and investment characteristics in Table 3. 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 Investor Type:			
	High Wealth (1)	Low Wealth (2)	Sophisticated (3)	Not sophisticated (4)
$TVPI_{i-1}$	0.093***	0.219***	0.137**	0.107***
	(0.032)	(0.069)	(0.053)	(0.032)
Observations	1,937	566	583	1,936
Adjusted R-squared	6.1%	7.3%	5.4%	5.5%
Calendar year FE	YES	YES	YES	YES
Firm age at investment FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES

Table 5: Firm-Level Performance Persistence

Table 5 reports logit estimates from running the regression model shown in Equation 3. The dependent variable is a dummy variable representing a firm's successful exit outcome (merger, acquisition or IPO) in Columns (1)–(4) and failure (bankruptcy or liquidation) in Columns (5)–(8). $Success_{i-1}(1/0)$ and $Failure_{i-1}(1/0)$ are the exit outcomes of the first lagged firm in which the angel investor invested before. In some specifications, we include controls (results untabulated) for investor and investment characteristics shown in Table 3. 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.

	Current Success (1/0)				Current Failure (1/0)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Success_{i-1}$ (1/0)	0.646***	0.431***	0.400***	0.408***				-0.078
	(0.120)	(0.120)	(0.119)	(0.131)				(0.124)
$Failure_{i-1}$ (1/0)				0.020	0.487***	0.320***	0.323***	0.295**
				(0.129)	(0.110)	(0.107)	(0.106)	(0.119)
Observations	7,165	7,165	7,165	7,165	7,165	7,165	7,165	7,165
Pseudo R-squared	1.4%	17.2%	18.6%	18.6%	0.7%	8.4%	8.5%	8.5%
Controls	NO	NO	YES	YES	NO	NO	YES	YES
Calendar year FE	NO	YES	YES	YES	NO	YES	YES	YES
Founding year FE	NO	YES	YES	YES	NO	YES	YES	YES
Industry FE	NO	YES	YES	YES	NO	YES	YES	YES

Table 6: What Contributes to Performance Persistence?

Table 6 Panel A (B) replicates Table 5 Column (3) ((7)) separately for firm success (failure) by the angel investor's type, her investment timing and her investment industry focus. The dependent variable is an indicator for success (merger, acquisition, IPO) in Panel A, while it is failure (bankruptcy or liquidation) in Panel B. $Success_{i-1}(1/0)$ and $Failure_{i-1}(1/0)$ are the exit outcomes of the first lagged firm in which the angel investor invested before. We include controls (results untabulated) for the investor and investment characteristics shown in Table 3. 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			
	High Wealth	Low Wealth	Sophisticated	Not Sophisticated	Close	Not Close	Same Broad	Different Broad	Same Narrow	Different Narrow
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Success_{i-1}$ (1/0)	0.375***	0.509**	0.462***	0.397***	0.518***	0.286*	0.585***	0.333**	1.252***	0.217
	(0.123)	(0.238)	(0.173)	(0.131)	(0.170)	(0.153)	(0.197)	(0.137)	(0.257)	(0.135)
Observations	5,649	1,464	1,718	5,445	3,584	3,581	2,465	4,436	1,065	5,783
Pseudo R-Squared	19.0%	23.0%	24.9%	18.2%	22.1%	16.8%	17.3%	19.6%	19.3%	18.8%
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Calendar year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Founding year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Panel B: Firm Failure

	Angel Investor				Investment Timing		Industry Focus			
	High Wealth	Low Wealth	Sophisticated	Not Sophisticated	Close	Not Close	Same Broad	Different Broad	Same Narrow	Different Narrow
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Failure_{i-1}$ (1/0)	0.249**	0.454***	0.343*	0.318***	0.335**	0.307**	0.330*	0.335***	0.919***	0.149
	(0.120)	(0.162)	(0.178)	(0.114)	(0.143)	(0.146)	(0.176)	(0.120)	(0.264)	(0.106)
Observations	5,649	1,460	1,699	5,445	3,584	3,581	2,692	4,436	1,332	5,783
Pseudo R-Squared	9.2%	11.0%	14.0%	7.9%	10.8%	8.4%	10.8%	10.5%	21.4%	8.7%
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Calendar year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Founding year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 7: Do Better Angels Attract Other Firm Financing?

Table 7 reports OLS estimates from running the regression model as shown in Equation 4. The dependent variable in Columns (1)–(2) is the natural logarithm (+1) of *Total Equity*, which is total equity raised by the firm over the sample period, excluding equity provided by the respective angel investor. The dependent variable in Columns (3)–(4) is the natural logarithm (+1) of *Follow − up Equity*, which is total equity raised by the firm in/after the year in which the respective angel investor first invested in the firm, excluding equity provided by the respective angel investor. The dependent variable in Columns (5)–(6) is the angel investor's ownership, calculated as the ratio of total equity provided by the respective angel investor to the total equity raised by the firm from all investors over the entire sample period. *Angel's TVPI* and *Angel's Fixed Effects* represent our two measures of angel investment performance, based upon which angel investors are sorted into performance quintiles, with the highest quintile representing the best-performing angel investors. *Angel's Equity* is the natural logarithm (+1) of the total equity amount provided by the respective angel investor to the firm. 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.

	Firm Financing excl. Angel's Equity				Angel's Ownership	
	Ln(Total Equity+1)		Ln(Follow-up Equity+1)			
	(1)	(2)	(3)	(4)	(5)	(6)
Angel's TVPI						
2nd quintile	-0.067		-0.025		0.011	
	(0.106)		(0.104)		(0.008)	
3rd quintile	0.146		0.156		-0.007	
	(0.119)		(0.115)		(0.008)	
4th quintile	0.196*		0.184*		-0.018**	
	(0.112)		(0.110)		(0.008)	
5th quintile	0.381***		0.322***		-0.039***	
	(0.077)		(0.073)		(0.006)	
Angel's Fixed Effects						
2nd quintile		0.302***		0.273***		-0.041***
		(0.056)		(0.051)		(0.007)
3rd quintile		0.534***		0.480***		-0.070***
		(0.071)		(0.067)		(0.007)
4th quintile		0.878***		0.806***		-0.090***
		(0.115)		(0.115)		(0.008)
5th quintile		0.947***		0.823***		-0.094***
		(0.109)		(0.105)		(0.008)
Angel's Equity	1.620***	1.294***	1.728***	1.392***	-0.008*	0.016***
	(0.073)	(0.051)	(0.065)	(0.049)	(0.005)	(0.005)
Observations	29,589	12,633	29,589	12,633	29,589	12,633
Adjusted R-squared	36.3%	35.6%	35.1%	35.1%	14.5%	13.4%
Calendar year FE	YES	YES	YES	YES	YES	YES
Founding year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES

Table 8: Do Better Angels Attract Venture Capitalists?

Table 8 reports logit (Columns (1)–(2)) and OLS (Columns (3)–(6)) estimates from running the regression model as shown in Equation 4. The dependent variable in Columns (1)–(2) is a dummy variable taking the value of one if a VC investor invests in the firm, either through a financing round or through secondary trades. Columns (3)–(6) condition on a VC investing in the firm. The dependent variable in Columns (3)–(4) is the natural logarithm (+1) of the $VC\ Equity$, which is the total VC equity invested in the company. The dependent variable in Columns (5)–(6) is the natural logarithm (+1) of the $Follow-up\ VC\ Equity$, which is the equity a VC invests in the firm in/after the year when the respective angel investor first invested in the firm. $Angel's\ TVPI$ and $Angel's\ Fixed\ Effects$ represent two measures of angel investment performance, based upon which angel investors are sorted into performance quintiles, with the highest quintile representing the best-performing angel investors. $Angel's\ Equity$ is the natural logarithm (+1) of the total equity amount provided by the respective angel investor to the firm. 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.

	VC Financing (1/0)		Ln(VC Equity+1)		Ln(Follow-up VC+1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Angel's TVPI						
2nd quintile	-0.016		-0.129		0.066	
	(0.233)		(0.307)		(0.300)	
3rd quintile	-0.178		-0.234		-0.160	
	(0.177)		(0.227)		(0.232)	
4th quintile	-0.016		0.250		0.148	
	(0.175)		(0.227)		(0.244)	
5th quintile	0.540***		0.536**		0.275	
	(0.177)		(0.228)		(0.233)	
Angel's Fixed Effects						
2nd quintile		-0.011		-0.018		-0.086
		(0.120)		(0.178)		(0.176)
3rd quintile		0.171		0.281		0.115
		(0.138)		(0.187)		(0.194)
4th quintile		0.219		0.584**		0.396*
		(0.168)		(0.233)		(0.240)
5th quintile		0.631***		0.734***		0.333
		(0.190)		(0.254)		(0.261)
Angel's Equity	0.623***	0.446***	0.378***	0.334***	0.442***	0.422***
	(0.087)	(0.088)	(0.085)	(0.082)	(0.089)	(0.086)
Observations	29,326	12,509	3,443	1,973	3,443	1,973
Pseudo/Adjusted R-squared	13.3%	10.5%	29.1%	28.2%	21.0%	19.9%
Calendar year FE	YES	YES	YES	YES	YES	YES
Founding year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES

Table 9: Do Better Angels Do Better in the Public Market?

Table 9 evaluates the relationship between angel investor's performance and their performance in the public market and reports OLS estimates from running the regression shown in Equation 5. The dependent variable is the market-adjusted daily (realized) return, which is computed as the daily stock return over the angel investor's investment period less the daily return of the Oslo Børs Benchmark Index (OSEBX) over the same period. For unrealized investments, we calculate paper gains with the realization date being the latest observable date with a quoted stock price. The dependent variable is winsorized at the 1^{th} and 99^{th} percentiles. $Performance$ is a continuous investor-level measure of angel investment performance, measured either as the natural logarithm (+1) of the investor's average realized $TVPI$ in all her angel investments (Columns (1)–(5)) or the investor-specific conditional mean return (Columns (6)–(10)) from recovering investor fixed effects from the regression in Equation 1, as shown in Table 2 Column (4). We include a set of dummy variables for different types of angel investors (single-firm, multifirm, wealthy, multifirm and wealthy and sophisticated angels). The omitted category in all estimations is the single-firm angel. We include controls (results untabulated) for the investor and investment characteristics shown in Equation 1 and Table 2. 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.

	Performance Measured as Angel Investor's TVPI					Performance Measured as Investor Fixed Effects				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Performance	0.015***	0.004	0.085***	0.011**	0.015**	0.021**	-0.026**	0.078***	-0.002	0.004
	(0.005)	(0.006)	(0.009)	(0.006)	(0.006)	(0.009)	(0.010)	(0.018)	(0.010)	(0.010)
Multifirm (1/0)		0.002					-0.015*			
		(0.008)					(0.009)			
Performance×Multifirm		0.033***					0.104***			
		(0.012)					(0.015)			
Wealthy (1/0)			0.235***					0.209***		
			(0.015)					(0.019)		
Performance×Wealthy			-0.085***					-0.071***		
			(0.010)					(0.020)		
Multifirm and Wealthy (1/0)				0.040***					0.015	
				(0.008)					(0.009)	
Performance×Multifirm and Wealthy				0.012					0.062***	
				(0.010)					(0.015)	
Sophisticated (1/0)					-0.073***					-0.129***
					(0.010)					(0.013)
Performance*Sophisticated					-0.009					0.021
					(0.008)					(0.016)
Observations	987,488	987,488	986,260	986,260	987,488	588,021	588,021	587,735	587,735	588,021
Adjusted R-squared	1.1 %	1.1 %	1.2 %	1.1 %	1.1 %	1.4 %	1.4 %	1.5 %	1.4 %	1.5 %
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 10: Better Angels and Risk-Adjusted Returns

Table 10 replicates Table 9 but replaces the dependent variable by the Sharpe ratio, calculated as the daily stock return less the average daily risk-free (Norwegian Overnight Interbank (NOWA)) rate, divided by the standard deviation of the daily stock return, all measured over the angel's investment period. For unrealized investments, we assume that the realization date is the latest observable date with a quoted stock price. The dependent variable is winsorized at the 1^{th} and 99^{th} percentiles. $Performance$ is a continuous investor-level measure of angel performance, measured either as the natural logarithm (+1) of the investor's average realized $TVPI$ in all her angel investments (Columns (1)–(5)) or the investor-specific conditional mean return (Columns (6)–(10)) from recovering investor fixed effects from the regression in Equation 1, as shown in Table 2 Column (4). We include a set of dummy variables for different types of angel investors (single-firm, multifirm, wealthy, multifirm and wealthy and sophisticated angels). The omitted category in all estimations is the single-firm angel. We include controls (results untabulated) for the investor and investment characteristics shown in Equation 1 and Table 2. 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.

	Performance Measured as Angel Investor's TVPI					Performance Measured as Investor Fixed Effects				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Performance	0.010***	0.010***	0.038***	0.013***	0.011***	0.022***	0.020***	0.052***	0.026***	0.022***
	(0.002)	(0.002)	(0.005)	(0.002)	(0.002)	(0.004)	(0.005)	(0.009)	(0.005)	(0.004)
Multifirm (1/0)		0.007*					0.002			
		(0.004)					(0.004)			
Performance$times$Multifirm		-0.000					0.007			
		(0.004)					(0.006)			
Wealthy (1/0)			0.092***					0.081***		
			(0.006)					(0.008)		
Performance$times$Wealthy			-0.033***					-0.035***		
			(0.005)					(0.009)		
Multifirm and Wealthy (1/0)				0.019***					0.010**	
				(0.004)					(0.004)	
Performance$times$Multifirm and Wealthy				-0.009**					-0.008	
				(0.004)					(0.006)	
Sophisticated (1/0)					-0.002					-0.016***
					(0.005)					(0.005)
Performance*Sophisticated					-0.004					-0.002
					(0.005)					(0.009)
Observations	835,196	835,196	834,154	834,154	835,196	490,554	490,554	490,272	490,272	490,554
Adjusted R-squared	1.4 %	1.4 %	1.5 %	1.4 %	1.4 %	1.5 %	1.5 %	1.6 %	1.5 %	1.5 %
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES