Angels and Venture Capitalists: Complementarity versus Substitution, Financing Sequence, and Relative Value Addition to Entrepreneurial Firms *

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Abstract

Using a large sample of angel and venture capital (VC) financing data from the Crunchbase and VentureXpert databases and private firm data from the NETS database, we address three important research questions. First, we analyze the relative extent of value addition by angels versus VCs to startup firms. We show that startups financed by angels rather than VCs are associated with a lower likelihood of successful exit (IPO or acquisition), lower sales and employment growth, lower quantity and quality of innovation, and lower net inflow of high-quality inventors. We disentangle selection and monitoring effects using instrumental variable (IV) and switching regression analyses and show that our baseline results are causal. Second, we investigate the complementarity versus substitution relationship between angel and VC financing. We find that a firm that received a larger fraction of VC or angel financing in the first financing round is likely to receive a larger fraction of the same type of financing in a subsequent round; however, when we include other non-VC financing sources such as accelerators and government grants into the analysis, a firm that received angel (rather than other non-VC) financing in the first round is also more likely to receive VC financing in a subsequent round. Third, we analyze how the financing sequence (order of investments by angels and VCs across rounds) of startup firms is related to their successful exit probability. We find that firms that received primarily VC financing in the first round and continued to receive VC financing in subsequent rounds (VC-VC) or those that received primarily angel financing in the first round and received VC financing in subsequent rounds (Angel-VC) have a higher chance of successful exit compared to those with other financing sequences (VC-Angel or Angel-Angel).

Keywords: Angels; VCs; Successful Exit; Value Addition; Financing Sequence
JEL Codes: G23, L26, O34

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1 Introduction

Angel Investors (angels) and venture capital (VC) investors are two of the most important types of financiers investing in entrepreneurial firms not only in the U.S., but also around the world. A 2011 report by the OECD mentions that in 2009 the total amount of capital investment made by angel investors (angels) in the U.S. was $17.7 billion, which is similar to the $18.7 billion investment made by VCs.[1] Practitioners, particularly VCs, often believe that, while angels are important in providing seed capital to firms, they lack in "due-diligence" ability compared to VCs. Further, they also assume that angels are less capable than VCs in adding value to start-up firms.[2] However, there is an alternative view that VCs and angels do not differ in terms of adding value to start-ups. For example, an article by AngelList mentions that the presence of top VCs in a seed funding round of a start-up does not affect the probability of receiving a Series A funding for the start-up.[3] It is therefore important to empirically analyze and compare the value added to start-ups by angels and VCs. However, the existing finance literature has not yet empirically analyzed and compared the value-addition by VCs versus angels.[4] The objective of this paper is to fill this gap in the literature.

In this paper, we use several private firm data sets to address three important research questions. First, we compare the extent of value addition by angels versus VCs. We use several important measures to capture value additions: the probability of successful exits (IPO or acquisitions), the quantity and quality of innovation output; sales growth; employment growth; and the net inflow of high-quality inventors to start-ups. Second, we analyze whether VCs and angel financing are complements or substitutes.[5] Third, we examine the effect of financing sequence or the order of investment by VCs and angels into a start-up firm on the likelihood of its successful exit.

We compile our private firm data from various sources. We collect round by round financing information on U.S. start-ups from CrunchBase and VentureXpert. While Crunch-

[1] Please refer to the following report for greater detail: http://www.oecd.org/sti/financinghigh-growthfirmstheroleofangelinvestors.htm

[2] Please refer to an article in the Wall Street Journal, titled, "AngelList And Beyond: What VCs Really Think Of Crowdfunding," which includes comments from VCs who mentioned that angels have a lower ability to add value compared to VCs.

[3] Please refer the article here: https://www.angellist.com/blog/top-vc-seed-performance.

[4] The existing literature has examined the impact of VC-backing on the performances of start-up firms (Bernstein, Giroud, and Townsend (2016); Chemmanur, Krishnan, and Nandy (2011); Hellmann and Puri (2000); Hellmann and Puri (2002) among others) and the impact of angel investors on start-ups (Denes, Howell, Mezzanotti, Wang, and Xu (2020); Kerr, Lerner, and Schoar (2014); Lerner, Schoar, Sokolinski, and Wilson (2018), among others), separately.

[5] Hellmann, Schure, and Vo (2021) have empirically analyzed the "complementarity" versus "substitutability" of angels and VC using data from British Columbia, Canada.

base provides information on aggregate funding per investment round at start-ups, VenturеXpert provides information on the investment made by an individual VC in each investment round. We obtain the fraction of VC investment in an investment round using the above two datasets. The successful exits of start-ups in terms of initial public offerings (IPO) or acquisitions are also collected from CrunchBase, which also provides information on the founding years of start-ups. We use the National Establishment Time Series (NETS) dataset to obtain information on the sales and employment levels of private firms. Our patent and inventor data is obtained from the United States Patent and Trademark Office (USPTO) dataset shared on PatentsView. Using the above datasets, we construct our main outcome variables for start-ups: the probability of a successful exit (IPO versus acquisition), the annual sales and employment growth of private firms, the quantity and quality of patents granted to start-up firms (standard measures of innovation output), and the net inflow of inventors and high-quality inventors. In most of our analysis, we focus on firms that have received only angel or VC-financing or both in the first round of investment at firms, i.e., we exclude firms that have received financing from other categories of investors such as accelerators or government grants. This allows us to use the fraction of angel financing received by a firm as the main independent variable.[6] Our main sample covers 5,586 U.S. start-up firms financed between 1990 to 2015.

We now discuss the results of our empirical analysis. We start with baseline analyses to compare the effects of VC versus angel financing on start-ups' performance. Our main independent variable is the fraction of angel investment in the first round of financing for a start-up. In our analyses, we focus on investor composition at the first investment round itself, since the types of investors who participate in later investment rounds are likely to be affected by the types of early-stage investors. This approach enables us to distinguish between the value added by angels versus that by VCs given that they invest at the same stage of a start-up's life cycle.[7]

First, we show that firms with a higher fraction of angel investment in their first financing round are associated with a smaller likelihood of successful exit either through an IPO or an acquisition. Our results are statistically and economically significant. A one standard deviation increase in the fraction of angel investment (relative to VC investment) in the first financing round is associated with a 0.6 percentage point decrease in the probability of a firm

[6]Note that in the sample of start-up firms with only angel or VC financing, the fraction of VC financing is the complement of the fraction of angel financing.

[7]Ewens, Nanda, and Rhodes-Kropf (2018) show that technological shocks changed the investment strategies of VCs, leading to VCs investing smaller amounts across a larger pool of startups ("spray and pray" investment strategy). They also mention that, following the technological shocks, there is an increase in the participation of VCs in early-stage financing rounds of startup firms.

conducting an IPO in the future. This is equivalent to a decrease of 11.1 percentage in the average probability of an IPO. Further, a one standard deviation increase in the fraction of angel investment in the first financing round is associated with a decrease of 17.7 percentage in the average probability of a successful exit.

Second, we show that firms with a higher fraction of angel investment in their first financing round are associated with smaller sales growth. A one standard deviation increase in the fraction of angel investment in the first financing round is associated with a 9.3 percentage point smaller growth rate of sales in one year after receiving the first round of investment. This is equivalent to a decrease of 25.6 percentage in the average sales growth in the next year after the first round of investment. We find similar results for sales growth for the second and the third year after the first financing round. Lastly, we show that firms with a higher fraction of angel investment in their first financing round are associated with smaller employment growth. A one standard deviation increase in the fraction of angel investment in the first financing round is associated with an 8.8 percentage point smaller annual employment growth rate one year after the first round of investment. We find similar results for employment growth for the second and the third year after the first financing round.

Third, we show that firms with a higher fraction of angel investment in their first financing round are associated with a smaller quantity and quality of innovation output. Our results are statistically and economically significant. A one standard deviation increase in the fraction of angel investment in entrepreneurial firms' first financing round is associated with a 13.2 percentage point decrease in the number of patents applied (and eventually granted) within the next three years after receiving investment, which is equivalent to a decrease of 24.8 percentage in the average number of patents applied (and eventually granted) within the next three years. Similarly, a one standard deviation increase in the fraction of angel investment in entrepreneurial firms' first financing round is associated with a decrease of 30.5 percentage in the average of citations on patents applied (and eventually granted) within the next three years. We find similar results for innovation output for the second and the third year after the first financing round.

Fourth, we show that firms with a higher fraction of angel investment in their first financing round are associated with a smaller net inflow of inventors and a smaller net inflow of top-quality inventors. Again, our results are statistically and economically significant. A one standard deviation increase in the fraction of angel investment in entrepreneurial firms' first round of financing is associated with a decrease of 1.3 percentage point in the net inflow of top inventors within the next three years, which is equivalent to a decrease of 33.9 percentage in the average net inflow of top inventors within the next three years.

Our baseline analyses may suffer from a common endogeneity concern in the entrepreneurial finance literature: "selection" versus "value-addition" (or monitoring). In other words, do VCs have a better ability to select start-ups or do they have better monitoring abilities compared to angel investors or do both factors play important roles? To disentangle the selection versus value-addition effect, we use two methodologies: instrumental variable (IV) analyses and switching regression analyses.

First, for our IV analyses, we construct two IVs for our key variable of interest, the fraction of angel investment in the first round of financing for entrepreneurial firms. Our first IV is a dummy variable for the angel tax credit following Denes et al. (2020), which equals one if a firm is located in a state that has an active angel tax credit program. The angel tax credit will affect the supply of angel funding, without affecting the supply of VC funding. Our second IV is constructed using the portfolio returns of limited partners (LPs) of VCs following Samila and Sorenson (2011). Given that it has been documented that LPs have a home bias in their investment strategies and that they allocate a fixed ratio of funds to VCs, past returns of LPs in a state will affect the supply of VC funding to start-ups in the state (see, e.g., Samila and Sorenson (2011)). Our IV analyses using the above two IVs show that angels add less value to start-ups than VCs. In other words, angels have lower monitoring ability compared to VCs. First, we show that a higher fraction of angel investment in the first round causally leads to a smaller probability of successful exit through an IPO or an acquisition. Second, we show that a higher fraction of angel investment in the first round causally leads to smaller sales and employment growth. Third, we show that a higher fraction of angel investment in the first round causally leads to a smaller quantity and quality of innovation output. Lastly, we show that a higher fraction of angel investment in the first round causally leads to a smaller net inflow of inventors and top-quality inventors to start-ups.

The second methodology we employ is the "switching regression with endogenous switching" approach, which accounts for unobservable factors that may affect both the probability of receiving angel or VC financing for a start-up firm as well as the start-up's future performance in terms of successful exit, sales growth, and employment growth, innovation output, and the net inflow of top-quality inventors. The results from this analysis can provide answers to the following "what-if" questions: what would be the future outcome for start-ups that are initially VC-backed if they had not received any VC financing, or in other words, received financing only from angel investors? Similarly, what would be the future outcome for start-ups that are initially only angel-financed if they had received financing from VCs? The difference between the actual outcome and the counterfactual outcome of entrepreneurial firms generated from the above analyses represents the gap caused by differences in the monitoring (value-adding) abilities of angels and VCs. Specifically, we find that VC-backed firms have a higher likelihood of having a successful exit, higher sales growth, and higher employment growth, greater quality and quantity of innovation output, and a larger net inflow of inventors compared to the counterfactual (hypothetical) scenario if they had received financing only from angels. Similarly, we find that firms financed by angels alone could have enjoyed a significant increase in the likelihood of having a successful exit, greater sales growth and employment growth, greater innovation output, and a greater net inflow of inventors had they received VC investment (counterfactual). In summary, our IV analyses and switching regression analyses disentangle the selection effect from the value addition effect and suggest that angels have a lower ability to add value to start-ups compared to VCs.

We also conduct additional robustness tests to address some potential concerns with our findings. One may argue that our results showing that angel investors add less value to start-ups than VCs are driven by unsophisticated angel investors, who provide funds to their friends and families. To address this concern, we restrict our sample to first-round angel investments that include at least one sophisticated angel investor, e.g., angel groups or "serial" angel investors. We show that all our main IV analyses hold in the above subsample. Further, we also repeat our IV analyses on subsamples of first investment rounds comprising only VCs or angel groups. We find that VCs add more value than angel groups, thereby addressing the above concern. Another potential concern is that VCs and angels invest in separate industries because of their different specializations. In order to test whether angels add less value than VCs only in certain industries, we conducted an additional subsample analysis based on industry categories. We identify high technology (HiTech), manufacturing, and healthcare as three industry categories where VCs may dominate in providing financing. We use the Fama-French 10 classification to identify the above industries. We find that angels add less value than VCs in both VC-dominated and other industries, thereby addressing the above concern.

Next, we study the relationship between angels and VCs: we test whether angels and VCs are "complements" or "substitutes." In other words, does a start-up receiving a larger fraction of angel financing in its first round make it more or less likely to receive VC financing in a subsequent round? Further, does receiving a larger fraction of VC financing in the first round of financing make the start-up more likely to receive a larger fraction of VC financing in its later round? For this analysis, we include firms financed by syndicates consisting of not only VCs and angels but also by other types of investors such as accelerators and governments.[8] We find that having a greater fraction of VC financing in the first round makes a firm more likely to have a larger fraction of VC financing in its next round of financing. However, having an angel investor present in the first round of financing also makes a firm more likely to receive a higher fraction of VC investment in the next round. Our result stands in contrast to the findings of Hellmann et al. (2021) using British Columbia (Canada) data on start-ups; they find that angels and VCs are substitutes and invest in different industries. Our findings support the prediction of the theoretical model of Chemmanur and Chen (2014), who suggest that angels and VCs are complements and that angels prepare start-ups for future VC investments. The above findings are consistent with angel financing serving as a way to make a start-up viable and "VC-ready" if it did not get VC financing in the first round. However, we also find that a greater fraction of VC investment in the first round is associated with a smaller likelihood of participation of angels in the next round, while the presence of angels rather than VCs in the first round is associated with a higher likelihood of participation of angels in the next round of financing. Overall, the above analyses suggest that angels and VCs cannot be classified solely as complements or substitutes in the financing of entrepreneurial firms. Further, they suggest that the relationship of angel investors and VCs is complex: angels and VCs may act as either complements or substitutes.

We also examine the relationship between start-ups' financing sequence (the order of investments made by angels and VCs in various rounds) and their probability of subsequent successful exits (IPOs or acquisitions). In this analysis, we only include firms that either received only angel or VC investments (or both) in their first two rounds of financing. Thus, we are able to define a dominant financier based on the fraction of investment in a funding round, i.e., we define VCs as a dominant financier if the fraction of aggregate VC investment in a round is greater than 50 percent, and similarly for angels. We categorize four financing sequences based on the first two rounds of investment: from angel-dominated to VC-dominated (angel-to-VC), from VC-dominated to angel-dominated (VC-to-angel), from VC-dominated to VC-dominated (VC-to-VC), and from angel-dominated to angel-dominated (angel-to-angel). We find that firms with VC-to-VC or angel-to-VC financing sequences have a greater likelihood of successful exit compared to angel-to-angel and VC-to-angel financing sequences. The above results are consistent with the theoretical predictions of Chemmanur and Chen (2014), who argue that venture capital investments in early rounds are positive signals of start-up firms' quality resulting in a higher chance of successful exit, while venture exits in later rounds convey negative signals about firm quality, leading to a smaller probability of successful exit for such firms.

[8] Given that we include intermediaries other than angels and VCs, the fraction of angel financing is no longer the complement of VC financing in the empirical analysis of this research question.

The rest of the paper is organized as follows. Section 2 discusses how our paper contributes to the related literature. Section 3 discusses the underlying theory that we use to develop our testable hypotheses. Section 4 describes our data sources and the construction of variables. Section 5 describes our baseline analysis, where we compare the effect of VCs versus angels on start-ups' performance. Section 6 presents our results using IV and switching regression analyses to disentangle the effects of screening and monitoring ability of angels and VCs on start-ups' future performance. Section 7 discusses our robustness tests. Section 8 presents the results of our analysis on whether angels and VCs are complements or substitutes. Section 9 presents our analysis of the impact of the financing sequence of investors at start-ups on the likelihood of start-up firms' successful exits. We conclude the paper in Section 10.

2 Related Literature and Contribution

Our paper contributes to several strands in the literature. First, we contribute to the recent growing literature on the impact of angel investors on the future performance of start-ups. Kerr et al. (2014) and Lerner et al. (2018) show that professional angel groups have significant positive impact on the performance of their portfolio firms. Denes et al. (2020) show that, although investor tax credits increase angel financing, they do not have a significant effect in promoting high-growth entrepreneurship. Lindsey and Stein (2019) have shown the impact of a regulatory change in the accreditation standard of angel investors on the aggregated employment, while Xu (2019) studies the impact of changes in the above accreditation standard of angel investors on the local economy in terms of entrepreneurial firms' innovation, sales, successful exits and the costs and benefits of above regulatory changes on the local economy. In contrast, ours is the first paper in the literature to show that VCs provide greater value addition to start-ups compared to angels, i.e., VCs are causally related to a higher likelihood of successful exit, higher innovation output, higher sales and employment growth for start-ups compared to angels.

Second, our paper also contributes to the large literature on the impact of VC investors in various dimensions of firm performance. Prior literature has shown that VCs improve the efficiency of private firms (Chemmanur et al. (2011)), enhance the professionalization of start-up firms (Hellmann and Puri (2002)), and VCs' monitoring and tolerance of failure leads to an increase in innovation and the likelihood of going public (Bernstein et al. (2016); Tian and Wang (2014)). Chemmanur, Loutskina, and Tian (2014) have compared the effect of independent versus corporate VCs on firm innovation. In contrast, our paper shows that VCs add greater value than angels and also provides evidence that the financing sequence of an entrepreneurial firm is associated with its successful exit. Thus, our paper connects the two strands of the finance literature on angel and VC financing by comparing the value added by the above two types of investors and analyzing the impact of different possible financing sequences involving these two investors.[9]

Third, we contribute to the literature studying the relationship between angels and VCs. Prior studies have posited contrasting predictions on the relationship between angels and VCs. While the theoretical analysis of Hellmann and Thiele (2015) predicts that angels and VCs act as substitutes, Chemmanur and Chen (2014) argue theoretically that angels provide early round of financing to start-ups followed by VC investments in later rounds, suggesting a complementary relationship between VCs and angels. Hellmann et al. (2021) empirically examine the above question using data on start-ups located in British Columbia, Canada, and find that angels and VCs are substitutes. While Hellmann et al. (2021) conduct their analysis on a sample restricted to British Columbia-based firms, we conduct our study, in contrast, using the entire universe of start-ups in the U.S. We find that angels and VCs have a complex relationship in making entrepreneurial firms successful: in other words, this relationship cannot be classified strictly as being either a complementary or a substitution relationship.

3 Theory and Hypotheses

In this section, we discuss the relevant theoretical literature and develop testable hypotheses.

3.1 Angels versus VCs and the Future Success and Performance of Entrepreneurial Firms

In this subsection, we develop our hypotheses on the impact of angels versus VCs on the future success of entrepreneurial firms. On the one hand, the existing theoretical literature has argued that VCs provide various value-adding services to firms that increase their probability of future success (e.g., Chemmanur et al. (2011), Ueda (2004), and others). On the other hand, Kerr et al. (2014) and Lerner et al. (2018) argue that angel investor groups also contribute to the future success of private firms. However, there is general belief among

[9] Existing studies comparing the efficacy of angels versus VC investments in start-ups are based mostly on surveys: see, e.g., Dutta and Folta (2016). In a cross-country study, Cumming and Zhang (2019) show that, compared to private equity (PE) or VC-funded firms, angel-funded firms are associated with a lower propensity for successful exit. However, they do not demonstrate causality in their analysis. In contrast, our paper provides causal evidence that angels add less value to startups than VCs. We do so by analyzing the relative effect of angel versus VC investments on startups' propensity for successful exit, their innovation output, their sales and employment growth, and the net inflow of inventors to these startups.

academics and practitioners that VCs are more capable of identifying and investing in better quality firms (selection) and are more capable in monitoring entrepreneurs and providing other value-adding services. Assuming that VCs are better than angels in selecting entrepreneurial firms and in providing value-adding services, we expect a negative relation between the fraction of angel investment in a start-up and the probability of future successful exit (IPO or acquisition) of the start-up (**H1**). Following the above arguments, we also expect a negative relation between the fraction of angel investment in a start-up and the future growth of the start-up firm as measured by sales growth and employment growth (**H2**).

Prior literature has argued that both angels and VCs contribute to improving the innovation output of investee firms. We expect that VCs are more likely to improve their investee firms' innovation output compared to angels. There are multiple reasons for that. We expect that VCs are better than angels in selecting higher quality firms, which, in turn, are more likely to be innovative, compared to angel-backed firms. We also expect that VCs are better equipped than angels in attracting higher quality talent to entrepreneurial firms, which, in turn, drives the innovation output of investee firms. We also expect that VCs (who act on behalf of limited partners) have greater tolerance for failure compared to angels (who invest their own money). Thus, we expect a negative relation between the fraction of angel investment in a start-up and the future innovation output of the start-up firms (**H3**). Assuming that VCs have a greater network and are more resourceful in attracting high-quality talent to start-ups, we also expect a negative relation between the fraction of angel investment in a start-up and the net inflow of high quality inventors to the start-ups (**H4**).

3.2 Angel and VC Financing: Complements or Substitutes?

In this subsection, we develop our hypotheses on the potential relationship between angels and VCs. There are two opposing sets of view on the relationship between angels and VCs in the investment life-cycle of start-ups. Using a theoretical model, Chemmanur and Chen (2014) show that VCs and angels act as complements and that angels prepare the start-ups to receive VC investment in the future. In other words, their model shows that angels are the early-stage investors and that VCs are the late-stage investor in start-ups, leading to a complementarity between the two kinds of investors. This effect is driven by the scarcity of VC funding. Thus, following the above argument, we expect VCs and angels to act as complements (**H5a**). However, Hellmann and Thiele (2015) and Hellmann et al. (2021) argue that VCs and angels act as substitutes. They argue that VCs and angels cater to different sets of companies and that companies that receive financing from one type of investors in a round are more likely to stick to that same type in future rounds of investment. Based on the later set of argument, we expect angels and VCs to act as substitutes (**H5b**).

3.3 Financing Sequence of Angel and VC Financing across Rounds and Probability of Successful Exit

In this subsection, we develop our hypothesis on the relationship between the financing sequence across investment rounds in firms and the likelihood of their future successful exit. In the setting of the multi-period theoretical model of Chemmanur and Chen (2014), VCs are able to add greater value to entrepreneurial firms, but VC financing is scarce (while angel financing is plentiful). Further, while initially (in earlier rounds) entrepreneurs have private information relative to the external financiers (VCs or angels), this information asymmetry disappears after the first financing round as the outside financier learns more about the firm during the interaction with the entrepreneur in earlier rounds (the entrepreneur's private information is about the nature of the firm and the ability of VCs or angels to add significant value to it). Finally, it is more efficient for the VC to start financing the firm in early rounds from a value-addition point of view (since the contracting between the entrepreneur and the VC is more efficient in the second and subsequent rounds in this case). Chemmanur and Chen (2014) predict the relationship between the financing sequences of start-ups and the probability of their future successful exit. First, firms that received VC funding in early stages followed by more VC funding in later stages (VC-VC) are of highest quality and are most likely to have a successful exit. Second, firms that received angel funding in early stages followed by VC funding in later stages (angel-VC) are of lower quality and are less likely to have a successful exit. Finally, firms that received angel investment in early rounds and continue to be angel financed in subsequent rounds (angel-angel) or firms that received VC investment in early rounds followed by angel investment in later rounds are of the lowest quality and are least likely to have a successful exit (**H6**). This is because in an environment with information asymmetry between the entrepreneur and outside investors regarding the quality of the start-up, early-stage VC investment in the start-up acts as a signal of the start-up's quality since VCs may have better abilities than angels in selecting higher quality firms to invest in. Similarly, if VCs continue to invest in a firm in subsequent rounds, this is an even better signal of a firm's quality. However, an exit of an early-stage VC investor from a start-up is a negative signal since the early-stage VC investor is likely to have negative information about the start-up firm.

4 Data

4.1 Data Sources and Sample Selection

We collate information on start-ups from multiple sources. The primary data source for our paper is Crunchbase, a leading open-source database collecting profiles of start-ups and information on their financing.[10] Specifically, we obtain the name, location, founding date, and the status of IPO or acquisition of firms and the names and types of investors as well as the total amount of investment for each round of transaction from CrunchBase. We supplement investor composition information from CrunchBase with data from VentureXpert, which provides information on the investment made by a given VC in an investment round at a firm. By merging our data on the total aggregate investment amount per round from CrunchBase with the investment made by an individual VC per round from VentureXpert, we calculate the percentage of the amount raised in a financing round from VC investors.

To measure the innovation output of entrepreneurial firms after receiving investment, we collect patent data from the United States Patent and Trademark Office (USPTO) dataset hosted on the website, PatentsView. The USPTO data on PatentsView provide detailed information on the application date, the technology classes, and citations of a patent as well as the name, unique identification number, and the location of assignees or firms filing the patents. The USPTO data also provides patent inventor information with a unique identifier. We obtain data on employment and sales for entrepreneurial firms from the National Establishment Time-Series (NETS), which is a longitudinal database provided by Dun & Bradstreet and is widely used in research on private firms.[11] We match firms in CrunchBase, VentureXpert, the USPTO database, and the NETS database based on firm name and location. Our final sample covers start-ups from 1991 to 2015.[12]

For our analysis comparing the value added to entrepreneurial firms by angel investors versus VCs and examining the impact of financing sequences on successful exits, we restrict our sample to firms that receive investments from either only VCs or only angel investors or both in their first investment round. For our analysis on complementarity versus substitutability of VCs and angels, we include firms financed by all categories of investors, which not only include VCs and angels, but also include other kinds of investors such as accelerators and government grants.

[10] Many studies have used data from CrunchBase, some examples include Denes et al. (2020), Wang (2018), Xu (2019), and Yu (2020).

[11] See Neumark, Wall, and Zhang (2010) for a more detailed description of the NETS data set.

[12] We restrict our sample to first-round investment to 2015 so that we have around five years to observe their future potential IPO or acquisition. However, our results on successful exits (IPOs or acquisitions) are robust to restricting our sample to 2010 so that we have more time to observe future exits of start-ups.

4.2 Variable Construction

The primary independent variable in our paper is the investor composition, or the percentage of investment made in the first investment round in a start-up by VCs. After merging data on start-ups from CrunchBase with the startup-data on VentureXpert, we compute the fraction of VC investment of the total investment received by a firm in its first financing round (*1st-round_VC%*).[13] Since we restrict our sample to include firms either receiving only angel or only VC investment or both in most of our analysis, the fraction of angel investment would naturally be one minus the fraction of VC investment and we denote it by *1st-round_angel%*. Using data from CrunchBase, we also construct a dummy, *1st-round_has_angel*, which is equal to one if there is at least one angel investor investing in the round and is equal to zero otherwise. We also show trends of VC and angel investments in the first investment round of start-ups. We identify VC- and angel-dominated investment rounds based on the fraction of investment by the two categories of investors in a round. If round receives at least fifty percentage investment from angel investors, it is classified as an angel-dominated round, otherwise, it is classified as a VC-dominated round. We show in figure 1 the trends in angel-dominated first investment rounds compared to VC-dominated rounds.[14]

[Insert Figure 1 about Here]

Following the existing literature, we construct standard measures of successful exits (IPO or acquisition) for entrepreneurial firms. Using data from CrunchBase, we construct three dummy variables, *IPO*, *Acq*, and *Exit*. *IPO* equals one if a firm has conducted an IPO after its first financing round and zero otherwise. *Acq* is equal to one if a firm has been acquired after the first financing round and zero otherwise. *Exit* takes a value of one if a firm either has been acquired or has gone public after the first round of financing and zero otherwise. We show trends of successful exits, IPOs, and acquisition for VC- and angel-dominated rounds in figures 1 and 2. We find that start-ups whose first investment rounds are dominated by VCs are associated with greater fraction of successful exits, IPOs, and acquisitions, compared to start-ups that have angel-dominated first investment rounds.

[Insert Figure 2 about Here]

To evaluate how angels and VCs have different effects on the future sales and employ-

[13] We focus on the first investment round since financing and value-addition at initial stages of start-ups are important for their future growth. This approach also enables us to distinguish between value added by angels versus that by VCs when they invest at the same investment round in a start-up. Further, the participation of different categories of investors in later rounds of investments may be driven by the original investors who participated in the first round of investment or fundraising for a start-up.

[14] Given that we restrict our sample to first round of investments where only VCs or angel investors are involved, our number of observations are smaller in the early 1990s. While plotting the trends on angel- and VC-dominated first rounds of investments, we restrict our sample to years where at least five start-ups received their first rounds of investments from only VCs or angel investors.

ment of entrepreneurial firms, we construct growth rates of sales and employment using our NETS data set. Specifically, we calculate the annual growth rate of sales in the first year after the first financing round (*Sales growth (Year 0 to 1)*), the growth rate of sales in the second year after the first round of investment (*Sales growth (Year 1 to 2)*), and the growth rate of sales in the third year after the first financing round (*Sales growth (Year 2 to 3)*). Similarly, we construct *Employment growth (Year 0 to 1)*, *Employment growth (Year 1 to 2)*, and *Employment growth (Year 2 to 3)* as the annual growth rate of employment in the first, second, and third year after the first financing round, respectively.

To compare angels and VCs on their impact on firms' innovation, we construct standard measures of the quantity and quality of patents generated in the years after the first round of financing. To measure the quantity of innovation, we construct the natural logarithm of one plus the total number of patents applied (and eventually granted) by a firm within one year after its first round of financing and denote the variable as *Patents (1 year)*. Similarly, we construct the natural logarithm of one plus the total number of patents applied (and eventually granted) within two and three years after its first round of financing as *Patents (2 years)* and *Patents (3 years)*, respectively. To measure the quality of innovation, we calculate the natural logarithm of one plus the total number of forward citations of the patents which were applied by a firm within one year after its first round of financing (*Citations (1 year)*), within two years after the first round of financing (*Citations (2 years)*), and in three years after the first round of financing (*Citations (3 years)*). Patents data are subject to truncation biases. First, there is a lag between when a patent is applied and when it is granted. Second, patents granted in earlier years are likely to have higher citations than patents granted in later years, on average. Following Seru (2014), we address this problem by dividing each patent of a firm in a filing year by the mean number of patents for all firms for that year having the same 3-digit technology class as the patent. We address truncation bias in citations by scaling the citations of a given patent by the total number of citations received by all patents filed in that year in the same 3-digit technology class as the patent (Seru (2014)).

We construct our inventor mobility measures following Chemmanur, Kong, Krishnan, and Yu (2019) and Marx, Strumsky, and Fleming (2009). For a given firm, an inventor's move-in year is the year when she filed her first patent in this firm (or when she files her first patent at the firm after moving our from a different firm); her move-out year is the year when she filed her first patent in a different firm. In case of the last patent filed by the inventor, we assume that she remains in the firm till the end of our sample period.[15] Once we identify each mobile inventor's move-in and move-out year, we aggregate the number

[15]Inventors that have only filed one patent are excluded from our sample as we can only identify the inventor flow based on at least two patent filings.

of mobile inventors that move in and move out at the firm-year level to obtain the total inflows and outflows of mobile inventors for a given firm in a year. We then construct a set of variables (*Net Inflow of Inventors (1 Year)*, *Net Inflow of Inventors (2 Years)*, and *Net Inflow of Inventors (3 Years)*), defined as the difference between the natural logarithm of one plus the inflow and the natural logarithm of one plus the outflow of inventors within the subsequent one, two, and three years, respectively, after an entrepreneurial firm received its first round of financing. To further examine the innovative ability of inventors, we look at a specific set of top-quality inventors who filed patents with a higher number of citations. We define top-quality inventors as those with average citations per patent for all the patents he has filed prior to the current year above the sample's top quartile (top 25 %) of citations in the year. Similarly, we construct the net inflows of the top-quality inventors for each entrepreneurial firm within one, two, and three years after they received their first-round of financing (*Net Inflow of Top 25% Inventors (1 Year)*, *Net Inflow of Top 25% Inventors (2 Years)*, and *Net Inflow of Top 25% Inventors (3 Years)*).

4.3 Summary Statistics

Table 1 shows the summary statistics of our sample. To alleviate the concern that outliers may drive our results, we winsorize all variables at the 1st and 99th percentiles in the regressions.

[Insert Table 1 about Here]

Our final sample contains 5,583 firms with their first round of investor composition information and future firm performances. We show in Table 1 that for our sample of firms receiving only angel or VC financing or both, the average fraction of angel investment is 30 percent of the total investment in the first round of financing (or 70 percent for VC investment). On average, 26 percent of the sample start-up firms have at least one angel investor participating in the first financing round. The IPO rate of firms in our sample is 6 percent and the rate of being acquired by other firms in our sample is 38 percent.

5 Angel versus VC and Entrepreneurial Firms' Future Performances: Baseline Analyses

In this section, we examine how investor composition for entrepreneurial firms in terms of angel versus VC is associated with their future performances, using ordinary least squares (OLS) analyses for our baseline analyses. Specifically, we analyze the impact of the fraction of angel investment on successful exits (i.e., IPO or acquisition), sales growth, and employment growth, the quantity and quality of innovation output, and the net inflow of inventors estimating the following the model:

$$Y_{i,t+X} = \alpha + \beta 1st - round\_angel\%_{i,t} + Controls_{i,t} + Year_t + Industry_i + \epsilon_{i,t+X}, \qquad (1)$$

where i represents a firm and t is the year of the first round of financing. $Y_{i,t+X}$ is a set of dependent variables related to the future performance of entrepreneurial firms after receiving their first financing round, which are described above. The key variable of interest is *1st-round_angel%*, which equals the fraction of angel investment in the total amount received in the financing round. A financing round is fully financed by angel investors if *1st-round_angel%* takes the value of one and is fully financed by VCs if *1st-round_angel%* equals zero. We control for the natural logarithm of one plus the age of the firm when receiving the investment (*lnage*) and the natural logarithm of one plus the amount of sales in the year (*lnsales*). We include a set of dummies each representing a two-digit SIC code ($Industry_i$) to account for unobservable industry-specific characteristics. We add investment year fixed effects ($Year_t$) to control for time-specific shocks that may affect our analysis. In all regressions, we cluster standard errors at the two-digit SIC code level.

5.1 Successful Exits

We first examine how the composition of angels and VCs affects successful exits of entrepreneurial firms. A successful exit for investors is defined as either having an IPO or being acquired by other firms.

[Insert Table 2 about Here]

Table 2 reports the results. In Column (1), the dependent variable is *IPO*, which takes the value of one if a firm becomes public after the first financing round and zero otherwise. The coefficient estimate on *1st-round_angel%* is negative and statistically significant at the 5 percent significance level. The magnitude suggests that a one standard deviation increase in the fraction of angel investment (relative to VC investment) in the first financing round is associated with a 0.6 percentage point decrease in the probability of a firm conducting an IPO in the future. This is equivalent to a decrease of 11.1 percentage in the average probability of an IPO. In Column (2), we replace the dependent variable with *Acq*, which equals one if a firm has been acquired after the first financing round and zero otherwise. The coefficient estimate on *1st-round_angel%* in Column (2) is also negative and statistically significant at the 1 percent level. The magnitude suggests that a one standard deviation increase in the fraction of angel investment (relative to VC investment) in the first financing round is associated with a 7.2 percentage point decrease in the probability of a firm getting acquired in the future, which is equivalent to a decrease of 18.8 percentage in the average probability of getting acquired. In Column (3), we use *Exit* as the dependent variable, which equals one if a firm has either been acquired or has conducted an IPO after the first financing round, and zero otherwise. The coefficient estimate on *1st-round_angel%* is both negative and statistically significant at the 1 percent level. A one standard deviation increase in the fraction of angel investment (relative to VC investment) in the first financing round is associated with a decrease of 17.7 percentage in the average probability of a successful exit.

The above results suggest that firms receiving more angel investment relative to VC investment in their first financing round are associated with a smaller probability of successful exits in the future, which supports our hypothesis **H1**.

5.2 Sales Growth and Employment Growth

Next, we examine how the composition of angels and VCs affects the sales growth and employment growth of entrepreneurial firms. We calculate sales growth and employment growth in years after the first round of financing using data from the NETS database.

[Insert Table 3 about Here]

Table 3 presents the results. In Column (1), we use *Sales Growth (Year 0 to 1)* as the dependent variable, which is defined as the growth rate of sales for a firm one year after the investment. We find that the coefficient estimate on 1st-round_angel% is negative and significant at the 1 percent level. Further, a one standard deviation increase in the fraction of angel investment in the first financing round is associated with a 9.3 percentage point lower growth rate of sales in the next year after receiving investment. This is equivalent to a decrease of 25.6 percentage in the average sales growth in the next year after the first round of investment. We replace the dependent variable with the growth rate of sales in the second year after the investment (*Sales Growth (Year 1 to 2)*) and the growth rate of sales in the third year after the investment (*Sales Growth (Year 2 to 3)*) in Columns (2) and (3), respectively. The coefficient estimates on *1st-round_angel%* in these two columns are both negative and significant at the 1 percent level. The above coefficients are also economically significant. The dependent variable in Column (4) is the growth rate of employment one year after receiving the first round of investment (*Employment Growth (Year 0 to 1)*). The coefficient estimate in Column (4) is negative and significant at the 1 percent significance level. The magnitude of the coefficient estimate shows that a one standard deviation increase in the fraction of angel investment in the first financing round is associated with an 8.8 percentage point smaller annual growth rate of employment one year after the investment, which is equivalent to a decrease of 29.2 percentage in the average employment growth. In Column (5) and (6), the dependent variables are replaced with the annual employment growth rates in the second year and the third year after the investment (*Employment Growth (Year 1 to 2)* and *Employment Growth (Year 2 to 3)*), respectively. The coefficient estimates are both negative and statistically significant at 1%.

The results shown above suggest that firms receiving a greater fraction of angel investment compared to VC investment in their first round of financing are associated with a lower growth rate of sales and employment, which supports our hypotheses **H2**.

5.3 Innovation and Human Capital

Next, we evaluate how the composition of angel investors and VCs in entrepreneurial firms' first financing round affects their future innovation activity and talent inflows. We use the number of patents applied (and eventually granted) after the financing and the number of citations on these patents to measure the quantity and quality of innovation output. We use the number of net inflows of inventors to measure the high-quality talent.

[Insert Table 4 about Here]

We show the results on the quantity of innovation output (i.e., the number of patents) in Table 4. In Columns (1)-(3), the dependent variables are defined as the number of patents applied (and eventually granted) within the next one, two, and three years after receiving the first financing round (*Patents (1 year)*, *Patents (2 years)*, and *Patents (3 years)*), respectively. The number of patents has been adjusted for truncation bias due to the lag between patent application and patent grant following Seru (2014). The coefficient estimates on *1st-round_angel%* are all negative and statistically significant at the 5 percent or the 1 percent levels in the above three columns. The magnitude of estimates indicates that the effect is also economically significant: a one standard deviation increase in the fraction of angel investment in entrepreneurial firms' first financing round is associated with a 13.2 percentage point decrease in the number of patents applied (and eventually granted) within the next three years after receiving investment, which is equivalent to a decrease of 24.8 percentage in the average of patents applied (and eventually granted) within the next three years. We also report the results on the quality of innovation output (i.e., the number of patent citations). In Column (4), (5), and (6), the dependent variables are *Citations (1 year)*, *Citations (2 years)*, and *Citations (3 years)*, respectively, which represent the number of total citations received by patents applied (and eventually granted) within the next one year, two years, and three years, respectively, after a firm receives its first financing round. The coefficient estimate on *1st-round_angel%* are negative and statistically significant at the

1 percent significance level.[16] The magnitude of the coefficient estimate suggests that a one standard deviation increase in the fraction of angel investment in entrepreneurial firms' first round of financing is associated with a decrease of 0.3 percentage point in the number of citations on patents applied (and eventually granted) within three years after receiving the investment, which is equivalent to a decrease of 30.5 percentage in the average of citations on patents applied (and eventually granted) within the next three years. The number of citations is also adjusted for potential truncation bias, since it takes years to receive citations after the patent application and grant.

[Insert Table 5 about Here]

We test our hypothesis related to attracting talents to entrepreneurial firms in Table 5. The outcome variables we test in Columns (1)-(3) are the net inflows of inventors in one, two, and three years after a start-up's first round of financing (*Net Inflow of Inventors (1 Year)*, *Net Inflow of Inventors (2 Years)*, and *Net Inflow of Inventors (3 Years)*), respectively. We observe that the coefficient estimates on *1st-round_angel%* are all negative and statistically significant at the 1 percent level in three columns, suggesting a higher fraction of angel investment (instead of VC investment) in entrepreneurial firms' first round of financing is associated with a smaller net inflow of inventors in the subsequent years. The results are also economically significant. A one standard deviation increase in the fraction of angel investment in entrepreneurial firms' first round of financing is associated with a decrease of 4.5 percentage points in the net inflow of inventors within the next three years, which is equivalent to a decrease of 25 percentage points in the average net inflow of inventors within the next three years. In Columns (4)-(6), we look at the net inflows of top-quality inventors with the top-quartile number of citations per patent within one, two, and three years after a start-up's first round of financing (*Net Inflow of Top 25% Inventors (1 Year)*, *Net Inflow of Top 25% Inventors (2 Years)*, and *Net Inflow of Top 25% Inventors (3 Years)*). The coefficient estimates on *1st-round_angel%* are all negative and statistically significant at the 1 percent level. A one standard deviation increase in the fraction of angel investment in entrepreneurial firms' first round of financing is associated with a decrease of 1.3 percentage point in the net inflow of top inventors within the next three years, which is equivalent to a decrease of 33.9 percentage in the average net inflow of top inventors within the next three years. The results show that start-ups with more angel investment than VC investment are less likely to attract inventors (top-quality inventors).

The above findings suggest that firms receiving relatively more angel investment than VC investment in their first round of financing are associated with smaller quantity and

[16] Our results are also robust to using Poisson regressions with the count of class-adjusted patents and citations as our dependent variables.

quality of innovation and fewer talent inflows, which supports our hypotheses **H3** and **H4**.

6 Are the Differences between Angels and VCs Driven by Screening or Monitoring?

6.1 IV Analysis

Our baseline analyses may suffer from common endogeneity concerns in entrepreneurial finance literature: selection versus value-addition. In other words, do VCs have a better ability to select start-ups or better monitoring abilities compared to angel investors, or do both factors play important roles? To disentangle the selection versus value-addition effect, we use the instrumental variable (IV) approach and construct two IVs for our key variable of interest, the fraction of angel investment in the first round of financing for entrepreneurial firms (*1st-round_angel%*). The first IV we construct is ATC to represent the shock affecting the regional supply of angel investor capital. ATC is a dummy that equals one if a firm is located in a state that has an active angel tax credit program. Denes et al. (2020) find that the staggered provision of angel investor tax credits in 31 U.S. states significantly increased the number of angel investments and average investment size, which suggests that the IV is relevant. Of course, our first stage results in our two stage least squares (2SLS) regressions provide direct evidence of the relevance of our instrument. In Denes et al. (2020), they also show that state-level economic, political, fiscal, and entrepreneurial activity factors do not predict the implementation of angel investor tax credits. Therefore, the provision of angel tax credits across states may affect firms' performances only through the following channel: an increase in the likelihood of receiving greater amount of angel investment. Thus, the above IV is likely to satisfy the exclusion restriction.

The second IV we construct is LPR, which represents the portfolio returns of VC limited partners as suggested by Samila and Sorenson (2011). The rationale behind using this IV is as follows. First, the returns of the limited partners will only affect the supply of VC funds, but will not affect the supply of funding from angel investors. This is based on the stylized fact that limited partners of VCs are typically institutional investors who adopt an investment strategy allocating a fixed ratio of funds into alternative assets (such as VCs and PEs). When the limited partners earn higher returns in their portfolios, they must invest more assets to venture capital to maintain their asset allocations. Angel investors, on the other hand, are wealthy individual investors who do not receive money from institutional investors and thus, would not be affected by changes in the returns of the limited partners. Our first stage results in our two stage least squares (2SLS) regressions provide direct evidence of the relevance of our instrument. Second, the intuition behind this IV also relies on another stylized fact that limited partners have a home bias to invest in locally headquartered VC funds, while VCs too have a tendency to invest in start-ups located closer to their headquarters (Chemmanur, Krishnan, and Yu (2016); Samila and Sorenson (2011)). Collectively, the above stylized facts suggest that higher portfolio returns earned by limited partners are likely to lead to greater VC investments in nearby start-ups in the subsequent years. The returns of the limited partners are not likely to be driven by local entrepreneurial activity and are only correlated to the supply of VC funds. Thus, our second instrument is also likely to satisfy the exclusion restriction. The construction of the IV is as follows,

$$LPR_{it} = \sum_{j} \sum_{s=t-1}^{t-3} \frac{ER_s lnLP_{js}}{1 + dist_{ij}}, \tag{2}$$

where i is the state of the start-up located in and t is a year. ER_s is the average return across all college endowments in year s, obtained from the study of the National Association Of College and University Business Officers. LP_{js} is equal to one plus the number of limited partners in a state j that had invested in venture capital at least ten years before year s. $dist_{ij}$ is the distance in miles between the centroid of state i and the centroid of state j. We use the returns weighted by the distances to account for the home bias of limited partners that they intend to invest in VC funds that locate near them.

We instrument the fraction of angel investment in the first round of financing *1st-round_angel%* with the provision of angel tax credits and the average past returns of the limited partners. Thus, we can distinguish the effect driven by the differences between angels and VCs in their respective monitoring abilities from the effect driven by their differences in selection ability or their ability to select firms. Specifically, we run the following first stage regression:

$$\textit{1st-round\_angel\%}_{i,t} = \alpha + \beta_1 LPR_{s,t} + \beta_2 ATC_{s,t} + \gamma_1 lnage_{i,t} + \gamma_2 lnsales_{i,t} + Year_t + Industry_i + \epsilon_{i,t}, \tag{3}$$

and the second-stage as

$$Y_{i,t+X} = \alpha + \beta \, \widehat{\textit{1st-round\_angel\%}}_{i,t} + \gamma_1 lnage_{i,t} + \gamma_2 lnsales_{i,t} + Year_t + Industry_i + \delta_{i,t+X}, \tag{4}$$

where i represents a firm, s is the state that a firm's headquarter is located in, and t is the year that the firm receives its first round of financing. Other variables are defined in the same manner as in our baseline regressions.

6.1.1 IV Analysis: Successful Exit

First, we show the results of our IV analysis of the impact of investor composition on the successful exits of entrepreneurial firms.

[Insert Table 6 about Here]

Table 6 shows the result. In the first stage of the analysis, we instrument the fraction of angel investment in the first round of financing (*1st-round_angel%*) using the provision of angel tax credits (ATC) and the weighted returns of limited partners (LPR). In the first stage, we find that, as expected, the coefficient on the past return of limited partners in firm-headquarter state is negative and significant (1 percent level), which is consistent with Samila and Sorenson (2011). The coefficient on the dummy variable for the state angel tax credit program is positive and significant (1 percent level), suggesting that when angel investment is encouraged by the government, a start-up is more likely to receive angel financing. The Kleibergen-Paap rk Wald statistic (Kleibergen and Paap (2006)), which tests directly whether the IV predicts a sufficient amount of the variance in the endogenous variables to identify our equations, has a value of 27.297 and is far beyond the critical value required by Stock and Yogo (2005) for the IV estimates to have no more than 10% of the bias of the OLS estimates. Thus, our instruments satisfy the relevance condition. In the second stage of the analysis, we regress the variables that represent successful exits on the predicted value of *1st-round_angel%* from the first stage. Column (1) shows the first-stage results. Columns (2) to (4) report the second-stage results of the IV analysis. The coefficient estimates are both negative and statistically significant at 5 percent or the 1 percent levels, suggesting a causal impact of having more angel investment relative to VC investment on the successful exits of entrepreneurial firms. In other words, the difference in value-adding abilities between angel and VC investors causally affects the probability of their portfolio firms' likelihood of getting a successful exit. Thus, the above results suggest that firms greater level of angel investment compared to VC investment causally leads to a smaller likelihood of successful exit in the future, which supports our hypothesis **H1**.

6.1.2 IV Analysis: Sales and Employment Growth

Second, we show the results of our IV analysis of the impact of investor composition on the sales and employment growth at start-ups.

[Insert Table 7 about Here]

We show our results in Table 7. Again, the first-stage regression exhibits a significantly positive estimate on ATC and a significantly negative coefficient estimate on LPR with the Kleibergen-Paap rk Wald statistic of 9.064. In the second-stage analysis, we observe from Column (4) that the coefficient estimate is negative and statistically significant at the 1 percent level, suggesting that having more angel investment relative to VC investment in the first round of financing is causally related with a lower sales growth rate in the third year after receiving the investment. We observe similar second-stage results for employment growth, indicating that having more angel investment relative to VC investment in the first round of financing is causally associated with smaller employment growth. We observe from Column (7) that the coefficient estimate is negative and statistically significant at the 1 percent level.[17]

The above IV analyses suggest that more angel investment (rather than VC investment) in entrepreneurial firms is causally associated with a lower level of sales and employment growth in the subsequent years, which supports our hypothesis **H2**.

6.1.3 IV Analysis: Innovation Output

Third, we show the results of our IV analysis of the impact of investor composition on the innovation output, measured using the quantity and quality of patents of entrepreneurial firms.

[Insert Table 8 about Here]

Table 8 reports the results. Similar to Table 6, we report the first-stage results in Column (1) and observe a significantly positive coefficient estimate on ATC and a significantly negative estimate on LPR with the Kleibergen-Paap rk Wald statistic of 27.297. In Columns (2) to (4), we show the second-stage results of the effects of *1st-round_angel%* on the number of patents applied, which were eventually granted, in one, two, and three years after a firm receives the first round of financing (*Patents (1 year)*, *Patents (2 years)*, and *Patents (3 years)*). We observe that all of the coefficient estimates on the predicted value of *1st-round_angel%* are negative and statistically significant at the 5 percent significance level or at the 1 percent significance level. In Columns (5) to (7), we use the number of citations on patents applied (and eventually granted) in one, two, and three years after receiving the first round of financing (*Citations (1 year)*, *Citations (2 years)*, and *Citations (3 years)*) as our dependent variable. All of the coefficient estimates on *1st-round_angel%* are negative in these three columns and statistically significant at the 5 percent significance level or at the 1 percent significance level. Our results in Table 8 suggest a causal impact of the composition of angel and VC investors on entrepreneurial firms' innovation output.

The above IV analyses suggest that more angel investment (rather than VC investment) in entrepreneurial firms is causally associated with a lower level of innovation output (quantity and quality) in the subsequent years, which supports our hypothesis **H3**.

[17] We do not observe the significance of the second-stage coefficient estimates on *1st-round_angel%* for the sales growth rate and employment growth rate of start-ups in the first year and the second year after receiving the financing. The potential explanation for the above results is that it takes time for investors to engage in the business of start-ups and turn their monitoring and expertise into real economic improvements of these firms. For example, it is possible that investors' efforts to promote innovation in start-ups and in attracting better talents to start-ups may lead to real economic benefits after a few years.

6.1.4 IV Analysis: Attracting Talents

Fourth, we show the results of our IV analysis of the impact of investor composition on attracting talents, measured using net inflows of inventors to start-up firms.

[Insert Table 9 about Here]

Table 9 reports the results. In Column (1), we report the first-stage results and observe a significantly positive coefficient estimate on ATC and a significantly negative estimate on LPR with the Kleibergen-Paap rk Wald statistic of 27.297. In Columns (2) to (4), we show the second-stage results of the effects of *1st-round_angel%* on the net inflows of inventors in one, two, and three years after a firm receives the first round of financing (*Net Inflow of Inventors (1 Year)*, *Net Inflow of Inventors (2 Years)*, and *Net Inflow of Inventors (3 Years)*). We observe that all of the coefficient estimates on the predicted value of *1st-round_angel%* are negative and statistically significant at the 1 percent significance level. In Columns (5) to (7), we focus on the net inflows of inventors with the top-quartile number of citations per patent in one, two, and three years after receiving the first round of financing (*Net Inflow of Top 25% Inventors (1 Year)*, *Net Inflow of Top 25% Inventors (2 Years)*, and *Net Inflow of Top 25% Inventors (3 Years)*) as our dependent variable. All of the coefficient estimates on *1st-round_angel%* are negative. In Column (4) the coefficient is statistically significant at the 10 percent level. The findings from Table 9 confirms our hypothesis **H4** that there is a causal impact of the composition of angel and VC investors on attracting talents for entrepreneurial firms

Overall, all of the above IV results suggest that the difference in the ability of angel and VC investors to add value to start-ups (due to differences in their respective ability to monitor or to ensure better resources for start-ups) at least partially drives the variation in their portfolio firms' performances.

6.2 Switching Regressions

In this section, we provide further empirical evidence to show the differences in terms of value added by angels versus VCs on entrepreneurial firms. To isolate the effect driven by the differences in the value-adding ability, we employ the following "what-if" analysis framework: what would be the outcome of start-ups that are initially angel-financed if they had not received any angel financing, or in other words, received financing only from VC funds (*VC-only*). Similarly, we test the outcome of firms that are initially financed only by VC funds if they had received financing from angel investors instead.

We run switching regressions with endogenous switching methodology (as discussed in detail in Heckman (1979) and Maddala (1983)) to disentangle the different impact of selection versus value-addition by angels and VCs on successful exits, sales, and employment growth of start-ups, innovation output, and on the net inflow of inventors. The above method, which is a generalized version of the traditional Heckman model, accounts for the impact of unobservables (which determines the selection effect) by using inverse Mills ratios. The inverse Mills ratios for angel-backed and non-angel-backed firms are obtained by running the first-stage regression to predict the probabilities of receiving angel funding. Next, we regress successful exits, innovation output, net inflow of inventors, and sales and employment growth on the inverse Mills ratios and control variables in the second stage of the estimation, separately for the sample of VC-only and angel-backed firms. Finally, the predicted values of the outcome variables from the second-stage estimates are used to conduct the above-mentioned counterfactual (i.e., "what-if") analysis. This method has been used in many finance studies, e.g., Fang (2005) uses switching regression to analyze the relationship between investment bank reputation and bond underwriting, while Chemmanur et al. (2011) study the impact of venture capitalists on the efficiency of private firms using switching regressions.

We control for firm-level characteristics that may affect investor-firm matching, such as the natural logarithm of firm age (*lnage*), sales of the firm (*lnsales*), and the 2-digit SIC industry dummy. We also control for the year of the first financing round for the firm. In addition, we also include the two instruments, which are described in Section 6.1, the past return of limited partners in the state where the firm's headquarter is located (LPR), and the dummy variable that represents whether the state has an active angel tax credit program or not (ATC). We include these instruments since they provide us with exogenous variation regarding the supply of VC funding and angel investment that affects investors' selection of firms, but does not directly affect firm outcomes.

In the following tables, we report the results of the switching regression analysis. In the first stage, the dependent variable is a dummy which equals one if a firm has angel backing in the first round of financing, otherwise it is equal to zero. The results are reported in Table A1 in the Internet Appendix. We find that the age and sales of a firm are both negative and statistically significant at the 1 percent level, suggesting that younger and smaller firms are more likely to receive angel financing (instead of VC funding). In terms of the instruments, we find that the coefficient on the past return of limited partners in firm-headquarter state is negative and significant (5 percent level), which is consistent with Samila and Sorenson (2011). The coefficient on the dummy variable for the state angel tax credit program is positive and significant (1 percent level), suggesting that when angel investment is encouraged by the government, a firm is more likely to receive angel financing. Next, we use the inverse Mills ratio calculated from the first stage to augment the second-stage regressions for our samples of VC-only firms and angel-backed firms to account for endogenous selection based on unobservable factors.

[Insert Table 10 about Here]

Tables 10 report the results when the outcome variables are related to successful exits. Panel A of Table 10 presents the results of the second-stage regressions. The inverse Mills ratio is statistically significant for VC-only firms at the 1 percent level in all three columns (while it is only marginally significant for angel-backed firms in Column (2) and insignificant in Columns (4) and (6)), suggesting that venture capitalists may have used more unobservable factors when they select which firms to invest relative to angel investors, and these unobservable factors have bigger impact on future successful exits through selection. Panel B of Table 10 shows the results of our counterfactual analysis of VC-only versus angel-backed firms. We obtain the counterfactual values for VC-only firms as the predicted values of the angel-backed regression and the corresponding inverse Mills ratio using data from VC-only firms, and vice versa. In the first part of the Panel B, we observe that angel-backed firms could have achieved a hypothetical improvement in the rate of IPO, acquisition, and successful exit by 0.9, 9.7, and 10.3 percentage points, respectively, compared to the hypothetical case had the same firms received only VC-financing. In the second part of the Panel B, we show that VC-only firms face smaller probability of either an IPO, or an acquisition, or a successful exit (IPO or acquisition) by 1.6, 14.1, and 14 percentage points, respectively, had they received angel financing. The estimates of these changes in the rate of successful exit are all statistically significant. Thus, our switching regression results show that VC-backing rather than angel-backing leads to greater likelihood of a successful exit for start-ups, supporting our hypothesis **H1**.

[Insert Table 11 about Here]

Tables 11 report the results when the outcome variables are related to growths of sales and employment in years after the financing. Panels A and B show the results of second-stage of switching regressions when the dependent variables are growths of sales and employment in the future years, respectively, after the first round of financing. Most of the coefficient estimates of the Inverse Mills ratio are statistically insignificant for both VC-only and angel-backed firms. Most of the coefficient estimates of firm sales are significantly negative, suggesting that larger firms have smaller future growths in both the samples of VC-only and angel-backed firms. In Panel C, we show the results of the counterfactual analysis for firms' sales and employment growth. The first part of Panel C shows that angel-backed firms could have achieved a higher value of both sales and employment growth in the first, second, and third year after the first round of financing compared to the hypothetical case had the same firms received only VC-financing. Our results are economically significant. For example, angel-backed firms experience higher sales growth by 24.7 percentage points compared to the hypothetical scenario of backing only from angel investors for one year after receiving the first round of financing. In the second part of the Panel C, we show that VC-only firms would experience a hypothetical drop in both sales and employment growth in the first, second, and third year after the first round of financing, had they received angel financing. Most estimates of these changes in the rate of sales and employment growth are statistically significant. Thus, our switching regression results show that VC-backing rather than angel-backing leads to a greater level of sales and employment growth for start-ups, supporting our hypothesis **H2**.

[Insert Table 12 about Here]

Tables 12 report the results when the outcome variables are related to innovation. Panels A and B show the results of second-stage switching regressions when the dependent variables are the number of patents and the number of patent citations in the future years, respectively, after the first round of financing. The coefficient of inverse Mills ratio is statistically significant for VC-only firms but insignificant for VC-backed firms, again suggesting that VCs may use some unobservable factors when selecting firms to invest in, and these factors may affect the quantity and quality of innovation output of entrepreneurial firms positively. In Panel C, we show the results of counterfactual analysis for firms' innovation output. The first part of Panel C shows that angel-backed firms could have experienced an increase in patents filed (and eventually granted) in the first, second, and third year after the first round of financing by 10.6, 29.9, and 34.8 percentage points, respectively, compared to the hypothetical case had the same firms received only VC-financing. We find similar results for the quality of patents filed by firms in our sample. In the second part of Panel C, we show that VC-only firms experience a hypothetical decrease in the rate of filing patents in the first, second, and third year after the first round of financing by 3.1, 16.9, and 12.5 percentage points, respectively, had they received angel financing. We find similar results for the quality of patents filed by firms in our sample. The estimates of these changes in the rate of filing quantity and quality of patents are all statistically significant. Thus, our switching regression results show that VC-backing rather than angel-backing leads to a greater quantity and quality of innovation output for start-ups, supporting our hypothesis **H3**.

[Insert Table 13 about Here]

Tables 13 report the results when we examine talent inflows. Panels A and B show the results of second-stage switching regressions when the dependent variables are the net inflows of inventors (all inventors and the top-quality inventors) in the future years after the first round of financing. In Panel C, we show the results of counterfactual analysis for firms' inventor inflows. The first part of Panel C shows that angel-backed firms could have experienced more net inflows of inventors in the subsequent years compared to the hypothetical case had the same firms received only VC-financing. We find similar results for top-quality inventors in our sample. In the second part of Panel C, we show that VC-only firms experience a hypothetical decrease in net inflows of inventors, had they received angel financing. We find similar results for top-quality inventors in our sample. The estimates of these changes in net inflows of inventors are all statistically and economically significant. Thus, our switching regression results show that VC-backing rather than angel-backing leads to significantly more inflows of talents to start-ups, supporting our hypothesis **H4**.

Overall, the above results show the impact of differences in the value-adding abilities (i.e., monitoring) of angel investors and VCs for entrepreneurial firms in our sample. Accounting for the endogenous selection of investors using switching regressions, we find that angel investors add less value, in terms of the rate of successful exits, the growths of sales and employment, the quantity and quality of innovation, and the inflows of talents, to their portfolio firms compared to VCs.

7 Robustness Tests

7.1 VCs vs Sophisticated Angel Investors

In this section, we discuss some robustness tests which support our main analysis comparing the impact of VC and angel investment on future outcomes of start-ups firms. One may argue that our results showing that angel investors add less value to start-ups than VCs are driven by unsophisticated angel investors, who provide funds to their friends and families irrespective of the quality of the underlying start-up and who may not have decent ability to monitor these start-ups. To address this concern, we restrict our sample to first-round angel investments that include at least one angel group or one "serial" angel investor. We define a serial angel investor in a firm-investment round as an angel investor that has invested in at least one different firm in the past, i.e., the angel investor has prior experience of investing. It is likely that serial angel investors and angel groups are sophisticated investors and contribute to the growth and success of start-ups. Indeed, prior literature has argued that angel groups add positive value to portfolio start-ups (Kerr et al. (2014) and Lerner et al. (2018)). Thus, our subsample enables us to compare VC investments with angel investments where at least one angel group or one serial investor is involved.

Tables A2, A3, A4, and A5 in the Internet Appendix report the results on successful exit, growth, innovation, and inventor inflow for the above subsample. We show that, in line with our main results, sophisticated angel investors are less likely to add value to start-ups compared to VCs. Further, we conduct additional analysis restricting our sample to firm-investment rounds involving either VCs or angel groups only. This subsample enables us to directly compare the impact of VCs vs angel groups on the future success of start-ups. We also show in table A6 in the Internet Appendix that greater fraction of angel group investment in the first investment round of a start-up is associated with smaller likelihood of the future successful exit of the start-up. Thus, our results suggest that angel groups are also inferior to VCs in ensuring successful exits of start-ups.[18]

7.2 Industry-wise Subsample Analysis

In this section, we discuss subsample analysis based on different industry categories. One potential concern is that VCs and angels invest in separate industries because of their different specializations. Prior literature has argued that VCs tend to invest in high-tech and biotechnology industry sectors (Graham, Merges, Samuelson, and Sichelman (2009)). In order to test whether angels add less value than VCs only in certain industries, we conducted an additional subsample analysis based on industry categories. We identified high technology (HiTech), manufacturing, and healthcare as three industries categories where VCs may dominate compared to angel investors. We define the above industry categories based on Fama-French 10 industry classification. One subsample consists of firms in the above industry categories. The other subsample consists of firms in remaining industry categories. We find that angel investors add less value than VCs in both subsamples. In table A7 in the Internet Appendix, we show that greater fraction of angel investment leads to smaller likelihood of successful exits for start-ups irrespective of their industry categories.[19] Thus, we show that angel investors add less value than VCs in general across industries.

8 Angels and VC Financing: Complements or Substitutes?

Next, we examine the question of whether angel investors and VCs are complements (**H5a**) or substitutes (**H5b**). Specifically, we look at how the participation of angel and VC investors in the first round of financing affects the participation of VC and angel investors in the second round. To perform this analysis, we use a sample that also includes other types of investors

[18] In untabulated analyses, we conducted additional tests directly comparing the impact of angel groups vs VCs on sales and employment growth, innovation, and inventor inflow. We find similar results compared to the above robustness tests. Thus, our analyses using different outcome variables show that even angel groups add less value than VCs to start-ups.

[19] We also conducted our above subsample analyses for cases where outcomes were sales and employment growth, innovation, and inventor inflow. In untabulated analyses, we find that angel investors add less value than VCs in term of the above parameters across different industries.

(accelerator and government grants) to analyze the complementarity and substitutability between angel investors and VCs. In addition, we restrict our sample to firms that have experienced at least two rounds of investment. We run regressions based on the following model,

$$\begin{aligned} \textit{2nd-round\_VC\%(has\_angel)}_i = \alpha + \beta_1 \textit{1st-round\_VC\%}_i + \beta_2 \textit{1st-round\_has\_angel}_i + \\ \gamma_1 lnage_i + \gamma_2 lnsales_i + Year_i + Industry_i + \delta_i, \quad (5) \end{aligned}$$

where the dependent variable is either the second-round fraction of VC investment (*2nd-round_VC%*) or a dummy variable indicating presence of angel investor (*2nd-round_has_angel*) in the second round or not. The key variables of interests are the first-round fraction of VC investment (*1st-round_VC%*) or the dummy variable for presence of angels (*1st-round_has_angel*). We use the fraction of VC investment and the dummy variable for presence of angels in this analysis, since we have included other types of investors (besides angels or VCs), and we only have the information on the amount of VC investment per round and the total amount of investment per round. We control for firm age (*lnage*) and firm sales (*lns*) in the year of receiving the first financing round. We also control for year fixed effects and industry fixed effects.

[Insert Table 14 about Here]

Table 14 reports the results. The dependent variable in Column (1) is *2nd-round_VC%*. The coefficient estimate on *1st-round_VC%* is positive and significant at the 1 percent level, which suggests that the fraction of VC investment in the first round is highly correlated with the fraction of VC investment in the second round. The coefficient estimate on the dummy *2nd-round_has_angel*, which equals one if there is at least one angel investor participating in the first round and zero otherwise, is also positive and significant at the 1 percent level. This result suggests that the presence of angel investors in the first round is associated with a larger percentage of VC financing in the second round. This result is different from Hellmann et al. (2021), who use data on firms in British Columbia, Canada, and find that angels and VCs are substitutes. In contrast, the results from our analysis are consistent with the theoretical paper by Chemmanur and Chen (2014), who argue that angel investors are complements of VCs (**H5a**). Next, in Column (2), we replace the dependent variable with the dummy variable representing the presence of angel investors in the second round of financing, *2nd-round_has_angel*. The coefficient estimate on *1st-round_VC%* is negative and significant at the 1 percent level, which suggests that having more VC investment in the first round is associated with a lower probability of having an angel investor the second round. The coefficient estimate on *1st-round_has_angel*, on the other hand, is positive and statistically significant at the 1 percent level, indicating that the presence of angel investors in the first round is associated with a higher probability of the presence of angel investors in the second round. This particular result suggests that angels and VCs may act as substitutes (**H5b**).

Overall, the above analyses suggest that angels and VCs cannot be classified either as complements or substitutes in the financing of entrepreneurial firms. The relationship between angel investors and VCs is complex: they may act as either complements or substitutes. The presence of angel investors in the first round is associated with greater VC-financing in the second round. However, greater VC-financing in the first round is associated with a smaller likelihood of the presence of an angel investor in the second round.

9 Financing Sequence of Angel and VC Financing across Rounds and Probability of Successful Exit

Next, we examine the relationship between the financing sequence of investors at start-ups in terms of the order of financing by angels and VCs, and start-up firms' subsequent successful exits either via IPOs or acquisitions (**H6**), which is one of the most important success parameters for start-ups.

In this analysis, we only include firms that either have VC investors or angel investors or both in their first two rounds of financing. Hence, we can define the dominance of an investor type (angel or VC) in a financing round by measuring whether the percentage of VC investment in a round is greater than 50 percent or not. The firms in our sample can, therefore, be categorized into four subgroups based on their financing sequence in the first two rounds: from angel-dominated to VC-dominated (*FinPath=Angel to VC*), from VC-dominated to angel-dominated (*FinPath=VC to Angel*), from VC-dominated to VC-dominated (*FinPath=VC to VC*), and from angel-dominated to angel-dominated (*FinPath=Angel to Angel*). Specifically, we run regressions based on the following model,

$$Exit_{i,T} = \alpha + \beta_1 FinPath\ (Angel\ to\ VC) + \beta_2 FinPath\ (VC\ to\ Angel) + \beta_3 FinPath\ (VC\ to\ VC) \\ + \gamma_1 lnage_{i,t} + \gamma_2 lnsales_{i,t} + Year_t + Industry_i + \delta_{i,T}, \quad (6)$$

where we include the three dummy variables each representing one type of financing sequence, and we use firms with angel-dominated first round and angel-dominated second round of financing (*FinPath=Angel to Angel*) as the comparison group. As in our previous analyses, we control for firm age (*lnage*) and firm sales (*lnsales*) in the year of the first financing round. We also include year fixed effects and industry fixed effects in our regressions.

[Insert Table 15 about Here]

The results are reported in Table 15. In Column (1), the dependent variable is *IPO*. We observe that coefficient estimate on *FinPath (Angel to VC)* is positive and statistically significant at the 5 percent level, suggesting that firms with a financing sequence from angel dominated to VC dominated (i.e., angel-to-VC) in the first two rounds have a 12.3 percentage point higher probability of going public in the subsequent years than firms have an angel-to-angel financing sequence. We replace the dependent variable with *Acq* in Column (2). The coefficient estimates on *FinPath (Angel to VC)* and *FinPath (VC to VC)* are both positive and statistically significant (1 percent level), suggesting that compared to firms with an angel-to-angel financing sequence, firms with an angel-to-VC or a VC-to-VC financing sequence, on average, enjoy a 18.5 percentage point and 23.9 percentage point higher probability of being acquired in the subsequent years, respectively. In Column (3), the dependent variable is *Exit*, which equals one if a firm has an IPO or is acquired in the following years and zero otherwise. Similar to the results in Column (2), firms with an angel-to-VC or VC-to-VC financing sequence have a significantly (1 percent level) higher (by 28.8 percentage point and 23.4 percentage point, respectively) probability of having a successful exit, compared to firms with an angel-to-angel financing sequence. The coefficient estimates on *FinPath (VC to Angel)* in all the three columns are not significant, indicating that firms with a VC-to-angel financing sequence do not exhibit a significant difference in the rate of having a successful exit compared to firms with an angel-to-angel financing sequence. In their theoretical paper, Chemmanur and Chen (2014) describe the intuition behind the above results. They posit that if firms obtain venture financing in their early rounds of investments, it will convey favorable information to outside private equity investors, who will revise their estimates of firms' valuation upwards. Further, later rounds of VC investments will also act as favorable signals to outside private equity investors. Lastly, exit by VCs from firms initially backed by them will convey negative signals to outside investors. Thus, firms which experience angel-to-VC or VC-to-VC financing sequence are likely to be of higher quality compared to firms that experience VC-to-angel or angel-to-angel financing sequence.

Thus, our results show that the financing sequence of entrepreneurial firms are associated with their future successful exits: firms experiencing VC-to-VC or angel-to-VC investment sequences have a better likelihood of successful exits compared to firms experiencing VC-to-angel or angel-to-angel investment sequences, which supports our hypothesis **H6**.

10 Conclusion

In this paper, using a large sample of angel and venture capital (VC) financing data from the Crunchbase and VentureXpert databases and private firm data from the NETS database, we addressed three important research questions. First, we analyzed the relative extent of value addition by angels versus VCs to start-up firms. We showed that start-ups financed by angels rather than VCs are associated with a smaller likelihood of successful exit (IPO or acquisition), smaller sales and employment growth, smaller quantity and quality of innovation, and a smaller net inflow of top-quality inventors. We disentangled selection and monitoring effects using instrumental variable (IV) and switching regression analyses and show that our baseline results are causal. Second, we investigated the complementarity versus substitution relationship between angel and VC financing. We found that a firm that received a larger fraction of VC or angel financing in the first financing round is likely to receive a larger fraction of the same type of financing in a subsequent round; however, when we include other non-VC financing sources such as accelerators and government grants into the analysis, a firm that received angel (rather than other non-VC) financing in the first round is also more likely to receive VC financing in a subsequent round. Third, we analyzed how the financing sequence (order of investments by angels and VCs across rounds) of start-up firms is related to their successful exit probability. We found that firms that received primarily VC financing in the first round and continued to receive VC financing in subsequent rounds or those that received primarily angel financing in the first round and received VC financing in subsequent rounds have the highest chance of successful exit compared to those with other financing sequences (VC-angel or angel-angel).

References

Bernstein, Shai, Xavier Giroud, and Richard R Townsend, 2016, The impact of venture capital monitoring, *The Journal of Finance* 71, 1591–1622.

Chemmanur, Thomas J, and Zhaohui Chen, 2014, Venture capitalists versus angels: The dynamics of private firm financing contracts, *The Review of Corporate Finance Studies* 3, 39–86.

Chemmanur, Thomas J, Lei Kong, Karthik Krishnan, and Qianqian Yu, 2019, Top management human capital, inventor mobility, and corporate innovation, *Journal of Financial and Quantitative Analysis* 54, 2383–2422.

Chemmanur, Thomas J, Karthik Krishnan, and Debarshi K Nandy, 2011, How does venture capital financing improve efficiency in private firms? a look beneath the surface, *The Review of Financial Studies* 24, 4037–4090.

Chemmanur, Thomas J., Karthik Krishnan, and Qianqian Yu, 2016, Venture capital backing, investor attention, and initial public offerings, Working Paper, Boston College.

Chemmanur, Thomas J, Elena Loutskina, and Xuan Tian, 2014, Corporate venture capital, value creation, and innovation, *The Review of Financial Studies* 27, 2434–2473.

Cumming, Douglas, and Minjie Zhang, 2019, Angel investors around the world, *Journal of International Business Studies* 50, 692–719.

Denes, Matthew, Sabrina Howell, Filippo Mezzanotti, Xinxin Wang, and Ting Xu, 2020, Investor tax credits and entrepreneurship: Evidence from us states, Working Paper, Carnegie Mellon University.

Dutta, Supradeep, and Timothy B Folta, 2016, A comparison of the effect of angels and venture capitalists on innovation and value creation, *Journal of business venturing* 31, 39–54.

Ewens, Michael, Ramana Nanda, and Matthew Rhodes-Kropf, 2018, Cost of experimentation and the evolution of venture capital, *Journal of Financial Economics* 128, 422–442.

Fang, Lily Hua, 2005, Investment bank reputation and the price and quality of underwriting services, *The Journal of Finance* 60, 2729–2761.

Graham, Stuart JH, Robert P Merges, Pam Samuelson, and Ted Sichelman, 2009, High technology entrepreneurs and the patent system: Results of the 2008 berkeley patent survey, *Berkeley Technology Law Journal* 1255–1327.

Heckman, James J, 1979, Sample selection bias as a specification error, *Econometrica* 153–161.

Hellmann, Thomas, and Manju Puri, 2000, The interaction between product market and financing strategy: The role of venture capital, *The Review of Financial Studies* 13, 959–984.

Hellmann, Thomas, and Manju Puri, 2002, Venture capital and the professionalization of start-up firms: Empirical evidence, *The Journal of Finance* 57, 169–197.

Hellmann, Thomas, Paul Schure, and Dan H Vo, 2021, Angels and venture capitalists: Substitutes or complements?, *Journal of Financial Economics* 141, 454–478.

Hellmann, Thomas, and Veikko Thiele, 2015, Friends or foes? the interrelationship between angel and venture capital markets, *Journal of Financial Economics* 115, 639–653.

Kerr, William R, Josh Lerner, and Antoinette Schoar, 2014, The consequences of entrepreneurial finance: Evidence from angel financings, *The Review of Financial Studies* 27, 20–55.

Kleibergen, Frank, and Richard Paap, 2006, Generalized reduced rank tests using the singular value decomposition, *Journal of Econometrics* 133, 97–126.

Lerner, Josh, Antoinette Schoar, Stanislav Sokolinski, and Karen Wilson, 2018, The globalization of angel investments: Evidence across countries, *Journal of Financial Economics* 127, 1–20.

Lindsey, Laura Anne, and Luke CD Stein, 2019, Angels, entrepreneurship, and employment dynamics: Evidence from investor accreditation rules, Working Paper, Arizona State University.

Maddala, G. S., 1983, *Limited-Dependent and Qualitative Variables in Econometrics*, Econometric Society Monographs (Cambridge University Press).

Marx, Matt, Deborah Strumsky, and Lee Fleming, 2009, Mobility, skills, and the michigan non-compete experiment, *Management science* 55, 875–889.

Neumark, David, Brandon Wall, and Junfu Zhang, 2010, Do small businesses create more jobs? new evidence for the united states from the National Establishment Time Series, *The Review of Economics and Statistics* 93, 16–29.

Samila, Sampsa, and Olav Sorenson, 2011, Venture capital, entrepreneurship, and economic growth, *Review of Economics and Statistics* 93, 338–349.

Seru, Amit, 2014, Firm boundaries matter: Evidence from conglomerates and r&d activity, *Journal of Financial Economics* 111, 381–405.

Stock, James, and Motohiro Yogo, 2005, Testing for weak instruments in linear IV regression, in Donald W.K. Andrews, ed., *Identification and Inference for Econometric Models*, 80–108 (Cambridge University Press, New York).

Tian, Xuan, and Tracy Yue Wang, 2014, Tolerance for failure and corporate innovation, *The Review of Financial Studies* 27, 211–255.

Ueda, Masako, 2004, Banks versus venture capital: Project evaluation, screening, and expropriation, *The Journal of Finance* 59, 601–621.

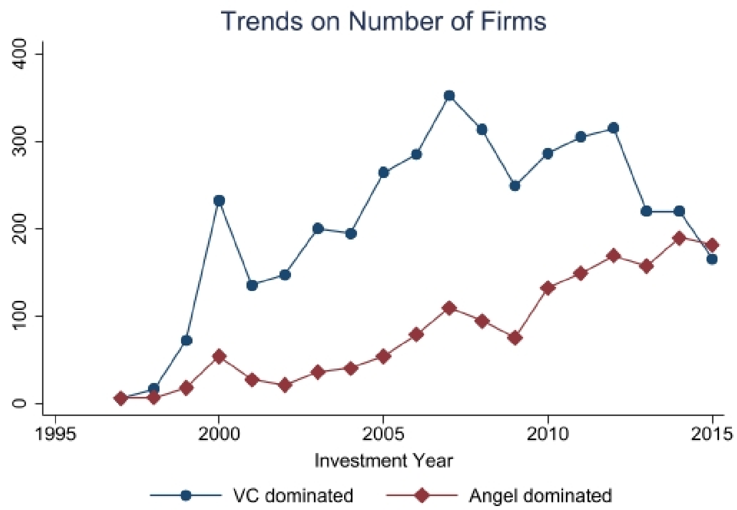
Wang, Xinxin, 2018, Catering innovation: Entrepreneurship and the acquisition market, Working Paper, UCLA Anderson School of Management.

Xu, Jiajie, 2019, Is there a trade-off between protecting investors and promoting entrepreneurial activity? evidence from angel financing, Working Paper, Boston College.

Yu, Sandy, 2020, How do accelerators impact the performance of high-technology ventures?, *Management Science* 66, 530–552.

Figure 1. Trends in the Number of Angel- and VC-dominated First Round Investments in Startups and their Eventual Successful Exit

This figure below shows the trends in first-round investment for our sample startups and trends in percentage of their future successful exit. We only include years that consist of at least five startup first-investment rounds in our sample. The blue line with circle markers indicates startups that have received more than fifty percentage of funding in the first round from VC investors (*VC-dominated*). The red line with diamond markers indicates startups that have received equal to or more than fifty percentage of funding in the first round from angel investors (*Angel-dominated*).



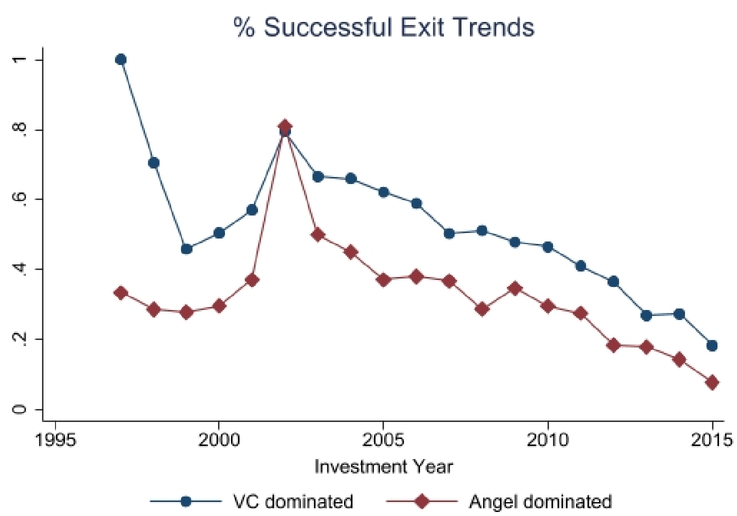


Figure 2. Trends in Acquisitions and IPOs of Angel- and VC-dominated First Round Investments

This figure below shows the trends in percentage of future acquisition and IPOs for angel-dominated and VC-dominated firms in our sample. We only include years that consist of at least five startup first-investment rounds in our sample. The blue line with circle markers indicates startups that have received more than fifty percentage of funding in the first round from VC investors (*VC-dominated*). The red line with diamond markers indicates startups that have received equal to or more than fifty percentage of funding in the first round from angel investors (*Angel-dominated*).

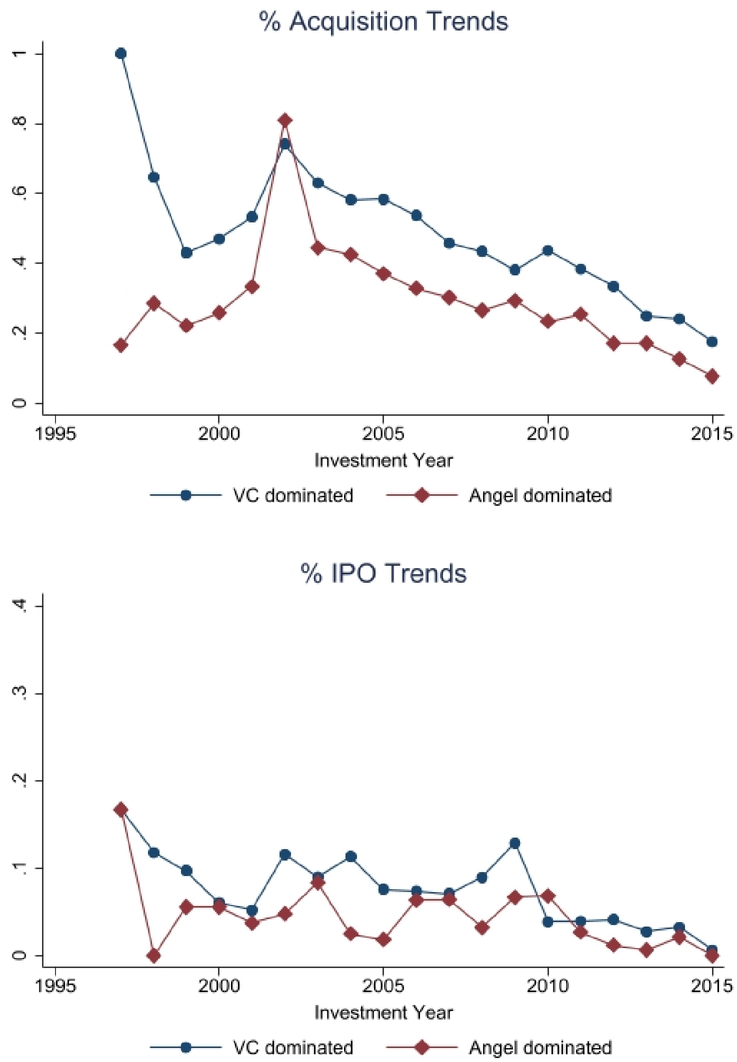


Table 1. Summary Statistics

This table displays summary statistics for the main variables in the analysis. This sample include all startup firms whose first financing rounds involved only angel and VC investors. *1st-round_angel%* is the fraction of angel investment in the first round of financing, which is measured as the amount of angel-investment scaled by total investment in the round. *Angel Investment (1st round)* is a dummy variable which equals one if there is at least one angel investor participating in the first round of financing. *IPO* is a dummy variable which equals to one if a firm has gone public in the future after its first-round of financing and zero otherwise. *Acq* is a dummy variable which equals to one if a firm has been acquired and zero otherwise. *Exit* is a dummy variable which equals one if a firm has either been acquired or gone public in the future after its first-round of financing. *Patents (3 years)* is the natural logarithm of one plus the number of patents applied (and eventually granted) to a startup within three years after its first-round of financing adjusted for the truncation bias, respectively. *Citations (3 years)* is the natural logarithm of one plus the number of citations on patents applied (and eventually granted) by startups within three years after its first-round of financing adjusted for the truncation bias, respectively. *Sales growth (Year 0 to 1)* is defined as the annual growth rate of sales in the first after the first-round of financing for a firm. *Employment growth (Year 0 to 1)* is defined as the annual growth rate of employment in the first year after a firm's first-round of financing. *Net Inflow of Inventors (3 Years)* is defined as the difference between the natural logarithm of one plus the inflow and the natural logarithm of one plus the outflow of inventors in the subsequent three years after an entrepreneurial firm received its first-round of financing. *Net Inflow of Top 25% Inventors (3 Years)* is defined as the difference between the natural logarithm of one plus the inflow and the natural logarithm of one plus the outflow of inventors, who are in the top quartile on the basis of prior citations on their patents, in the subsequent three years after the first investment round. *lnage* and *lnsales* are the natural logarithms of firm age and firm sales in the year of the first investment round.

Variable	**N**	**Mean**	**SD**	**Min**	**Median**	**Max**
1st_round_angel%	5583	0.30	0.37	0.00	0.09	1.00
Angel Investment (1st round)	5583	0.26	0.44	0.00	0.00	1.00
IPO	5583	0.06	0.23	0.00	0.00	1.00
Acq	5583	0.38	0.49	0.00	0.00	1.00
Exit	5583	0.42	0.49	0.00	0.00	1.00
Patents (3 years)	5583	0.53	2.38	0.00	0.00	14.61
Citations (3 years)	5583	0.01	0.05	0.00	0.00	0.31
Sales Growth (Year 0 to 1)	3951	0.36	1.24	-1.00	0.00	6.50
Employment Growth (Year 0 to 1)	3952	0.30	0.96	-1.00	0.00	4.50
Net Inflow of Inventors (3 years)	5583	0.18	0.53	-1.10	0.00	2.08
Net Inflow of Top 25% Inventors (3 years)	5583	0.04	0.25	-0.69	0.00	1.10
lnage	5583	1.24	0.78	0.00	1.10	2.71
lnsales	5583	10.78	6.40	0.00	13.55	21.53

Table 2. Investor Composition and Successful Exits

This table shows the results of examining how investor composition for entrepreneurial firms in the first round of financing is associated with these firms' successful exits in the subsequent years. This sample include all startup firms whose first financing rounds involved only angel and VC investors. The dependent variables are dummy variables representing whether a firm has gone public (*IPO*), has been acquired (*Acq*), or has either been acquired or gone public (*Exit*) in the years after its first-round of financing. *1st-round_angel%* is the fraction of angel investment in the first round of financing, which is measured as the amount of angel-investment scaled by total investment in the round. We control for the natural logarithms of firm age (*lnage*) and firm sales (*lnsales*) in the year of the first round. We control for the year that firms receive their first-round of financing and the two-digit SIC code of firms' primary industry. Constants are suppressed. The standard errors are clustered at the two-digit SIC code level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1) *IPO*	(2) *Acq*	(3) *Exit*
1st_round_angel%	-0.017**	-0.192***	-0.199***
	(0.007)	(0.015)	(0.013)
lnage	0.001	0.014	0.016
	(0.006)	(0.010)	(0.011)
lnsales	0.002***	0.001	0.002
	(0.001)	(0.001)	(0.001)
Observations	5,583	5,583	5,583
R-squared	.074	.126	.138
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

Table 3. Investor Composition and Sales Growth and Employment Growth

This table reports the results of examining how investor composition for entrepreneurial firms in the first round of financing is associated with firms' subsequent sales growth and employment growth. This sample include all startup firms whose first financing rounds involved only angel and VC investors. The dependent variables are the annual growth rates of sales in the first, second, and third year after its first-round of financing (*Sales_growth (Year 0 to 1)*, *Sales_growth (Year 1 to 2)*, and *Sales_growth (Year 2 to 3)*), respectively. In Columns (4)-(6), the dependent variables are the annual growth rates of employment in the first, second, and third year after its first-round of financing (*Employment growth (Year 0 to 1)*, *Employment growth (Year 1 to 2)*, and *Employment growth (Year 2 to 3)*), respectively. *1st-round_angel%* is the fraction of angel investment in the first round of financing, which is measured as the amount of angel-investment scaled by total investment in the round. We control for the natural logarithms of firm age (*lnage*) and firm sales (*lnsales*) in the year of the first round. We control for the year that firms receive their first-round of financing and the two-digit SIC code of firms' primary industry. Constants are suppressed. The standard errors are clustered at the two-digit SIC code level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Sales Growth			*Employment Growth*		
Variables	Year 0 to 1	Year 1 to 2	Year 2 to 3	Year 0 to 1	Year 1 to 2	Year 2 to 3
1st_round_angel%	-0.248***	-0.206***	-0.140***	-0.236***	-0.193***	-0.101***
	(0.050)	(0.025)	(0.037)	(0.034)	(0.022)	(0.030)
lnage	0.067**	0.009	-0.044	0.017	-0.030**	-0.064***
	(0.026)	(0.017)	(0.028)	(0.017)	(0.014)	(0.016)
lnsales	-0.150***	-0.007*	-0.006	-0.093***	-0.002	-0.004
	(0.018)	(0.004)	(0.004)	(0.012)	(0.003)	(0.003)
Observations	3,951	4,239	3,973	3,952	4,244	3,977
R-squared	.075	.031	.03	.081	.047	.044
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 4. Investor Composition and Patent Quantity and Quality

This table shows the results of examining how investor composition for entrepreneurial firms in the first round of financing is associated with patent applications and citations in the subsequent years. This sample include all startup firms whose first financing rounds involved only angel and VC investors. The dependent variables in columns (1) to (3) are the natural logarithm of one plus the number of patents applied (and eventually granted) in the next one, two, and three years after its first-round of financing adjusted for the truncation bias (*Patents (1 year)*, *Patents (2 years)*, and *Patents (3 years)*), respectively. The dependent variables in columns (4) to (6) are the natural logarithm of one plus the number of citations on patents applied (and eventually granted) in the next one, two, and three years after its first-round of financing adjusted for the truncation bias (*Citations (1 year)*, *Citations (2 years)*, and *Citations (3 years)*). *1st-round_angel%* is the fraction of angel investment in the first round of financing, which is measured as the amount of angel-investment scaled by total investment in the round. We control for the natural logarithms of firm age (*lnage*) and firm sales (*lnsales*) in the year of the first round. We control for the year that firms receive their first-round of financing and the two-digit SIC code of firms' primary industry. Constants are suppressed. The standard errors are clustered at the two-digit SIC code level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		Patents			*Citations*	
Variables	1 Year	2 Years	3 Years	1 Year	2 Years	3 Years
1st_round_angel%	-0.101**	-0.294***	-0.352***	-0.002***	-0.007***	-0.008***
	(0.038)	(0.081)	(0.079)	(0.001)	(0.002)	(0.002)
lnage	-0.110***	-0.313***	-0.379***	-0.002***	-0.007***	-0.009***
	(0.023)	(0.048)	(0.053)	(0.000)	(0.001)	(0.001)
lnsales	-0.004***	-0.011***	-0.009	-0.000***	-0.000**	-0.000*
	(0.001)	(0.004)	(0.005)	(0.000)	(0.000)	(0.000)
Observations	5,583	5,583	5,583	5,583	5,583	5,583
R-squared	.048	.078	.076	.048	.072	.072
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 5. Investor Composition and Inventor Inflows

This table shows the results of examining how investor composition for entrepreneurial firms in the first round of financing is associated with inventor net inflows in the subsequent years. This sample include all startup firms whose first financing rounds involved only angel and VC investors. The dependent variables in columns (1) to (3) are the net inflow of inventors in one, two, and three years after its first-round of financing (*Net Inflow of Inventors (1 Year)*, *Net Inflow of Inventors (2 Years)*, and *Net Inflow of Inventors (3 Years)*), respectively, defined as the difference between the natural logarithm of one plus the inflow and the natural logarithm of one plus the outflow of inventors in the subsequent one, two, and three years after an entrepreneurial firm received its first-round of financing. The dependent variables in columns (4) to (6) are the net inflow of the inventors with the top-quartile number of citations in one, two, and three years after its first-round of financing (*Net Inflow of Top 25% Inventors (1 Year)*, *Net Inflow of Top 25% Inventors (2 Years)*, and *Net Inflow of Top 25% Inventors (3 Years)*), respectively. *1st-round_angel%* is the fraction of angel investment in the first round of financing, which is measured as the amount of angel-investment scaled by total investment in the round. We control for the natural logarithms of firm age (*lnage*) and firm sales (*lnsales*) in the year of the first round. We control for the year that firms receive their first-round of financing and the two-digit SIC code of firms' primary industry. Constants are suppressed. The standard errors are clustered at the two-digit SIC code level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Net Inflow of Inventors			*Net Inflow (Top 25% Inventors)*		
Variables	1 Year	2 Years	3 Years	1 Year	2 Years	3 Years
1st_round_angel%	-0.065***	-0.110***	-0.119***	-0.021***	-0.032***	-0.035***
	(0.011)	(0.015)	(0.016)	(0.005)	(0.005)	(0.007)
lnage	-0.054***	-0.085***	-0.103***	-0.016***	-0.026***	-0.031***
	(0.008)	(0.011)	(0.012)	(0.003)	(0.004)	(0.007)
lnsales	0.002	0.001	0.002	-0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Observations	5,583	5,583	5,583	5,583	5,583	5,583
R-squared	.045	.061	.07	.029	.038	.043
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 6. IV Analysis: Successful Exits

This table shows the results of the IV analysis of the impact of investor composition on entrepreneurial firms' successful exits in the subsequent years. This sample include all startup firms whose first financing rounds involved only angel and VC investors. *ATC* is the IV which is a dummy variable that equals one if the state where a firm is located in has an active angel tax credits program and zero otherwise. *LPR* is the IV which proxies for the returns of the limited partners in the past three years. Column (1) shows the first-stage of the IV analysis. In Column (2)-(4), the dependent variables are dummy variables representing whether a firm has gone public (*IPO*), has been acquired (*Acq*), or has either been acquired or gone public (*Exit*) in the years after its first-round of financing, respectively. *1st-round_angel%* equals the fraction of angel investment in the first round of financing. We control for the natural logarithms of firm age (*lnage*) and firm sales (*lnsales*) in the year of the first round. We also include the year that firms receive their first-round of financing and the two-digit SIC code of firms' primary industry. Constants are suppressed. We also report Kleibergen-Paap rk Wald F statistic. The standard errors are clustered at the two-digit SIC code level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1) *1st-stage*	(2) *IPO*	(3) *Acq*	(4) *Exit*
LPR	-0.081***			
	(0.015)			
ATC	0.041***			
	(0.009)			
1st_round_angel%		-0.308**	-0.610***	-0.872***
		(0.146)	(0.233)	(0.292)
lnage	-0.074***	-0.019**	-0.015	-0.031**
	(0.006)	(0.008)	(0.012)	(0.015)
lnsales	-0.005***	0.001	-0.001	-0.002
	(0.001)	(0.001)	(0.002)	(0.003)
Observations	5,583	5,583	5,583	5,583
R-squared	.132	-	-	-
F-stat	27.297	-	-	-
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Table 7. IV Analysis: Sales Growth and Employment Growth

This table shows the results of the IV analysis of the impact of investor composition on the sales growth of entrepreneurial firms in the subsequent years. This sample include all startup firms whose first financing rounds involved only angel and VC investors. ATC is the IV which is a dummy variable that equals one if the state where a firm is located in has an active angel tax credits program and zero otherwise. LPR is the IV which proxies for the returns of the limited partners in the past three years. Column (1) shows the first-stage of the IV analysis. In Column (2)-(4), the dependent variables are the annual growth rates of sales in the first, second, and third year after its first-round of financing (*Sales Growth (Year 0 to 1)*, *Sales Growth (Year 1 to 2)*, and *Sales Growth (Year 2 to 3)*), respectively. In Column (5)-(7), the dependent variables are the annual growth rates of employment in the first, second, and third year after its first-round of financing (*Employment growth (Year 0 to 1)*, *Employment growth (Year 1 to 2)*, and *Employment growth (Year 2 to 3)*), respectively. *1st-round_angel%* equals the fraction of angel investment in the first round of financing. We control for the natural logarithms of firm age (*lnage*) and firm sales (*lnsales*) in the year of the first round. We also include the year that firms receive their first-round of financing, the state that firms locate in, and the two-digit SIC code of firms' primary industry. Constants are suppressed. We also report Kleibergen-Paap rk Wald F statistic. The standard errors are clustered at the two-digit SIC code level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Sales Growth			*Employment Growth*	
Variables	1st-stage	Year 0 to 1	Year 1 to 2	Year 2 to 3	Year 0 to 1	Year 1 to 2	Year 2 to 3
LPR	-0.064***						
	(0.017)						
ATC	0.040***						
	(0.012)						
1st_round_angel%		-0.294	0.960	-1.949***	-0.670	-0.013	-0.930***
		(0.626)	(0.974)	(0.551)	(0.429)	(0.559)	(0.332)
lnage	-0.057***	0.064**	0.061	-0.108***	-0.007	-0.022	-0.094***
	(0.006)	(0.031)	(0.042)	(0.034)	(0.027)	(0.024)	(0.019)
lnsales	-0.027***	-0.151***	-0.003	-0.013***	-0.104***	-0.002	-0.008**
	(0.007)	(0.028)	(0.003)	(0.005)	(0.017)	(0.002)	(0.003)
Observations	3,951	3,951	4,239	3,973	3,952	4,244	3,977
R-squared	.119	-	-	-	-	-	-
F-stat	9.064	-	-	-	-	-	-
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8. IV Analysis: Patent Quantity and Quality

This table shows the results of the IV analysis of the impact of investor composition on entrepreneurial firms' innovation quantity and quality in the subsequent years. This sample include all startup firms whose first financing rounds involved only angel and VC investors. *ATC* is the IV which is a dummy variable that equals one if the state where a firm is located in has an active angel tax credits program and zero otherwise. *LPR* is the IV which proxies for the returns of the limited partners in the past three years. In Column (2)-(4), the dependent variables are the natural logarithm of one plus the number of patents applied (and eventually granted) in one, two, and three years after its first-round of financing adjusted for the truncation bias (*Patents (1 year)*, *Patents (2 years)*, and *Patents (3 years)*), respectively. In Column (5)-(7), the dependent variables are the natural logarithm of one plus the number of citations on patents applied (and eventually granted) in one, two, and three years after its first-round of financing adjusted for the truncation bias (*Citations (1 year)*, *Citations (2 years)*, and *Citations (3 years)*), respectively. *1st-round_angel%* equals the fraction of angel investment in the first round of financing. We control for the natural logarithms of firm age (*lnage*) and firm sales (*lnsales*) in the year of the first round. We also include the year that firms receive their first-round of financing and the two-digit SIC code of firms' primary industry. Constants are suppressed. We also report Kleibergen-Paap rk Wald F statistic. The standard errors are clustered at the two-digit SIC code level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Patents			*Citations*	
Variables	1st-stage	1 Year	2 Years	3 Years	1 Year	2 Years	3 Years
LPR	-0.081***						
	(0.015)						
ATC	0.041***						
	(0.009)						
1st_round_angel%		-1.139***	-2.944**	-3.214**	-0.016***	-0.044**	-0.053**
		(0.336)	(1.311)	(1.568)	(0.004)	(0.017)	(0.025)
lnage	-0.074***	-0.184***	-0.500***	-0.582***	-0.003***	-0.009***	-0.012***
	(0.006)	(0.028)	(0.109)	(0.132)	(0.000)	(0.001)	(0.002)
lnsales	-0.005***	-0.010***	-0.026***	-0.024***	-0.000***	-0.000***	-0.001***
	(0.001)	(0.002)	(0.006)	(0.006)	(0.000)	(0.000)	(0.000)
Observations	5,583	5,583	5,583	5,583	5,583	5,583	5,583
R-squared	.132	-	-	-	-	-	-
F-stat	27.297	-	-	-	-	-	-
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9. IV Analysis: Inventor Inflows

This table shows the results of the IV analysis of the impact of investor composition on entrepreneurial firms' inventor inflows in the subsequent years. This sample include all startup firms whose first financing rounds involved only angel and VC investors. *ATC* is the IV which is a dummy variable that equals one if the state where a firm is located in has an active angel tax credits program and zero otherwise. *LPR* is the IV which proxies for the returns of the limited partners in the past three years. In Column (2)-(4), the dependent variables are the net inflow of inventors in one, two, and three years after its first-round of financing (*Net Inflow of Inventors (1 Year)*, *Net Inflow of Inventors (2 Years)*, and *Net Inflow of Inventors (3 Years)*), respectively. The dependent variables in columns (5) to (7) are the net inflow of the inventors with the top-quartile number of citations in one, two, and three years after its first-round of financing (*Net Inflow of Top 25% Inventors (1 Year)*, *Net Inflow of Top 25% Inventors (2 Years)*, and *Net Inflow of Top 25% Inventors (3 Years)*), respectively. *1st-round_angel%* equals the fraction of angel investment in the first round of financing. We control for the natural logarithms of firm age (*lnage*) and firm sales (*lnsales*) in the year of the first round. We also include the year that firms receive their first-round of financing and the two-digit SIC code of firms' primary industry. Constants are suppressed. We also report Kleibergen-Paap rk Wald F statistic. The standard errors are clustered at the two-digit SIC code level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Net Inflow of Inventors			*Net Inflow (Top 25% inventors)*		
Variables	1st-stage	1 Year	2 Years	3 Years	1 Year	2 Years	3 Years
LPR	-0.081***						
	(0.015)						
ATC	0.041***						
	(0.009)						
1st_round_angel%		-0.455***	-0.910***	-0.713***	-0.125*	-0.182	-0.110
		(0.156)	(0.233)	(0.171)	(0.071)	(0.126)	(0.104)
lnage	-0.074***	-0.082***	-0.142***	-0.145***	-0.023***	-0.036***	-0.036***
	(0.006)	(0.011)	(0.021)	(0.014)	(0.007)	(0.012)	(0.012)
lnsales	-0.005***	-0.000	-0.003**	-0.002	-0.001**	-0.001**	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Observations	5,583	5,583	5,583	5,583	5,583	5,583	5,583
R-squared	.132	-	-	-	-	-	-
F-stat	27.297	-	-	-	-	-	-
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 10. Switching Regressions: Successful Exits

This table reports the results from an endogenous switching regression model, examining the impact of investor composition on firm's successful exits. Panel A reports the results of the second-stage regressions where dependent variables are related to successful exits and independent variables are the *Inverse Mills Ratio* reported from the first stage and all the other independent variables the same as in the first stage (results reported in the Table A1 Internet Appendix). In the second stage of regressions, standard errors are bootstrapped and are clustered at the two-digit SIC code level. Panel B shows the "what-if" analysis based on the results of the switching regression model. Panel B first displays the counterfactual analysis for firms which received angel financing in their first round of financing and then shows the counterfactual analysis for firms which only received VC financing in their first round of financing. The actual outcome, the hypothetical value predicted from the switching regression model, the difference between actual value and the hypothetical value, and the t-statistics of the difference are shown in each panel. This means that for the sample of angel-backed, firms hypothetical scenario represents the case where the angel-backed firms did not receive any angel financing (but only VC investment), while for the sample of VC-only firms, hypothetical scenario represents the case where such firms received angel financing. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Switching Regressions with Endogenous Switching: Successful Exits

	(1)	(2)	(3)	(4)	(5)	(6)
Variable:	*IPO*		*Acq*		*Exit*	
Sub-sample:	*VC Only*	*Angel-backed*	*VC Only*	*Angel-backed*	*VC Only*	*Angel-backed*
Inverse Mills Ratio	0.176***	0.090*	0.316***	0.039	0.448***	0.157
	(0.052)	(0.048)	(0.101)	(0.117)	(0.112)	(0.107)
lnage	-0.045***	-0.020	-0.058**	0.001	-0.090***	-0.027
	(0.013)	(0.015)	(0.023)	(0.027)	(0.025)	(0.026)
lnsales	-0.000	0.000	-0.005**	0.002	-0.006***	0.002
	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)	(0.003)
Observations	4,126	1,443	4,126	1,443	4,126	1,443
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

(Continued)

Panel B. Counterfactual Analysis on Successful Exits

	Actual	Hypothetical	Diff	t-statistics
Comparisons for Angel-Backed Firms				
IPO	0.028	0.038	-0.009	-2.101
Acq	0.229	0.326	-0.097	-8.854
Exit	0.252	0.355	-0.103	-9.159
Comparisons for VC-Only Firms				
IPO	0.068	0.052	0.016	4.105
Acq	0.436	0.296	0.141	18.661
Exit	0.481	0.341	0.140	18.595

Table 11. Switching Regressions: Sales Growth and Employment Growth

This table reports the results from an endogenous switching regression model, examining the impact of investor composition on firm's growth of sales and employment. Panel A reports the results of the second-stage regressions where dependent variables are related to sales growth and independent variables in the second stage of the regressions are the *Inverse Mills Ratio* reported from the first stage and all the other independent variables the same as in the first stage (results reported in the Table A1 Internet Appendix). In the second stage of regressions, standard errors are bootstrapped and are clustered at the two-digit SIC code level. Panel B reports the results of the second-stage regressions where dependent variables are related to employment growth. Panel C shows the "what-if" analysis based on the results of the switching regression model for sales growth and employment growth. Panel C first displays the counterfactual analysis for firms which received angel financing in their first round of financing and then shows the counterfactual analysis for firms which only received VC financing in their first round of financing. The actual outcome, the hypothetical value predicted from the switching regression model, the difference between actual value and the hypothetical value, and the t-statistics of the difference are shown in each panel. This means that for the sample of angel-backed firms, hypothetical scenario represents the case where the angel-backed firms did not receive any angel financing (but only VC investment), while for the sample of VC-only firms, hypothetical scenario represents the case where such firms received angel financing. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Switching Regressions with Endogenous Switching: Sales Growth

	(1)	(2)	(3)	(4)	(5)	(6)
	Sales Growth					
Variables	1 Year		2 Years		3 Years	
Sub-sample:	*VC Only*	*Angel-backed*	*VC Only*	*Angel-backed*	*VC Only*	*Angel-backed*
Inverse Mills Ratio	-0.115	-0.509	-0.509	-0.164	0.354	0.527**
	(0.265)	(0.346)	(0.311)	(0.313)	(0.228)	(0.255)
lnage	0.098	0.185**	0.122	0.069	-0.140**	-0.134*
	(0.066)	(0.083)	(0.079)	(0.088)	(0.068)	(0.070)
lnsales	-0.163***	-0.087***	0.001	-0.003	-0.014***	-0.004
	(0.019)	(0.030)	(0.005)	(0.005)	(0.004)	(0.005)
Observations	3,105	838	3,368	864	3,214	752
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

(Continued)

Panel B. Switching Regressions with Endogenous Switching: Employment Growth

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Employment Growth					
	1 Year		2 Years		3 Years	
Sub-sample:	*VC Only*	*Angel-backed*	*VC Only*	*Angel-backed*	*VC Only*	*Angel-backed*
Inverse Mills Ratio	-0.033	-0.093	-0.050	0.192	0.070	0.366
	(0.184)	(0.319)	(0.187)	(0.240)	(0.110)	(0.239)
lnage	0.027	0.043	-0.036	-0.044	-0.087***	-0.129**
	(0.047)	(0.074)	(0.048)	(0.065)	(0.033)	(0.065)
lnsales	-0.103***	-0.040*	-0.001	-0.004	-0.007**	-0.006**
	(0.013)	(0.024)	(0.003)	(0.004)	(0.003)	(0.003)
Observations	3,106	838	3,373	864	3,218	752
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel C. Counterfactual Analysis on Sales Growth and Employment Growth

	Actual	Hypothetical	Diff	t-statistics
Comparisons for Angel-Backed Firms				
Sales Growth (Yr 0 to 1)	0.221	0.468	-0.247	-6.887
Sales Growth (Yr 1 to 2)	0.129	0.421	-0.292	-10.396
Sales Growth (Yr 2 to 3)	0.204	0.296	-0.092	-2.479
Employment Growth (Yr 0 to 1)	0.171	0.380	-0.209	-8.021
Employment Growth (Yr 1 to 2)	0.097	0.334	-0.238	-11.294
Employment Growth (Yr 2 to 3)	0.151	0.225	-0.075	-2.532
Comparisons for VC-Only Firms				
Sales Growth (Yr 0 to 1)	0.399	0.225	0.174	7.485
Sales Growth (Yr 1 to 2)	0.408	0.178	0.230	10.115
Sales Growth (Yr 2 to 3)	0.297	0.275	0.021	0.994
Employment Growth (Yr 0 to 1)	0.339	0.197	0.142	7.921
Employment Growth (Yr 1 to 2)	0.345	0.145	0.200	11.333
Employment Growth (Yr 2 to 3)	0.208	0.185	0.023	1.513

Table 12. Switching Regressions: Patent Quantity and Quality

This table reports the results from an endogenous switching regression model, examining the impact of investor composition on firm's patent quantity and quality. Panel A reports the results of the second-stage regressions where dependent variables are related to patent quantity and independent variables in the second stage of the regressions are the *Inverse Mills Ratio* reported from the first stage and all the other independent variables the same as in the first stage (results reported in the Table A1 Internet Appendix). In the second stage of regressions, standard errors are bootstrapped and are clustered at the two-digit SIC code level. Panel B reports the results of the second-stage regressions where dependent variables are related to patent quality. Panel C shows the "what-if" analysis based on the results of the switching regression model for patent quantity and quality. Panel C first displays the counterfactual analysis for firms which received angel financing in their first round of financing and then shows the counterfactual analysis for firms which only received VC financing in their first round of financing. The actual outcome, the hypothetical value predicted from the switching regression model, the difference between actual value and the hypothetical value, and the t-statistics of the difference are shown in each panel. This means that for the sample of angel-backed firms, hypothetical scenario represents the case where the angel-backed firms did not receive any angel financing (but only VC investment), while for the sample of VC-only firms, hypothetical scenario represents the case where such firms received angel financing. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Switching Regressions with Endogenous Switching: Patent Quantity

	(1)	(2)	(3)	(4)	(5)	(6)
	Patents					
	1 Year		2 Years		3 Years	
Variables Sub-sample:	*VC Only*	*Angel-backed*	*VC Only*	*Angel-backed*	*VC Only*	*Angel-backed*
Inverse Mills Ratio	0.348**	0.404	1.026***	0.424	1.182**	0.686
	(0.142)	(0.270)	(0.380)	(0.561)	(0.499)	(0.614)
lnage	-0.229***	-0.117*	-0.650***	-0.227	-0.776***	-0.314*
	(0.033)	(0.067)	(0.119)	(0.152)	(0.157)	(0.170)
lnsales	-0.011***	-0.007	-0.031***	-0.008	-0.032***	-0.008
	(0.003)	(0.004)	(0.007)	(0.009)	(0.008)	(0.010)
Observations	4,126	1,443	4,126	1,443	4,126	1,443
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

(Continued)

Panel B. Switching Regressions with Endogenous Switching: Patent Quality

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Citations					
	1 Year		2 Years		3 Years	
Sub-sample:	*VC Only*	*Angel-backed*	*VC Only*	*Angel-backed*	*VC Only*	*Angel-backed*
Inverse Mills Ratio	0.003	0.007	0.007	0.008	0.009	0.014
	(0.002)	(0.004)	(0.006)	(0.010)	(0.009)	(0.013)
lnage	-0.003***	-0.002*	-0.010***	-0.004	-0.013***	-0.006*
	(0.000)	(0.001)	(0.002)	(0.003)	(0.002)	(0.004)
lnsales	-0.000***	-0.000*	-0.000***	-0.000	-0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	4,126	1,443	4,126	1,443	4,126	1,443
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel C. Counterfactual Analysis on Patent Quantity and Quality

	Actual	Hypothetical	Diff	t-statistics
Comparisons for Angel-Backed Firms				
Patents in the next 1 yr	0.079	0.185	-0.106	-6.680
Patents in the next 2 yrs	0.198	0.497	-0.299	-8.299
Patents in the next 3 yrs	0.255	0.603	-0.348	-7.864
Citations of patents in the next 1 yr	0.001	0.003	-0.002	-6.627
Citations of patents in the next 2 yrs	0.003	0.010	-0.007	-9.421
Citations of patents in the next 3 yrs	0.005	0.013	-0.008	-9.169
Comparisons for VC-Only Firms				
Patents in the next 1 yr	0.187	0.156	0.031	2.231
Patents in the next 2 yrs	0.511	0.342	0.169	5.020
Patents in the next 3 yrs	0.629	0.504	0.125	3.116
Citations of patents in the next 1 yr	0.003	0.002	0.001	2.161
Citations of patents in the next 2 yrs	0.009	0.006	0.003	4.889
Citations of patents in the next 3 yrs	0.012	0.009	0.003	3.188

Table 13. Switching Regressions: Inventor Inflows

This table reports the results from an endogenous switching regression model, examining the impact of investor composition on firm's inventor net inflows. Panel A reports the results of the second-stage regressions where dependent variables are related to all inventor net flows and independent variables in the second stage of the regressions are the *Inverse Mills Ratio* reported from the first stage and all the other independent variables the same as in the first stage (results reported in the Table A1 Internet Appendix). In the second stage of regressions, standard errors are bootstrapped and are clustered at the two-digit SIC code level. Panel B reports the results of the second-stage regressions where dependent variables are related to net inflows of inventors with the top-quartile of number of citations. Panel C shows the "what-if" analysis based on the results of the switching regression model for inventor net inflows. Panel C first displays the counterfactual analysis for firms which received angel financing in their first round of financing and then shows the counterfactual analysis for firms which only received VC financing in their first round of financing. The actual outcome, the hypothetical value predicted from the switching regression model, the difference between actual value and the hypothetical value, and the t-statistics of the difference are shown in each panel. This means that for the sample of angel-backed firms, hypothetical scenario represents the case where the angel-backed firms did not receive any angel financing (but only VC investment), while for the sample of VC-only firms, hypothetical scenario represents the case where such firms received angel financing. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Switching Regressions with Endogenous Switching: All Inventor Net Inflows

	(1)	(2)	(3)	(4)	(5)	(6)
	Net Inflow of Inventors					
	1 Year		2 Years		3 Years	
Variables Sub-sample:	*VC Only*	*Angel-backed*	*VC Only*	*Angel-backed*	*VC Only*	*Angel-backed*
Inverse Mills Ratio	0.145**	0.205**	0.361***	0.236*	0.212***	0.289**
	(0.068)	(0.088)	(0.077)	(0.130)	(0.070)	(0.116)
lnage	-0.111***	-0.058**	-0.203***	-0.084***	-0.194***	-0.086***
	(0.015)	(0.024)	(0.025)	(0.032)	(0.019)	(0.026)
lnsales	-0.000	-0.001	-0.005***	-0.001	-0.001	-0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Observations	4,126	1,443	4,126	1,443	4,126	1,443
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

(Continued)

Panel B. Switching Regressions with Endogenous Switching: Top Inventor Net Inflows

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Net Inflow of Inventors (Top 25% Inventors)					
	1 Year		2 Years		3 Years	
Sub-sample:	*VC Only*	*Angel-backed*	*VC Only*	*Angel-backed*	*VC Only*	*Angel-backed*
Inverse Mills Ratio	0.026	0.111***	0.036	0.103*	-0.033	0.168**
	(0.018)	(0.037)	(0.037)	(0.059)	(0.039)	(0.067)
lnage	-0.028***	-0.030***	-0.042***	-0.035**	-0.035***	-0.042**
	(0.006)	(0.009)	(0.012)	(0.015)	(0.011)	(0.017)
lnsales	-0.000	-0.002***	-0.001	-0.002*	0.000	-0.003**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	4,126	1,443	4,126	1,443	4,126	1,443
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel C. Counterfactual Analysis on Inventor Net Inflows

	Actual	Hypothetical	Diff	t-statistics
Comparisons for Angel-Backed Firms				
All inventor net inflows in the next 1 yr	0.052	0.129	-0.077	-10.279
All inventor net inflows in the next 2 yrs	0.005	0.026	-0.021	-7.784
All inventor net inflows in the next 3 yrs	0.082	0.205	-0.123	-12.237
Top inventor net inflows in the next 1 yr	0.016	0.051	-0.035	-8.552
Top inventor net inflows in the next 2 yrs	0.090	0.240	-0.150	-14.100
Top inventor net inflows in the next 3 yrs	0.022	0.070	-0.048	-10.296
Comparisons for VC-Only Firms				
All inventor net inflows in the next 1 yr	0.115	0.086	0.029	4.472
All inventor net inflows in the next 2 yrs	0.016	0.011	0.004	1.725
All inventor net inflows in the next 3 yrs	0.188	0.103	0.084	10.074
Top inventor net inflows in the next 1 yr	0.037	0.018	0.019	5.021
Top inventor net inflows in the next 2 yrs	0.210	0.124	0.086	9.712
Top inventor net inflows in the next 3 yrs	0.045	0.032	0.013	3.052

Table 14. Angels and VC Financing: Complements or Substitutes?

This table reports the results of a test examining how the initial investor composition between VC and angel investors affect the investor composition in the next round, irrespective of the type of investors involved. This sample includes all startups that have received at least two rounds of investment. The dependent variable in Column (1) is the fraction of VC investment in the second round of financing (*2nd-round_VC%*). The dependent variable in Column (2) is a dummy variable of whether or not a firms receives angel investment in the second round (*2nd-round_has_angel*). *1st-round_VC%* equals the fraction of VC investment in the total amount invested in the first round. *1st-round_has_angel* is a dummy which equals one if there is at least one angel invests in the first round and zero otherwise. We control for the natural logarithms of firm age (*lnage*) and firm sales (*lnsales*) in the year of the first round. We control for the year that firms receive their first-round of financing and the two-digit SIC code of firms' primary industry. Constants are suppressed. Standard errors are clustered at the two-digit SIC code level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1) *2nd round VC%*	(2) *2nd round has Angel*
1st-round VC%	0.700***	-0.163***
	(0.014)	(0.030)
1st-round has Angel	0.042***	0.282***
	(0.011)	(0.025)
lnage	0.003	-0.030***
	(0.007)	(0.006)
lnsales	0.002***	0.000
	(0.001)	(0.001)
Observations	5,392	5,392
R-squared	0.575	0.237
Year FE	Yes	Yes
Industry FE	Yes	Yes

Table 15. Financing Sequence of Angel and VC Financing across Rounds and Probability of Successful Exit

This table reports the results of a test examining how the initial investor composition between VC and angel investors affect the investor composition in the next round. This sample includes all the startups that have received at least two rounds of investment involving either VCs or angels without the involvement of any other category of investors. We categorize sample firms into four subgroups based on their financing path in the first two rounds, from angel-dominated to VC-dominated (*FinPath=Angel to VC*), from VC-dominated to angel-dominated (*FinPath=VC to Angel*), from VC-dominated to VC-dominated (*FinPath=VC to VC*), and from angel-dominated to angel-dominated (*FinPath=Angel to Angel*). The dominance of a financing round is defined by looking at whether the percentage of VC investment in a round is larger than 50% or not. We use firms that have both angel-dominated first round and second round of financing as the control group and thus drop the variable *FinPath=Angel to Angel* in the regressions. We control for the natural logarithms of firm age (*lnage*) and firm sales (*lnsales*) in the year of the first round. We control for the year that firms receive their first-round of financing and the two-digit SIC code of firms' primary industry. Constants are suppressed. Standard errors are clustered at the two-digit SIC code level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1) *IPO*	(2) *Acq*	(3) *Exit*
FinPath=(Angel to VC)	0.123**	0.185***	0.288***
	(0.050)	(0.066)	(0.074)
FinPath=(VC to Angel)	-0.040	0.087	0.086
	(0.052)	(0.085)	(0.096)
FinPath=(VC to VC)	0.009	0.239***	0.234***
	(0.019)	(0.028)	(0.022)
lnage	0.049***	-0.001	0.045*
	(0.014)	(0.024)	(0.025)
lnsales	0.005***	0.001	0.004
	(0.001)	(0.003)	(0.004)
Observations	2,294	2,294	2,294
R-squared	0.112	0.173	0.149
Last-round Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

Internet Appendix

A Additional Tests

Table A1. First-Stage of Switching Regressions

This table shows the results of the first stage of the regressions. The dependent variable is whether or not a firm receives angel financing (*Angel Backing Dummy*) and the independent variables are the natural logarithm of firm age (*lnage*) and firm sales (*lnsales*), and our instruments: the dummy of whether or not a firm's headquarter is located in a state that has an active angel tax credit program (*ATC*), and the average past returns of limited partners in the firm-headquarter state (*LPR*). We also include dummies for the year of the first round of financing and the industry of the firm. The standard errors are clustered at the two-digit SIC code level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable	*Angel Backing Dummy*
lnage	-0.347***
	(0.019)
lnsales	-0.021***
	(0.002)
LPR	-0.168**
	(0.069)
ATC	0.139***
	(0.040)
Constant	0.276***
	(0.099)
Observations	5,569
Year	Yes
Industry	Yes

Table A2. Robustness Tests: Successful Exits in case of 1st Investment Rounds having either VCs or Sophisticated Angel Investors (IV Analysis)

This table shows the results of the IV analysis of the impact of investor composition on entrepreneurial firms' successful exits in the subsequent years for a subsample of first-investment rounds containing either VCs or at least one sophisticated angel investor. We define angel groups and serial angel investors as sophisticated angel investors. A serial angel investor for a firm-investment round is an angel investor that has made at least one angel investment in a different firm in the past. ATC is the IV which is a dummy variable that equals one if the state where a firm is located in has an active angel tax credits program and zero otherwise. LPR is the IV which proxies for the returns of the limited partners in the past three years. Column (1) shows the first-stage of the IV analysis. In Column (2)-(4), the dependent variables are dummy variables representing whether a firm has gone public (IPO), has been acquired (*Acq*), or has either been acquired or gone public ($Exit$) in the years after its first-round of financing, respectively. *1st-round_angel%* equals the fraction of angel investment in the first round of financing. We control for the natural logarithms of firm age (*lnage*) and firm sales (*lnsales*) in the year of the first round. We also include the year that firms receive their first-round of financing and the two-digit SIC code of firms' primary industry. Constants are suppressed. We also report Kleibergen-Paap rk Wald F statistic. The standard errors are clustered at the two-digit SIC code level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1) 1st-stage	(2) *IPO*	(3) *Acq*	(4) *Exit*
LPR	-0.090***			
	(0.019)			
ATC	0.045***			
	(0.016)			
1st_round_angel%		-0.175	-0.685**	-0.857**
		(0.133)	(0.343)	(0.404)
lnage	-0.068***	-0.014*	-0.033***	-0.046***
	(0.008)	(0.007)	(0.012)	(0.013)
lnsales	-0.005***	0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.004)	(0.005)
Observations	3,183	3,183	3,183	3,183
R-squared	.137	-	-	-
F-stat	15.727	-	-	-
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Table A3. Robustness Tests: Sales and Employment Growth in case of 1st Investment Rounds having either VCs or Sophisticated Angel Investors (IV Analysis)

This table shows the results of the IV analysis of the impact of investor composition on entrepreneurial firms' sales and employment in the subsequent years for a subsample of first-investment rounds containing either VCs or at least one sophisticated angel. We define angel groups and serial angel investors as sophisticated angel investors. A serial angel investor for a firm-investment round is an angel investor that has made at least one angel investment in a different firm in the past. ATC is the IV which is a dummy variable that equals one if the state where a firm is located in has an active angel tax credits program and zero otherwise. LPR is the IV which proxies for the returns of the limited partners in the past three years. Column (1) shows the first-stage of the IV analysis. In Column (2)-(4), the dependent variables are the annual growth rates of sales in the first, second, and third year after its first-round of financing (*Sales_growth (Year 0 to 1)*, *Sales_growth (Year 1 to 2)*, and *Sales_growth (Year 2 to 3)*), respectively. In Column (5)-(7), the dependent variables are the annual growth rates of employment in the first, second, and third year after its first-round of financing (*Employment growth (Year 0 to 1)*, *Employment growth (Year 1 to 2)*, and *Employment growth (Year 2 to 3)*), respectively. *1st-round_angel%* equals the fraction of angel investment in the first round of financing. We control for the natural logarithms of firm age (*lnage*) and firm sales (*lnsales*) in the year of the first round. We also include the year that firms receive their first-round of financing and the two-digit SIC code of firms' primary industry. Constants are suppressed. We also report Kleibergen-Paap rk Wald F statistic. The standard errors are clustered at the two-digit SIC code level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Sales Growth			*Employment Growth*	
Variables	1st-stage	Year 0 to 1	Year 1 to 2	Year 2 to 3	Year 0 to 1	Year 1 to 2	Year 2 to 3
LPR	-0.069**						
	(0.030)						
ATC	0.048***						
	(0.018)						
1st_round_angel%		-1.637**	1.250	-1.432	-1.128**	0.400	-1.112
		(0.678)	(1.004)	(1.175)	(0.569)	(0.555)	(0.893)
lnsales	-0.041***	-0.210***	-0.002	-0.015**	-0.137***	-0.002	-0.012**
	(0.008)	(0.036)	(0.005)	(0.007)	(0.025)	(0.003)	(0.005)
lnage	-0.047***	0.009	0.072*	-0.101**	-0.002	0.007	-0.094***
	(0.009)	(0.052)	(0.040)	(0.041)	(0.033)	(0.028)	(0.027)
Observations	2,243	2,243	2,382	2,215	2,244	2,385	2,218
R-squared	.152	-	-	-	-	-	-
F-stat	6.623	-	-	-	-	-	-
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A4. Robustness Tests: Patent Quantity and Quality in case of 1st Investment Rounds having either VCs or Sophisticated Angel Investors (IV Analysis)

This table shows the results of the IV analysis of the impact of investor composition on entrepreneurial firms' patenting in the subsequent years for a subsample of first-investment rounds containing either VCs or at least one sophisticated angel. We define angel groups and serial angel investors as sophisticated angel investors. A serial angel investor for a firm-investment round is an angel investor that has made at least one angel investment in a different firm in the past. ATC is the IV which is a dummy variable that equals one if the state where a firm is located in has an active angel tax credits program and zero otherwise. LPR is the IV which proxies for the returns of the limited partners in the past three years. Column (1) shows the first-stage of the IV analysis. In Column (2)-(4), the dependent variables are the natural logarithm of one plus the number of patents applied in one, two, and three years after its first-round of financing adjusted for the truncation bias (*Patents (1 year)*, *Patents (2 years)*, and *Patents (3 years)*), respectively. In Column (5)-(7), the dependent variables are the natural logarithm of one plus the number of citations of patents applied in one, two, and three years after its first-round of financing adjusted for the truncation bias (*Citations (1 year)*, *Citations (2 years)*, and *Citations (3 years)*), respectively. *1st-round_angel%* equals the fraction of angel investment in the first round of financing. We control for the natural logarithms of firm age (*lnage*) and firm sales (*lnsales*) in the year of the first round. We also include the year that firms receive their first-round of financing and the two-digit SIC code of firms' primary industry. Constants are suppressed. We also report Kleibergen-Paap rk Wald F statistic. The standard errors are clustered at the two-digit SIC code level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Patents			*Citations*	
Variables	1st-stage	1 Year	2 Years	3 Years	1 Year	2 Years	3 Years
LPR	-0.090***						
	(0.019)						
ATC	0.045***						
	(0.016)						
1st_round_angel%		-0.623**	-1.317	-1.481	-0.008*	-0.022	-0.030
		(0.283)	(1.000)	(1.169)	(0.004)	(0.015)	(0.022)
lnage	-0.068***	-0.158***	-0.423***	-0.507***	-0.002***	-0.008***	-0.011***
	(0.008)	(0.034)	(0.108)	(0.123)	(0.000)	(0.002)	(0.002)
lnsales	-0.005***	-0.007***	-0.012***	-0.009	-0.000**	-0.000**	-0.000**
	(0.001)	(0.002)	(0.004)	(0.006)	(0.000)	(0.000)	(0.000)
Observations	3,183	3,183	3,183	3,183	3,183	3,183	3,183
R-squared	.137	-	-	-	-	-	-
F-stat	15.727	-	-	-	-	-	-
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A5. Robustness Tests: Inventor Inflows in case of 1st Investment Rounds having either VCs or Sophisticated Angel Investors (IV Analysis)

This table shows the results of the IV analysis of the impact of investor composition on inventor inflows in entrepreneurial firm in the subsequent years for a subsample of first-investment rounds containing either VCs or at least one sophisticated angel. We define angel groups and serial angel investors as sophisticated angel investors. A serial angel investor for a firm-investment round is an angel investor that has made at least one angel investment in a different firm in the past. *ATC* is the IV which is a dummy variable that equals one if the state where a firm is located in has an active angel tax credits program and zero otherwise. *LPR* is the IV which proxies for the returns of the limited partners in the past three years. Column (1) shows the first-stage of the IV analysis. In Column (2)-(4), the dependent variables are the net inflow of inventors in one, two, and three years after its first-round of financing (*Net Inflow of Inventors (1 Year)*, *Net Inflow of Inventors (2 Years)*, and *Net Inflow of Inventors (3 Years)*), respectively. The dependent variables in columns (5) to (7) are the net inflow of the inventors with the top-quartile number of citations in one, two, and three years after its first-round of financing (*Net Inflow of Top 25% Inventors (1 Year)*, *Net Inflow of Top 25% Inventors (2 Years)*, and *Net Inflow of Top 25% Inventors (3 Years)*), respectively. *1st-round_angel%* equals the fraction of angel investment in the first round of financing. We control for the natural logarithms of firm age (*lnage*) and firm sales (*lnsales*) in the year of the first round. We also include the year that firms receive their first-round of financing and the two-digit SIC code of firms' primary industry. Constants are suppressed. We also report Kleibergen-Paap rk Wald F statistic. We also report Kleibergen-Paap rk Wald F statistic. The standard errors are clustered at the two-digit SIC code level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Net Inflow of Inventors			*Net Inflow (Top 25% inventors)*		
Variables	1st-stage	1 Year	2 Years	3 Years	1 Year	2 Years	3 Years
LPR	-0.090***						
	(0.019)						
ATC	0.045***						
	(0.016)						
1st_round_angel%		-0.490**	-0.669**	-0.491*	-0.113	-0.149*	-0.112
		(0.207)	(0.277)	(0.254)	(0.087)	(0.082)	(0.108)
lnage	-0.068***	-0.079***	-0.131***	-0.135***	-0.022***	-0.040***	-0.042***
	(0.008)	(0.018)	(0.018)	(0.014)	(0.008)	(0.010)	(0.011)
lnsales	-0.005***	-0.001	-0.002	-0.000	-0.000	-0.001	-0.000
	(0.001)	(0.002)	(0.003)	(0.002)	(0.000)	(0.000)	(0.001)
Observations	3,183	3,183	3,183	3,183	3,183	3,183	3,183
R-squared	.137				-	-	-
F-stat	15.727	-	-	-	-	-	-
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A6. Robustness Tests: Successful Exits in case of 1st Investment Rounds having either VCs or Angel Groups only (IV Analysis)

This table shows the results of the IV analysis of the impact of investor composition on entrepreneurial firms' successful exits in the subsequent years for a subsample of first-investment rounds containing either VCs or angel groups only. APR is the IV which is a dummy variable that equals one if the state where a firm is located in has an active angel tax credits program and zero otherwise. LPR is the IV which proxies for the returns of the limited partners in the past three years. Column (1) shows the first-stage of the IV analysis. In Column (2)-(4), the dependent variables are dummy variables representing whether a firm has gone public (IPO), has been acquired (*Acq*), or has either been acquired or gone public (*Exit*) in the years after its first-round of financing, respectively. *1st-round_angel%* equals the fraction of angel investment in the first round of financing. We control for the natural logarithms of firm age (*lnage*) and firm sales (*lnsales*) in the year of the first round. We also include the year that firms receive their first-round of financing and the two-digit SIC code of firms' primary industry. Constants are suppressed. We also report Kleibergen-Paap rk Wald F statistic. The standard errors are clustered at the two-digit SIC code level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1) *1st-stage*	(2) *IPO*	(3) *Acq*	(4) *Exit*
LPR	-0.117***			
	(0.017)			
ATC	0.038**			
	(0.016)			
1st_round_angel%		-0.131	-0.762**	-0.890**
		(0.127)	(0.302)	(0.361)
lnage	-0.010	-0.008	0.013	0.007
	(0.007)	(0.006)	(0.017)	(0.017)
lnsales	-0.005***	0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.003)	(0.004)
Observations	2,724	2,724	2,724	2,724
R-squared	.097	-	-	-
F-stat	30.371	-	-	-
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Table A7. Industry Subsample Analysis: Successful Exits (IV Analysis)

This table shows the results of the second stage of the IV analysis of the impact of investor composition on entrepreneurial firms' successful exits in the subsequent years for subsamples of firms that are in VC-specific industries and other industries. VCs tend to invest in Hitech, manufacturing, and healthcare industries. We classify the above industries using the Fama-French 10 industry classification. Hitech, manufacturing, and healthcare industries are classified as 5, 3, and 8, respectively in the Fama-French 10 industry categories. Column (1) shows the first-stage of the IV analysis. In Column (2)-(4), the dependent variables are dummy variables representing whether a firm has gone public (IPO), has been acquired (*Acq*), or has either been acquired or gone public (*Exit*) in the years after its first-round of financing, respectively. *1st-round_angel%* equals the fraction of angel investment in the total amount invested in the first round of financing. We control for the natural logarithms of firm age (*lnage*) and firm sales (*lnsales*) in the year of the first round. We also include the year that firms receive their first-round of financing and the two-digit SIC code of firms' primary industry. Constants are suppressed. The standard errors are clustered at the two-digit SIC code level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Other Industries			HiTech + Manufacturing + Healthcare		
Variables	*IPO*	*Acq*	*Exit*	*IPO*	*Acq*	*Exit*
1st_round_angel% *(instrumented)*	-0.080	-0.593**	-0.762***	-0.550**	-0.575*	-0.921**
	(0.141)	(0.258)	(0.285)	(0.261)	(0.294)	(0.405)
lnage	-0.004	-0.025	-0.040	-0.021	-0.005	-0.016
	(0.013)	(0.024)	(0.027)	(0.013)	(0.008)	(0.010)
lnsales	0.001	-0.003	-0.004	0.001	0.001	0.002
	(0.001)	(0.003)	(0.003)	(0.001)	(0.002)	(0.002)
Observations	2,885	2,885	2,885	2,698	2,698	2,698
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes