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Three Essays in Entrepreneurial Finance and Innovation

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by

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Abstract

My doctoral dissertation consists of three chapters focused on topics in entrepreneurial finance and corporate innovation. In the first chapter, I analyze secondary market patent transactions from public assignors (seller firms) to assignees (buyer firms). I show that firms with higher innovation productivity (more able to innovate) but with lower production efficiency (less able to commercialize) are more likely to sell patents distant from their operations. Using a linked assignor-assignee dataset, I find that patents technologically closer to buyer than to seller firms are more likely to be sold in a patent transaction, implying gains from trading patents. I document that, in the three years following patent transactions, seller firms experience a positive and statistically significant improvement in their ROA and operating profitability. I find that the improvement in ROA and operating profitability is concentrated in seller firms which increase their R&D focus after patent transactions, suggesting that an increase in innovation focus is one of the channels driving these results. Consistent with this channel, I find that inventors who are either newly hired by or remaining in assignor firms over the three years subsequent to patent transactions have technological expertise more similar to those of assignor firms.

In the second chapter, co-authored with Xi Chen, we study how venture capitalists (VCs) create value in the product market for the entrepreneurial firms backed by them. By constructing a novel dataset based on Nielsen Retail Scanner and VentureXpert, we document that, compared to non-VC-backed firms, VC-backed startups have more than doubled their sales and seized more nationwide market share in the five years following the first VC investment. A further decomposition indicates that VC-backed firms achieve the growth in sales and market share by lowering their product prices.

In addition, subsequent to the first VC investment, VC-backed firms enlarge their product portfolios by introducing new products and establishing new product lines, and they expand their products to more stores and geographic locations. Using the limited partner return as an instrument for the supply of VC financing, we show that the above effects are causal. We document heterogeneous value creation effects of VC financing for firms with different market share and for firms with different geographic proximity to the lead VC investors. This suggests that, apart from providing capital, VCs also add value to startups by directing their marketing strategy and monitoring their operations.

In the third chapter, co-authored with Thomas Chemmanur, Jiajie Xu, and Xiang Zheng, we analyze the effect of the composition of venture capital (VC) syndicates on value creation to the entrepreneurial firms they invest in. We hypothesize that VCs may learn about each other's skills at value creation when they co-invest together in entrepreneurial firms, allowing for more efficient value creation when they co-invest in subsequent syndicates. Further, if VCs view syndication as a repeated game, this may generate incentives to co-operate to a greater extent with each other when investing together in a syndicate, reducing the probability of conflicts among VCs. We empirically analyze the implications of these hypotheses and find the following. First, prior collaboration between a lead VC and any of the VCs in a syndicate leads to greater short-term value creation, as evidenced by greater sales growth, employment growth, probability of patented innovation, and the quality of innovations generated during the three years subsequent to VC syndicate investment. Second, prior collaboration between the lead VC and at least one of the syndicate members leads to greater long-term value creation, as evidenced by the higher probability of a successful exit (IPO or acquisition). Third, if the prior collaboration is very successful (leading to an IPO exit resulting from the previous collaboration), then there is even greater value creation by the VC syndicate compared to the case where the prior collaboration was less successful. Finally, consistent with prior collaboration allowing VCs to learn about each other's value creation skills and reducing potential conflicts among the VCs forming a syndicate, syndicates with prior collaboration between the lead VC and at least one syndicate member are characterized by more uniform syndicate compositions across financing rounds.

Keywords: Corporate Innovation, Patent Transactions, Entrepreneurial Finance, Venture Capital

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Chapter 1: Why Do Innovative Firms Sell Patents? An Empirical Analysis of the Causes and Consequences of Secondary Market Patent Transactions

1. Introduction

How do firms manage their patent portfolios? An important way for firms to efficiently manage their patent portfolios is through a well-functioning secondary market for patents. Such a secondary market is critical not only to firms but also to the economy at large. By allowing firms with different comparative advantages to specialize in R&D and commercialization, an efficient secondary market for patents enables a more productive use of the existing technology and provides further incentives for firms to invest in R&D. This could be beneficial to firms' long-term growth. For policymakers and the whole economy, an efficient secondary market is equally important. A well-functioning secondary market for patents is critical for diffusing innovation and curtailing duplicate R&D efforts. Moreover, it also improves social welfare by enabling patents to be used by more efficient market participants.

Over the past decade, researchers have gained considerable insight into the factors that affect the innovation productivity of firms.[1] However, how firms manage their innovation output (i.e., patents) after they are developed remains largely underexplored. When hiring research staff to conduct in-house R&D activity, firms usually promise research freedom and give research personnel large discretion in the specifics of the projects they can work on. This decentralized R&D process, combined with the uncertain nature of new inventions, often leads to researchers employed by a firm generating patents that may not all be an exact fit with the firm's needs. As a result, among the patents in a firm's patent portfolio, the firm may choose to commercialize only a part of them that are closely related to its main line of business while leaving the remaining patents "sitting on the shelf".

The above situation raises a number of research questions that I explore in this paper for the first

[1] For example, see Manso (2011), Ederer and Manso (2013), Aghion, Van Reenen and Zingales (2013), Chemmanur, Loutskina and Tian (2014), and Tian and Wang (2014)), among others.

time in the literature. First, what are the determinants of innovative firms selling some of their patents to others? When these innovative firms sell some of their patents, which patents do they choose to sell? Second, what are the implications of secondary market patent transactions for the future economic and financial performance of seller firms? This paper aims to address these questions.

The secondary market for patents has grown significantly over the last several decades. Figures 1 and 2 give an overview of this landscape. Figure 1 shows the number and percentage of innovative firms (both private and public) selling their patents in the secondary market from 1980 to 2017. The number of firms selling patents prior to 1980 was small. However, this number has grown dramatically since then and has remained steady in the last decade. We can also observe an upward trend in the percentage of innovative firms selling patents. Figure 2 displays the number of patents sold in the secondary market from 1980 to 2017. The magnitude is also large. Notably, the number of patents being traded (excluding those traded due to other reasons, such as mergers & acquisitions, mortgage, security interest etc.) has risen over 120,000 in 2014, which is approximately over a third of the new patents granted in the U.S. in the same year. These figures, taken together, point to a very large and stable secondary market for patents. However, there have been few attempts so far in the literature to gain a thorough understanding of the secondary market for patents as well as its implications for firms. My paper aims to fill this gap in the literature.

Prior to my empirical analysis, I develop testable hypotheses based on the existing theoretical literature and new conjectures on my part. First, I develop testable hypotheses regarding the determinants of secondary market patent transactions for seller firms. Innovation has long been argued to be critical to firms' long-term growth. Innovative firms constantly conduct innovation activity so that they can build valuable products around their innovation output and gain an advantage in the product market. Throughout the process of innovative firms developing their innovation output, high-quality inventors play a pivotal role. In order to attract high-quality research personnel, apart from offering a competitive salary and other compensations, an innovative firm usually promises research freedom and does not put many restrictions on the specifics of the projects the research personnel could work on. During this decentralized R&D process, combined with the uncertain nature of new inventions, the research staff of a firm may not always come up with innovation output (in the form of patents) that perfectly aligns with the firm's main line of business. If some of the developed patents are far away from the firm's operations, they could be very costly to commercialize, since the firm needs different complementary technology and assets in place before it can commercialize such patents and release the final products to the market.

Therefore, based on this argument, I conjecture two sets of determinants (firm-level and patent-level) of secondary market patent transactions of seller firms. In terms of the firm-level determinants of patent transactions of seller firms, I hypothesize that firms with higher innovation productivity (i.e., more able to innovate) but with lower production efficiency (i.e., less able to commercialize their innovation output) are more likely to sell some of their patents. In terms of the patent-level determinants, I posit that patents that are less relevant to a seller firm's operations are more likely to be sold in a patent transaction. In addition, the closeness of a patent to a buyer firm's operations also matters for the probability of the patent to be sold in a patent transaction. Thus, I hypothesize that patents that are relatively closer to the assignees (buyers) than to the assignors (sellers) firms are more likely to be sold in the secondary market.

Second, I develop testable hypotheses regarding the economic and financial consequences of secondary market patent transactions for assignor firms. The effect of patent transactions on seller firms' future operating performance is ambiguous *ex ante*. Whether a secondary market patent transaction increases or decreases a seller firm's long-run operating performance depends on whether commercializing the patent in-house is a positive or a negative NPV transaction. If commercializing a patent in-house is very costly, selling it to another firm and thus monetizing the value of the patent to some extent (rather than letting it sit on the shelf) will increase a seller firm's operating performance. Further, selling patents further away from its core activity also means that the seller firm is increasing its R&D focus. This leads to the seller firm innovating more in areas closer to its expertise and utilizing its R&D resources more efficiently in the future. This will also result in an increase in the firm's operating performance following the selling of a patent. However, by re-assigning the entire rights and ownership of a patent to others, a seller firm would lose control of where this patent flows and how this patent will be used in the future. If this patent ends up in the portfolio of a product market competitor of the seller firm, or if this patent flows to a buyer firm that uses products/services provided by a product market competitor of the seller firm, this may result in greater product market competition. This increased product market competition may cannibalize the seller firm's market share and its product market advantage, which, in turn, may lead to a decline in the operating performance of the seller firm following the patent transaction. In sum, the effect of patent transactions on seller firms' subsequent operating performance could be positive or negative, and hence determining its effect is ultimately an empirical question.

I test the above hypotheses using a unique dataset of secondary market patent transactions collected from the USPTO. This unique data, namely the USPTO Patent Reassignment Dataset, is compiled by the Office of Chief Economist of the USPTO and spans from 1970 to 2019. It contains detailed information about over 8 million patent transactions in the secondary market that affect a patent's title (e.g., patent reassignments and patent transfers as a result of M&As) or that are relevant to patent ownership (e.g., patent licensing, security agreements, and others). In this paper, I focus only on between-firm patent reassignments, where patents are sold by assignor (i.e., seller) to assignee (i.e., buyer) firms. By merging this data with other standard datasets often used in the corporate innovation literature, I am able to explore the determinants and consequences of secondary market patent transactions from seller firms' points of view. In addition, by using a linked assignor-assignee dataset, I also test my hypothesis regarding the relationship between the relative distance of a patent from the assignor versus the assignee and the probability of the patent to be sold in a patent transaction.

The findings of my empirical analyses can be summarized as follows. First, at the firm level, I find that firms with higher innovation quantity (as proxied by the number of patents a firm applies for during a certain period that are eventually granted) or innovation quality (as proxied by the number of citations per patent for the patents applied by a firm during a certain period) are more likely to sell some of their patents. In addition, firms with lower prior production efficiency (used as a proxy for firms' commercialization efficiency) are more likely to sell some of their patents in the subsequent year. This effect is greater for firms with higher innovation quantity or quality.

Second, at the patent level, I find that a patent more technologically distant from a seller firm's operations is more likely to be sold. This effect is stronger for firms with a larger number of patents in their patent portfolio. Further, in my empirical analysis using a linked assignor-assignee dataset, I find that a patent technologically closer to a buyer than to a seller firm is more likely to be sold in a patent transaction, implying there are gains from trading the patent by the seller to the buyer firm.

Third, I turn to the economic and financial consequences of secondary market patent transactions. Using a matched sample of seller and non-seller firms, I find that seller firms, on average, experience a positive and statistically significant improvement in their ROA and operating profitability over the three years after selling some of their patents. To delve deeper and gain a better understanding of the sources of increase in seller firms' ROA, I explore separately the effect of secondary market patent transactions on individual components of ROA, as well as its effect on firm-level total factor productivity (TFP). I find that seller firms increase their sales and decrease their overhead costs following patent transactions. More importantly, over the next three years following patent transactions, seller firms experience a significant improvement in their total factor productivity (TFP). Using a difference-in-differences (DiD) framework based on the 1999 American Inventors Protection

Act as an exogenous shock to the patent transaction incidence, I show that the positive effect of the patent transactions on seller firms' operating performance is causal. In addition, I find that the equity of seller firms enjoys a positive and significant buy-and-hold abnormal return (BHAR) subsequent to the patent transactions.

By utilizing a triple-DiD model to investigate the heterogenous treatment effect of patent transactions, I find that the improvement of operating performance is concentrated in seller firms which increase their R&D focus following patent transactions, suggesting that an increase in the innovation focus of seller firms is an important mechanism driving my results. Further supporting this channel, I examine the expertise of seller firms' inventors, as well as seller firms' innovation productivity and patenting behavior following the patent transactions. I first find that inventors who are either newly hired by or remaining in assignor firms over the three years subsequent to patent transactions have technology expertise more similar to assignor firms' own technology expertise, compared to those hired by or remaining in assignor firms in other periods. In addition, I document that, following the patent transactions, seller firms increase their patenting activity (as evidenced by them generating a larger number of patents) and also generate patents that are technologically closer to their main line of businesses.

The rest of the paper is organized as follows. Section 2 discusses the related literature. Section 3 outlines the underlying theory and develops some testable hypotheses. Section 4 describes the data used in my study and details the construction of some key variables. Section 5 presents the results on the determinants of patent transactions from the seller firms' perspective. Section 6 presents the results on the financial consequences of patent transactions for seller firms. Section 7 concludes.

2. Relation to the Existing Literature and Contribution

My paper contributes to several strands of literature. The first strand of literature related to my paper is on the market for technology.[2] Serrano (2010) studies the secondary market for patents at the patent level. He provides a theoretical model of patent transfers and renewals and develops some empirical analysis of the transfers and renewals of patents. While he documents that the probability of a patent being traded depends on the age of the patent and the number of citations received by a given age, he does not study any of the issues I analyze here, such as the determinants of an assignor firm selling patents or the economic and financial consequences of such patent sale. In their theory paper, Akcigit et al. (2016) build an endogenous growth model where an innovative firm develops various innovation ideas at different points in time. In this model, some of the ideas (patents) developed by the firm are closer to its operations and hence could contribute more to the firm's productivity, while others may be further away from its operations; the firm can sell these patents. In an unpublished working paper, Bowen (2016) studies the secondary market for patents from the buyers' point of view (i.e., a mirror image of what I do in this paper, which is studying the secondary market for patents from the sellers' perspective). He documents that firms purchase patents to complement their R&D rather than substitute for it. Ma et al. (2022) study innovative firms in bankruptcy. They find that firms sell the core patents in their patent portfolio after filing for Chapter 11 reorganization. Different from the above papers, my paper is the first large-sample study to focus on the secondary market for patents from the assignor firms' perspective and to study the causes and economic and financial consequences of patent transactions for assignor firms.

Second, my paper extends the broader literature on corporate innovation (e.g., Manso (2011), Aghion, Van Reenen and Zingales (2013), Chemmanur, Loutskina and Tian (2014), Tian and Wang (2014), Brav, Jiang, Ma and Tian (2018), Chemmanur, Kong, Krishnan and Yu (2019) and others). The existing literature focuses on how different firm characteristics, organizational forms, and regulations affect the success of corporate innovation activities. My paper is different from these papers, since I

[2] See also Kwon et al. (2020) who analyze the patent transactions in the biotechnology industry only.

focus on how firms deal with their innovation output (i.e., patents) once they are developed and how this will affect the future economic and financial performance of firms.

Third, my paper is related to the literature on asset sales or reallocation of assets (e.g., John and Ofek (1995), Maksimovic and Philips (1998), Bernstein, Colonnelli and Iverson (2019), and others). This strand of literature focuses mostly on the sale or allocation of tangible assets. Different from this literature, my paper studies the firms' decisions to sell or reallocate their intangible assets (specifically, patents) and the economic and financial consequences of such decisions for firms.

Fourth, my paper is distantly related to the literature on non-practicing entities, or "patent trolls" (e.g., Cohen, Gurun, and Kominers (2019), Appel, Farre-Mensa, and Simintzi (2019), Abrams, Akcigit, Oz, and Pearce (2019) and others). Existing literature on patent trolls mostly focuses on how patent trolls affect firms' innovation and employment. However, my paper focuses on assignor firms in the secondary market for patents. These firms are fundamentally different from patent trolls for two reasons. First, patent trolls usually acquire patents and license them to other firms. In other words, they are more likely to be assignee rather than assignor firms in patent transactions. Second, the baseline sample of my study is Compustat public firms. Since patent trolls do not have any real operations or production and profit mainly from exerting patent rights against infringements, they are unlikely to appear in my sample.

3. Theory and Hypothesis Development

In this section, I discuss the underlying theory and develop some testable hypotheses. I first develop hypotheses regarding the determinants of patent transactions from assignor firms' perspective. Innovation has long been argued to be critical to a firm's long-term growth. Firms with high innovation capacity can build valuable products around their innovation output and use them to gain an advantage in the product market. Throughout the process of a firm developing its innovation output, high-quality inventors play a pivotal role. In order to attract the finest research personnel, apart from offering a competitive salary and other compensations, a firm usually promises research freedom and does not put many restrictions on the specifics of the projects the research personnel could work on. During this decentralized R&D process, the research staff of the firm may not always come up with innovation output (in the form of patents) that perfectly aligns with the firm's main line of business.[3] As a result, among all the patents in a firm's patent portfolio, the firm may choose to commercialize only a part of them that are closely related to its main line of business, while leaving the remaining patents "sitting on its shelf". These "sitting-on-the-shelf" patents may be far away from the firm's operations and hence could be very costly to commercialize, since the firm needs different complementary technology and assets in place before it can commercialize an invention and release the final product to the market.

Therefore, based on the above argument, I hypothesize that firms with higher innovation productivity (i.e., more able to innovate) but with lower production efficiency (i.e., less able to commercialize all of their innovation output) can sell some of the patents.[4] In addition, I conjecture that the effect of production efficiency on the probability of firms selling patents will be greater for those with higher innovation productivity. This is because these firms will have a greater degree of flexibility to decide which patent to sell when their production efficiency is lower and hence cannot efficiently utilize all the patents. This argument leads to the following two testable hypotheses.

Hypothesis 1: Firms with greater innovation quantity or innovation quality are more likely to sell some of their patents

[3] This point can be best illustrated by a statement from Scott Frank, President and CEO of AT&T Intellectual Property, after AT&T sold one particular patent to Uber in 2017. This patent is titled "Methods and Systems for Routing Travel Between Origin and Destination Service Locations Using Global Satellite Positioning". Scott commented on the deal: "AT&T has one of the world's great research operations, with thousands of talented scientists and engineers breaking new ground in a variety of fields. But not all of these inventions end up being deployed in our core business..."

[4] Another real-world patent transaction that seems to be in line with this argument is the sale of patents by IBM to Alibaba. On Sep 30, 2013, International Business Machine (IBM) Corporation sold 22 patents to Alibaba. One patent is particularly relevant to Alibaba's main line of business (while distant from IBM's operations), which is titled "Automatic Sales Promotion Selection System and Method" (patent number: 5774868). This patent was invented by employees of IBM and was assigned to IBM in the first place, which was later sold to Alibaba in this patent transaction. This patent appears to be closer to Alibaba's main line of business (i.e., online shopping and promotion) than to IBM's main operation.

in a patent transaction.

Hypothesis 2: Firms with lower production efficiency are more likely to sell some of their patents. The effect of production efficiency on the probability of firms selling patents increases with firms' innovation productivity or innovation quality.

In terms of the patent-level determinants of patent transactions, I hypothesize that a seller firm is more likely to sell in a patent transaction a patent distant from its main line of business. A firm's existing patent portfolio defines the knowledge space in which the firm specializes and operates. If a patent is located further away from the knowledge space of the firm, the patent is more likely to be a poor fit with the firm's operations and hence would not be efficiently commercialized. Further, the effect of the technological distance of a patent on the probability of it to be sold would be greater for firms with higher innovation productivity (i.e., a larger number of patents in their patent portfolios). This is because firms with higher innovation productivity have a greater degree of flexibility in deciding which patent to sell. They are thus more likely to sell patents distant from their operations to recoup the cost of developing them in the first place.

However, in a patent transaction, a patent distant from the knowledge space of the assignor firm could be, at the same time, even further away from that of the assignee firm, suggesting the relative technological distance of a patent (between the seller and the buyer firm) could also play a role in determining the probability of the patent to be sold. I argue that the technological distance of a patent can be viewed as a measure of the patent's fit with a firm's operation. If a focal patent is technologically closer to a buyer than to a seller firm, then the buyer can create greater value making use of the patent than the seller can. In this case, there are gains from trading (or selling) the patent by the seller to the buyer firm, in exchange for a fraction of the greater value (in the form of financial returns) created by the buyer firm using that patent. The aforementioned argument leads to the following testable hypotheses.

Hypothesis 3: A patent distant from a seller firm's main operations is more likely to be sold in a patent transaction.

This effect will be greater for firms with higher innovation productivity.

Hypothesis 4: A patent technologically closer to a buyer than to a seller firm is more likely to be sold in a patent transaction.

The third set of hypotheses is regarding the firm-level consequences of patent transactions. The effect of patent transactions on seller firms' future operating performance is ambiguous *ex ante*. On the one hand, seller firms may experience an improvement in their operating performance following patent sales. By selling patents to buyer firms, sellers will be able to monetize the value of patents to some extent (rather than letting the patents sleep on the shelf), which could lead to increased operating performance. In addition, by selling patents less relevant to their core business, seller firms increase their innovation focus after the patent transactions. If seller firms increase their R&D focus and innovate more in the areas in which they specialize subsequent to the patent transactions, this will lead to the management and research personnel of seller firms allocating and utilizing their R&D resources in a more efficient and focused way. The more efficient use of their R&D resources (and hence an increase in focus) is then reflected in the improvement of the seller firms' operating performance following the patent transactions. On the other hand, patent transactions could be associated with a decrease in the seller firms' future operating performance. By re-assigning the entire rights of a patent to others, a seller firm would not have any control of how this patent will be used in the future. If this patent flows into the portfolio of a product market competitor of the seller firm, this may induce greater product market competition for the seller firm. This increased product market competition may cannibalize the seller firm's market share and its product market advantage, which, in turn, may lead to a decline in its operating performance following the patent transaction. Therefore, I develop the following two opposing hypotheses with respect to the firm-level consequences of patent transactions.

Hypothesis 5A: The operating performance of seller firms improves following the patent transactions.

Hypothesis 5B: The operating performance of seller firms declines following the patent transactions.

4. Data and Sample Selection

4.1 Sample and Data Sources

The baseline sample of my study is Compustat innovative firms. The innovative firms in my study are defined to be those that have an active R&D program or have filed for at least one patent (that is eventually granted) during the sample period. I study patent transactions from year 1980 to 2017. My sample starts at the year 1980 because the data on secondary market patent transactions prior to 1980 is scarce. My sample ends at the year 2017 because I want to study the three-year operating performance of a seller firm after a patent transaction, so I need a 3-year gap between the last date of my patent transaction dataset and that of the Compustat firm fundamentals dataset. In addition, I focus on patent transactions of non-financial firms, so firms with SIC code 6000-6799 are excluded from my sample.

The data used in my study comes from several sources. The main source from which the patent transaction-related information is collected is the United States Patent and Trademark Office (USPTO) Patent Assignment Dataset. In 37 CFR (Code of Federal Regulations) 3.1, an assignment of a patent is defined as the transfer to another of a party's entire ownership interest or a percentage of that party's ownership interest in the patent. It should be noted that recording patent assignments at USPTO is not mandatory. However, such recording is recommended by both patent statute and federal regulations, since it ensures the buyer's proper ownership of the focal patent or patent application. According to 35 U.S.C. (United States Codes) 261, "…an interest that constitutes an assignment, grant, or conveyance shall be void as against any subsequent purchaser or mortgagee for valuable consideration, without notice, unless it is recorded in the Patent and Trademark Office within three months from its date or prior to the date of such subsequent purchase or mortgage…" Therefore, the patent reassignment data collected from USPTO should have a relatively good coverage of the secondary market patent transactions in the U.S.

The USPTO Patent Assignment Dataset is compiled by the Office of Chief Economist of the USPTO.[5] This comprehensive dataset covers the period from 1970 to 2019. It has detailed information about 8.6 million patent transactions in the secondary market that affect a patent's title (e.g., patent assignments and patent transfers as a result of M&As) or are relevant to patent ownership (e.g., patent licensing, security agreements, and others). This dataset contains information about assignors (i.e., seller) firms and assignees (i.e., buyer) firms, patents involved in every transaction, types of different transactions, and the transaction execution dates.

In this study, I focus on between-firm patent reassignments, so I exclude cases of patent transfers as a result of corporate M&As, as well as other patent transactions relevant to patent ownership (e.g., patent licensing, name change, security agreements, mortgages, and others). Further, in the case of patent assignments, I remove two types of within-firm patent transfer. The first type is the employer assignment. According to the U.S. patent laws, for all patent applications filed before September 16, 2012, the granted patents must be issued to human inventors.[6] Inventors who work in a firm are usually contractually obligated to transfer their interests and ownership of granted patents to their employers. One example of employer assignment is from Philip Barrett and others to the Microsoft Corporation on November 10, 1988.[7] The involved patent (patent number: 4974159) is titled "Method of Transferring Control in a Multitasking Computer System". This type of patent assignment is essentially a within-firm transfer, since it does not alter the ownership status of a patent beyond a firm's boundary. So, this type of patent assignment is excluded from my sample.

The second type of within-firm patent transfer I remove from my sample is the transfer of patents between different subsidiaries of the same parent firm. This type of patent assignment arises

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[5] See Marco et al. (2015) for a thorough explanation of this dataset.
[6] This condition does not hold after September 16, 2012.
[7] The reel frame id for this patent assignment is 4974/870.

primarily due to tax considerations.[8] A typical example of this type of patent assignment is the transfer of a patent between different subsidiaries of the Dow Inc.[9] The patent (patent number: 4789690), titled as "Polyurethane Foam and Process for Its Preparation", was transferred from Dow Chemical Europe S.A. and Dow Chemical (Nederland) B.V. to the Dow Chemical Company on March 30, 1987. Since this type of transfer does not change the ownership status of a patent beyond a firm's boundary (i.e., the focal patent still belongs to the same organization) either, I manually check and remove them from my sample.

In addition to the USPTO Patent Assignment Dataset, I collect information on patent applications and grants, as well as patent-level statistics (e.g., backward and forward citations, number of patent claims, patent scope, among others), from the USPTO PatentsView Database. I collect patents' economic value from Noah Stoffman's website.[10] This dataset was originally constructed and used in Kogan et al. (2017), and it is extended to the year 2019 by the authors. I collect data on firms' fundamentals from Compustat and stock price information from CRSP. In terms of matching the USPTO patent data with Compustat firm records, I first standardize the name of USPTO corporate entities based on the name cleaning and standardization algorithm developed by the NBER Patent Data Project.[11] Next, I use the matching keys (based on standardized names obtained in the last step) to match the USPTO corporate entities with Compustat firm records. Finally, I manually check each entry to ensure the quality of my matching is good. I report the firm- and patent-level summary statistics in Table 2. Univariate firm comparisons and some descriptive statistics are given in Tables A1 and A2 of Appendix A of the Internet Appendix.

4.2 Construction of Key Variables

[8] For example, Dischinger and Riedel (2011) document that multinational firms have an incentive to locate their intangible assets at affiliates with a relatively low corporate tax rate.
[9] The reel frame id for this patent assignment is 4996/23.
[10] See https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data.
[11] See https://sites.google.com/site/patentdataproject/Home/posts/namestandardizationroutinesuploaded.

4.2.1 Innovation Productivity and Quality

Following the existing literature on corporate innovation, I use patent-based metrics to measure firm-level innovation productivity and innovation quality. I construct three different variables used as proxies for a firm's innovation productivity. The first variable, *Num_Pat_3*, is the natural logarithm of 1 plus the number of patents filed by a firm in the last three years up to a given year. The second variable, *Num_Pat*, is the natural logarithm of 1 plus the number of patents filed by a firm in a given year. The third variable, *Num_Pat_Total*, is the natural logarithm of 1 plus the total number of patents filed by a firm up to a given year. I add 1 to the number of patents to avoid losing observations when a firm does not file any patent in a given year.

In addition, I construct three different variables used as proxies for a firm's innovation quality. The first variable, *Num_Cite_3*, is the natural logarithm of 1 plus the number of lifetime citations received by patents filed by a firm in the last three years up to a given year scaled by the number of patents filed by the firm in the last three years (i.e., number of citations per patent). The second variable, *Num_Cite*, is the natural logarithm of 1 plus the number of lifetime citations received by patents filed by a firm in a given year divided by the number of patents filed by the firm in that year. The third variable, *Num_Cite_Total*, is the natural logarithm of 1 plus the total number of lifetime citations received by all patents a firm files in a given year. Similarly, I add 1 to the number of citations to avoid losing any observation when a firm's patents do not receive any citations over their lifetime.

There are two types of truncation problems associated with patent data. The first problem is related to the patent count. A patent filed by a firm shows up in the USPTO patent dataset only after it is granted, and according to the data from USPTO, the average time lag between the filing and grant of a patent is two years. Therefore, toward the end of the sample period, the number of patents filed by a firm in a given year (or in the last three years) is likely to be reduced compared to earlier years of the sample period. The second problem is related to the number of citations received by a given patent.

Patents filed and granted in earlier years of the sample period are expected to receive a larger number of citations than patents filed in later years. To mitigate these two types of truncation problems, I follow a similar methodology to that of Hall et al. (2001) and Seru (2014). Specifically, I scale a patent (number of citations received by a patent) by the total number of patents (citations received by all the patents) filed in the same year and technology class. I aggregate these class-adjusted measures to the firm level, which are then used in all the firm-level analyses. Throughout the empirical analysis I also include year fixed effects, which, to some extent, accounts for the trend of innovation across years.

4.2.2 Total Factor Productivity

I construct this firm-level measure following the methodology in Olley and Pakes (1996). This revenue-based measure is extensively used in other papers (e.g., see İmrohoroğlu and Tüzel (2014) and Kogan et al. (2017)). I begin by assuming a Cobb-Douglas production function of a firm:

$$y_{i,t} = \beta_0 + \beta_1 k_{i,t} + \beta_2 l_{i,t} + \omega_{i,t} + \eta_{i,t} \tag{1}$$

In this production function, $y_{i,t}$ is the log of the value added of firm i in year t. I use the total revenue of firm i in year t as a proxy. $k_{i,t}$ is the log of firm i's capital input, and $l_{i,t}$ is the log of firm i's labor input in year t. Following the existing literature, I use firm's capital expenditure as a proxy for capital input and employees' wage for labor input. $\omega_{i,t}$ is the (unobservable) log of firm i's total factor productivity (TFP) in year t. $\eta_{i,t}$ is the unobservable error term, and it could be either a measurement error or a unforecastable shock to productivity, according to Olley and Pakes (1996).

To estimate the set of parameters (β_0, β_1, β_2), I use the semi-parametric approach of Olley and Pakes (1996), since this approach accounts for the selection and simultaneity bias in the estimation process. The first step of the estimation process projects $y_{i,t}$ onto the space spanned by $l_{i,t}$ and the third order polynomial $\Phi_{i,t}$ (including a full set of interaction terms) of investment $I_{i,t}$ and capital expenditure $k_{i,t}$. Olley and Pakes (1996) approximate the polynomial $\Phi_{i,t}$ with fourth order, but my results are robust to different choices of the order of the polynomial. This step leads to the consistent estimate of β_2 in model (1), which accounts for the simultaneity bias.

The second step involves estimating the survival probability of a firm. I regress a survival indicator (which equals one if a firm survives from year t to t+1) on the third order polynomial $\Phi_{i,t}$ (including a full set of interaction terms) of investment $I_{i,t}$ and capital expenditure $k_{i,t}$ using a probit model, and I obtain the fitted values as the estimated probability (i.e., propensity score) of the firm i surviving from year t to t+1.

The third step of the estimation process involves estimating the following regression:

$$y_{i,t+1} - \hat{\beta}_2 l_{i,t+1} = \beta_1 k_{i,t+1} + g\left(P_{i,t}, \phi_{i,t} - \beta_0 - \beta_1 k_{i,t}\right) + \eta_{i,t+1} \tag{2}$$

I substitute β_2 on the left-hand side of model (2) with the estimated coefficient obtained from the first step of the estimation procedure. I substitute $P_{i,t}$ and $\Phi_{i,t}$ with corresponding fitted values from the second step of the estimation procedure. I estimate the coefficients β_0 and β_1 in model (2) using non-linear least squares to account for the possible non-linear nature of function g(·) in (2). Following Olley and Pakes (1996), by conditioning on the survival probability (propensity score), this approach also accounts for the selection problem that may arise in the estimation.

After I estimate the set of parameters (β_0, β_1, β_2), the (log) TFP of firm i in year t is obtained as follows:

$$\widehat{\omega}_{i,t} = y_{i,t} - \hat{\beta}_0 - \hat{\beta}_1 k_{i,t} - \hat{\beta}_2 l_{i,t} \tag{3}$$

4.2.3 Technological Distance

This patent-level measure is constructed following the methodology suggested by Akcigit et al. (2016) and others. The technological distance of a patent captures the extent of how close the patent is to the owning firm's knowledge space (as represented by the firm's existing patent portfolio).

The construction of this measure consists of two steps. The first (and the most important) step is to figure out how close one technology class is to another by examining the citation pattern of these two classes. The closeness between patent technology class X and Y can be calculated using the following expression:

$$d(T_X, T_Y) \equiv 1 - \frac{\#(T_X \cap T_Y)}{\#(T_X \cup T_Y)} \tag{4}$$

The numerator $\#(T_X \cap T_Y)$ in the expression (4) represents the number of patents that cite patents in technology class X and Y simultaneously, while the denominator $\#(T_X \cup T_Y)$ represents the number of patents that cite patents in either technology class X or Y. This symmetric measure is intuitive: among all the patents that cite patents in either technology class X or Y, if the number of patents that simultaneously cite patents in technology class X and Y is larger, then it indicates that technology class X and Y is more proximate in the knowledge space. This in turn leads to the distance measure $d(T_X, T_Y)$ closer to zero. Therefore, the closer this measure $d(T_X, T_Y)$ is to zero, the more proximate the technology class X is to technology class Y.[12]

After I obtain the distance between every pair of technology class, the technological distance between a patent *p* and the owning firm's existing patent portfolio, $d_\iota(p, P_f)$, can be calculated as follows:

$$d_\iota(p, P_f) \equiv \left[\frac{1}{\|P_f\|} \sum_{p' \in P_f} d(T_p, T_{p'})^\iota\right]^{\frac{1}{\iota}} \tag{5}$$

Specifically, to calculate the technological distance of the focal patent p from the owning firm's existing patent portfolio P_f (i.e., portfolio of all the patents that had been invented prior to the focal patent p), I figure out the distance between technology class of patent *p* and that of every other patent *p'* in the patent portfolio P_f. Next I aggregate these individual technological distances into a single master variable according to (5). Here, $\| P_f \|$ denotes the number of patents in the firm's patent portfolio, and ι is set to 2/3 following the existing literature.[13] The larger this measure, the further away the focal patent is from the owning firm's knowledge space (as represented by its existing patent portfolio).

12 Note that the distance between technology class X and itself is exactly zero.

13 The results are robust to different values of ι (e.g., ι=1/3 or ι=1).

5. Determinants of Patent Transactions: Assignor Firms' Perspective

5.1 Firm-Level Determinants of Patent Transactions

5.1.1 Innovation Capacity and the Probability of Firms Selling Patents

I use the following firm-level baseline specification to test Hypothesis 1, where the unit of observation is firm-year.

$$I(Selling\ Patent_{i,t}) = \alpha_j + \alpha_t + \beta Innovation_{i,t} + X_{i,t-1}\gamma + u_{i,t} \tag{6}$$

In the specification (6), the dependent variable, $I(Selling\ Patent_{i,t})$, is a dummy variable equal to 1 if firm i sells some of its patens in year t. It is equal to 0 otherwise. The main right-hand side variable of interest is $Innovation_{i,t}$. It comprises two sets of variables that capture a firm's innovation capacity. The first set captures a firm's innovation productivity, which measures the amount of innovation output (i.e., patents) a firm produces within a certain period. In this paper I use three different variables as proxies for a firm's innovation productivity: $Num\_Pat\_3_{i,t}$, $Num\_Pat_{i,t}$, and $Num\_Pat\_Total_{i,t}$. The second set of variables captures a firm's innovation quality, which measures the quality of innovation output (i.e., patents) a firm produces within a certain period. I also use three different variables as proxies for a firm's innovation quality: $Num\_Cite\_3_{i,t}$, $Num\_Cite_{i,t}$, and $Num\_Cite\_Total_{i,t}$. The details on how to construct these variables are outlined in Section 4.2.1. $X_{i,t-1}$ represents a vector of firm-level lagged control variables, which includes total assets, R&D, ROA, leverage, current, cash, and capital expenditure. The details of how to construct these control variables are in Table 1. I also include 3-digit SIC industry (α_j) and year (α_t) fixed effects to absorb any industry-specific and time-varying factors that could affect a firm's decision to sell some of its patents. Standard errors are robust and clustered by firms. Tables 3 and 4 present the results related to this baseline specification.

Table 3 reports the relationship between a firm's innovation productivity and the probability of the firm selling some of its patents. Columns (1), (3), and (5) report the effect of innovation productivity on the probability of a firm selling some of its patents in a univariate regression. Columns (2), (4), and (6) report the effect in a multivariate framework. Overall, on average, a firm's innovation productivity has a positive and statistically significant effect (at 1% level) on the probability of the firm selling some of its patents, and this positive and significant effect is consistent with different proxies for a firm's innovation productivity. This effect is also economically significant. For example, one standard deviation increase in the (log) number of patents generated by a firm in the last three years is associated with an 8.8% increase in the probability of the firm selling some of its patents. This effect is approximately 1.8 times greater than the unconditional probability of a firm selling some of its patents (5.4%). This evidence suggests that firms with greater innovation productivity (as measured by the number of patents firms produce within a certain period) are more likely to sell some of their patents in the patent transactions.[14]

Table 4 presents the results on the relationship between a firm's innovation quality and the probability of it selling some of its patents. Columns (1), (3), and (5) of Table 4 report the effect of innovation quality on the probability of a firm selling some of its patents in a univariate regression, while Columns (2), (4), and (6) report such effect in a multivariate framework. Across different specifications, I document that a firm's innovation quality is positively associated with the probability of the firm selling some of its patents. This relationship is also statistically significant at 1% level and is consistent with different proxies for firm's innovation quality. This suggests that firms with higher innovation quality (as measured by higher citations per patent at the firm level) are more likely to sell some of their patents. Therefore, Tables 3 and 4 together confirm the predictions of Hypothesis 1.

5.1.2 Production Efficiency and the Probability of Firms Selling Patents

To test Hypothesis 2, I employ the following firm-level regression specification, where the unit

[14] In Table A3 of Appendix B of the Internet Appendix, I conduct a robustness test using alternative measures of a firm's innovation productivity, where I scale $Num\_Pat\_3_{i,t}$, $Num\_Pat_{i,t}$, and $Num\_Pat\_Total_{i,t}$ by a firm's R&D ratio in year t. The results remain robust to different measures of innovation productivity.

of observation is firm-year.

$$I(Selling\ Patent_{i,t}) = \alpha_j + \alpha_t + \beta TFP_{i,t-1} + \delta Num\_Pat\_3_{i,t} + \theta TFP_{i,t-1} \times Num\_Pat\_3_{i,t} + X_{i,t-1}\gamma + u_{i,t} \quad (7)$$

In this specification, the dependent variable is identical to that in specification (6). The main independent variable of interest is $TFP_{i,t-1}$, which is the firm i's Total Factor Productivity (TFP) in year t-1. Here I only use *$Num\_Pat\_3_{i,t}$*, which is the number of patents filed by firm i in the last three years up to year t, as the main proxy for a firm's innovation productivity, but the results are qualitatively similar when I use other proxies for firm's innovation productivity. A vector of firm-level lagged control variables is defined the same as in (6). 3-digit SIC industry (α_j) and year (α_t) fixed effects are included. Standard errors are robust and clustered by firms.

Table 5 reports the empirical results corresponding to the baseline specification (7). From Column (1) of Table 5 we can see that in a univariate regression, firm-level lagged TFP has a negative effect on the probability of a firm selling some of its patents. This negative and statistically significant coefficient suggests that firms with lower prior production efficiency are more likely to sell some of their patents in the subsequent year. This inference remains unchanged in Column (2) when I examine this relation in a multivariate framework. The magnitude of the effect of TFP on the probability of a firm selling some of its patents becomes larger, and the effect remains significant at 1% level. The effect of a firm's lagged TFP on the probability of it selling some of its patents is also economically significant: one standard deviation decrease in the TFP (0.859) is associated with a 4.4% increase in the probability of the firm selling patents, which translated into more than 80% of the unconditional probability. This evidence supports the first part of Hypothesis 2 that firms are more likely to sell some of their patents when their production efficiency is lower.

Next I include in the regression the interaction term of TFP and firm's innovation productivity, as proxied by the number of patents a firm generates in the past 3 years. The results are reported in

Column (3) of Table 5. The coefficients on both the TFP and the interaction term are both negative and significant at 1% level. Together, this suggests that the effect of a firm's TFP on the probability of the firm selling its patents is negative, and this effect is stronger for firms with higher innovation productivity. If we evaluate the interaction term at the mean of *Num_Pat_3* (0.91), then the coefficient on the interaction term indicates that when a firm files the sample average number of patents in the last three years, one standard deviation decrease in the TFP is associated with a 1.3% increase in the probability of the firm selling patents, or 24% of the unconditional sample mean. This effect is also statistically significant at 1% level. The results and interpretations are very similar when I replace *Num_Pat_3* with *Num_Cite_3*, the number of citations per patent firms receive in the last 3 years. This is consistent with the prediction of the second part of Hypothesis 2. Overall, the results in Table 5 show that firms with lower production efficiency are more likely to sell some of their patents in the subsequent year, and this effect increases with firms' innovation quantity or quality.

5.2 Patent-Level Determinants of Patent Transactions

5.2.1 Patent's Technological Distance and the Probability of It Being Sold

To test Hypothesis 3, I use the following patent-level regression specification, where the unit of observation is patent-filing-year.

$$I(Patent_{i,j,t} \text{ is sold}) = \alpha_j \times \alpha_t + \beta Tech\_Dist_{i,j,t} + \delta Patent\_Num_{i,j,t} + \theta Tech\_Dist_{i,j,t} \times Patent\_Num_{i,j,t} + X_{i,t}\gamma + u_{i,t} \quad (8)$$

The dependent variable in (8) is an indicator variable equal to 1 if patent i filed by firm j in year t is ever sold and equal to 0 otherwise. The main independent variable of interest is $Tech\_Dist_{i,j,t}$. It represents the technological distance of patent i filed in year t from the owning firm j's patent portfolio. $Patent\_Num_{i,j,t}$ denotes the number of patents in firm j's patent portfolio in year t when patent i is filed. I also include an interaction term to test the second part of Hypothesis 3. $X_{i,t}$ is a vector of patent-level control variables pertaining to patent i filed in year t. It includes number of forward citations, number of claims, patent scope, number of backward citations, and patent litigation dummy. The definition of these variables is in Table 1. In addition, owning firm (α_j) by filing-year (α_t) fixed effects are included, so that I am essentially comparing patents within the same firm that are filed in the same year. Standard errors are robust and clustered at the patent technology class level.

The empirical results associated with this specification are reported in Table 6. The positive and significant coefficient on the technological distance in Column (2) suggests that a patent with a greater distance to the owning firm's patent portfolio is more likely to be sold in a patent transaction. This is consistent with the prediction of the first part of Hypothesis 3. It suggests that a patent that is more likely to be a poor fit with the owning firm's operation is more likely to be reallocated to others. To test the second part of Hypothesis 3, I include in the regression the interaction term between technological distance and the size of a firm's patent portfolio. The results are reported in Column (3) of Table 6. The coefficient on the interaction term is positive and statistically significant at 1% level. This indicates that the technological distance of a patent is positively associated with the probability of the patent to be sold, and this effect is greater for firms with a larger number of patents in their portfolio. This result supports the prediction of the second part of Hypothesis 3. Overall, in terms of the patent-level determinant of patent transactions, I show that patents more distant from the seller firms' main operations are more likely to be sold in the patent transactions, and this effect increases with firms' innovation productivity.

5.2.2 Patent's Relative Technological Distance and the Probability of It Being Sold

To test Hypothesis 4, I use the following patent-level regression specification, where the unit of observation is patent-filing-year.

$$I(Patent_{i,j,k,t}\ is\ sold) = \alpha_j + \alpha_k + \alpha_t +$$

$$\beta Relative\_Tech\_Dist_{i,j,k,t} + X_{i,t}\gamma + u_{i,t} \quad (9)$$

The dependent variable in (9) is identical to the one in specification (8). Different from (8), the main independent variable of interest now becomes $Relative\_Tech\_Dist_{i,j,k,t}$. It is defined as the technological distance of patent i to the buyer firm k minus the technological distance of patent i to the seller firm j. More negative this measure, technologically closer the patent i is to the buyer firm k than to the seller firm j. A vector of patent-level control variables $X_{i,t}$ pertaining to patent i filed in year t is defined identically to that in specification (8). It includes number of forward citations, number of claims, patent scope, number of backward citations, and patent litigation dummy. In addition, seller firm (α_j), buyer firm (α_k), and filing-year (α_t) fixed effects are included. Standard errors are robust and clustered at the patent technology class level.

Table 7 reports the results on the relationship between a patent's relative technological distance and the probability of it to be sold in a patent transaction. Column (1) reports the results in a univariate regression. The coefficient on the relative technological distance variable is negative and statistically significant at 1% level. This indicates that when a patent is technologically closer to a buyer firm than to a seller firm (i.e., this measure is negative), the patent is more likely to be sold in a patent transaction. In addition, the closer this patent is to the buyer firm than to the seller firm (i.e., the more negative this measure becomes), the more likely the patent is sold in a patent transaction. When I include a vector of patent-level control variables in Column (2), the implication remains unchanged. Together, these results support the prediction of Hypothesis 4.

In Table A4 of Appendix B of the Internet Appendix, I also examine the relationship between a patent's value and the probability of it to be sold in a patent transaction. $Eco\_Value_{i,j,t}$ represents the economic value of patent i filed in year t to the owning firm j. I obtain the economic value of patent i following the methodology of Kogan et al. (2017). Specifically, a patent's economic value is measured as the announcement return on the owning firm's stock during the time window around the grant of the patent. $Forward\_Citations_{i,t}$ is the truncation-adjusted number of forward citations received by patent i filed in year t. $X_{i,t}$ is defined exactly the same as in the specification (9). Owning firm (α_j) by filing-year (α_t) fixed effects are included. Standard errors are robust and clustered at the patent technology class level. The coefficient on either $Eco\_Value_{i,j,t}$ or $Forward\_Citations_{i,t}$ is positive and at least significant at 5% level. This suggests that a patent with a higher value (as measured by either economic value or scientific value) is more likely to be sold in a patent transaction.

6. Firm-Level Financial Consequences of Patent Transactions

6.1 Baseline Results

I utilize a matched-sample analysis to study the baseline financial consequences of patent transactions for seller firms. I match seller firms with all the non-seller firms in the same 3-digit SIC industry and transaction year. I then combine the seller and matched non-seller firms into different industry-year groups and stack all the groups to conduct the matched-sample analysis.[15]

I use the following specification to estimate a panel data of a three-year window around patent transactions. The unit of observation is firm-year.

$$Y_{i,j,t} = \alpha_j \times \alpha_t + \beta_1 Assignor_i \times Post_t + \beta_2 Assignor_i + X_{i,t}\gamma + u_{i,t} \qquad (10)$$

The dependent variables include return on assets (ROA) and operating profitability of firm i in industry j in year t. ROA is constructed as a firm's earnings before interest (EBIT) in year t scaled by total assets, while operating profitability is constructed as a firm's operating income before depreciation in year t divided by total assets. $Assignor_i$ is a dummy variable equal to one if firm i is an assignor firm and equal to zero otherwise. $Post_t$ is a dummy variable that equals one if the observation is within three years after a patent transaction and equals zero otherwise. $X_{i,t}$ denotes a vector of firm-level controls, which include total assets, R&D, leverage, current, cash, and capital expenditure. I do

[15] In Table A6 of Appendix B of the Internet Appendix, I report the results of a robustness test of the effect of patent transactions of operating performance using a matched sample of seller and non-seller firms based on the closest propensity score. I match each seller firm with one non-seller firm (with replacement) in the same 3-digit SIC industry and transaction year that has the closest propensity score, which is estimated based on the number of patents filed by a firm in the transaction year, total assets, R&D ratio, current year's ROA, leverage, current, cash, and capital expenditure. The results are qualitatively similar to my baseline results.

not include $Post_t$ dummy in the regression, since it is subsumed by the industry-by-year fixed effects. The standard errors are robust and clustered by firms. The main independent variable of interest is the interaction term $Assignor_i \times Post_t$.

Table 8 shows the results of the baseline estimation. In Column (1) where the dependent variable is ROA, the coefficient on the interaction estimator $Assignor_i \times Post_t$ is positive and statistically significant at 1% level. This indicates that in the three years following the patent transactions, the seller firms, on average, experience an increase in their ROA compared to non-seller firms. In Column (2) where the dependent variable is operating profitability, I also document a positive and statistically significant coefficient, suggesting that over the three years following the patent transactions, the seller firms, on average, have better operating profitability than non-seller firms. These results, taken together, implies that the seller firms experience an improvement in their operating performance (as measured by either ROA or operating profitability) after the patent transactions. The above findings are consistent with the prediction of Hypothesis 5A.[16]

This improvement in operating performance is also accompanied by the positive and significant long-run buy-and-hold abnormal return (BHAR) of seller firms' stocks. I report the results on BHAR in Table A5 of Appendix B of the Internet Appendix. I construct the BHAR of seller firms' stocks using different investment periods (1 quarter, 1 year, 2 years, and 3 years following the patent transaction dates) and benchmark portfolios. Following the methodology in Loughran and Ritter (1995), I construct a size-matched benchmark portfolio against which the stocks of assignor firms are compared, along with other major stock indexes. I document that the stocks of assignor firms, on

[16] To gain a better understanding of the sources of increase in ROA, I explore separately the effect of secondary market patent transactions on individual components of ROA, as well as its effect on firm-level total factor productivity (TFP). I use a similar specification as in (10) and report the results in Table A7. I find that seller firms increase their sales in the next three years subsequent to patent transactions. In addition, seller firms experience a decrease in their overhead costs and an increase in their cost of goods sold following the patent transactions. More importantly, I document seller firms also experience a significant improvement in their production efficiency as measured by the TFP following patent sales.

average, outperform that of size-matched firms and major stock indexes across the spectrum of different holding periods following patent transactions.

6.2 Identification

In the baseline regressions, I establish that, compared to non-seller firms, seller firms experience an increase in their operating performance following the patent transactions. However, one could argue that the baseline results may suffer from several endogeneity biases. One such concern is the omitted variable bias. Even though I could control for different firms' fundamentals in the regression that arguably affect the firms' decision to sell patents, there could be unobservables that also affect such decisions. Therefore, to address this concern and establish the causality between patent transactions and operating performance, I utilize a DiD framework based on the American Inventors Protection Act of 1999 as a positive exogenous shock to the patent transaction incidence.

Enacted on November 29, 1999, this Act has one key part specifying that, upon its passage, patent applications filed in the U.S. are disclosed after 18 months, as opposed to when the patent is granted. This provision took effect in November 2020. The existing literature argues that this change results in faster knowledge diffusion.[17] After the passage of this Act, on average, a patent application is made available to the public sooner than before. I argue that this expedited publication process positively affect the patent transaction incidence in two ways. First, the Act makes it easier for the buyer firms to identify a potentially useful patent earlier. Second, the Act has facilitated a better knowledge spillover between firms and hence could potentially promote a better match between potential sellers and buyers. To empirically show that the passage of this Act has a positive effect on the patent transaction incidence, I regress the indicator variable of firms selling patents on the dummy $I(Year_t>2000)$, which is a year dummy equal to one if an observation is after the year 2000. I control

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[17] For example, Johnson and Popp (2003) find evidence that the passage of this Act expedites the patent publication disclosure and facilitates knowledge diffusion.

for other factors that could affect a firm's decision to sell patents (as in my baseline specification of determinants of patent transactions). I include year trend in all the regressions to account for the potential trend in the firm's propensity to sell patents over time.[18] In addition, I also include industry or firm fixed effects for different specifications, and the standard errors are clustered at the firm level. The results are reported in Table A8 of Appendix B of the Internet Appendix. The positive and statistically significant coefficients on the dummy $I(Year_t>2000)$ across all the columns of Table A8 indicates that, after the year 2000, it is more likely for a firm to engage in a secondary market patent transaction. This seems to suggest that the Act could serve as a valid positive exogenous shock to the patent transaction incidence in my setting.

Therefore, to establish the causality between patent transactions and firms' operating performance, I estimate the following DiD framework using a panel data of a three-year window around the year 2000, where the part of the Act related to patent application disclosure was in effect.

$$Y_{i,j,t} = \alpha_j \times \alpha_t + \beta_1 Assignor_i \times Post_t + \beta_2 Assignor_i + X_{i,t}\gamma + u_{i,t} \tag{11}$$

This regression specification is very similar to that in (10), but the difference is that now the $Post_t$ dummy is defined to be equal one if the observation is within three years after the year 2000. It is equal to zero otherwise. I include industry-by-year fixed effects so that I could compare firms within the same industry at every point in time.

The results associated with specification (11) are reported in Table 10. In Column (1) where the dependent variable is ROA, the coefficient on the DiD estimator *Assignor* × *Post* is positive and statistically significant at 1% level. This suggests that in the three years following the enactment of the American Inventor Protection Act, seller firms, on average, experience an improvement in their ROA compared to non-seller firms. The implication remains consistent when I change the dependent

[18] In this particular table I do not include year fixed effects, since this would subsume my main independent variable of interest, $I(Year_t>2000)$.

variable from ROA to operating profitability in Column (2).

One central assumption of the DiD estimation before we could establish causality of the results is the lack of pre-trend. Specific to my setting, there should be no clear pre-trend before the passage of this Act, so that the non-seller firms would serve as a valid counterfactual for seller firms if the Act had not been enacted. To empirically examine this assumption, I estimate the following regression.

$$Y_{i,j,t} = \alpha_j \times \alpha_t + \sum_{t=-3,\, t\neq -1}^{3} \beta_t Assignor_i \times Year_t + \delta Assignor_i + X_{i,t}\gamma + u_{i,j,t} \qquad (12)$$

The dependent variables of this regression include ROA and operating profitability. $Year_t$ is a dummy variable equal to one if the year of an observation is t years away from the year 2000. It is equal to zero otherwise. I drop the year 1999 to avoid the collinearity problem and use it as the base group for comparison. Other variables are defined the same as those in specification (11).

The plots of coefficient β_t for two different outcome variables are given in Figures 3 and 4. The solid blue lines in both graphs represent the point estimates, and the red spike lines represent the 90% confidence interval of the coefficient estimates. From Figures 3 and 4, we can see that when the dependent variables are ROA or operating profitability, there are no clear pre-trends prior to the year 1999 (the point estimates are not statistically different from 0).

Further, to ensure the internal validity of my DiD estimator associated with the American Inventors Protection Act of 1999 documented in Table 10, I conduct a falsification test. The results are reported in Table A9 of Appendix B of the Internet Appendix. Specifically, I falsely assume that the part of the Act related to the expedited disclosure of patent applications was effective three years before it actually did (i.e., the year 2000). Therefore, based on the sample of all seller and non-seller firms, I estimate a three-year window around the year 1997 such that the panel ends before the actual year when the part of the Act related to patent application disclosure was in effect. The positive but insignificant coefficients on the DiD estimators in Table A9 for both dependent variables suggest that the results documented in Table 10 are likely to be driven by the Act itself instead of some alternative forces. Therefore, putting these pieces of evidence together, I argue that the positive relationship between secondary market patent transactions and seller firms' operating performance documented in the baseline analysis is likely causal.

6.3 Mechanism

This section discusses one of the potential underlying mechanisms that could drive the above results, which is seller firms increase their R&D focus following the patent transactions. To investigate the heterogenous treatment effect of patent transactions, I use a triple difference-in-differences model as follows.

$$Y_{i,j,t} = \alpha_j \times \alpha_t + \gamma Assignor_i \times Post_t \times Focus\_Increase_{i,t} + \beta_1 Assignor_i \times Post_t + \beta_2 Assignor_i \times Focus\_Increase_{i,t} + \beta_3 Post_t \times Focus\_Increase_{i,t} + \beta_4 Assignor_i + \beta_5 Focus\_Increase_{i,t} + X_{i,t}\gamma + u_{i,t} \quad (13)$$

The outcome variables, other right-hand side variables, and fixed effects are identical to those defined in (10). The new independent variable is $Focus\_Increase_{i,t}$. It is a dummy variable equal to one if the average technological distance of patents filed by firm i in the next 3 years is smaller than that of patents filed in year t. It is equal to zero otherwise. In other words, if firm i files patents that have a smaller technological distance on average in the next three years compared to year t, this means that the firm is conducting R&D activity closer to its main operations in the following years, and it hence represents an increase in its innovation focus. The coefficient on the triple interaction term, γ, identifies the difference between seller firms that increase focus after the patent transactions and those that do not. If the seller firms' increase in innovation focus is indeed the underlying channel driving the results, then I would expect to find the coefficient to be positive.

The results are reported in Table 11. For brevity, I only report the triple interaction term, $Assignor_i \times Post_t \times Focus\_Increase_{i,t}$, which is the main independent variable of interest, and the DiD estimator

Assignor$_i$ × *Post*$_t$. The coefficient on this triple interaction term is positive and statistically significant at 5% level, while the coefficient on the DiD estimator is indistinguishable from zero. This indicates that the improvement in the seller firms' operating performance after the patent transactions is concentrated in the sub-sample where seller firms increase their innovation focus. It should also be noted that the magnitude of this coefficient is over three times as large as that in Table 8 for either of the two dependent variables (i.e., the baseline results of the consequences of patent transactions). This evidence suggests that the source of improvement in the operating performance mostly comes from seller firms which increase their R&D focus following the patent transactions.

I document some additional evidence further supporting this increase in innovation focus channel. First, I focus on the inventors' expertise and examine the technological similarity between patents of inventors and that of firms. I examine such relationship using the data on inventors obtained from the Harvard Patent Dataverse. This database contains the career trajectory of different inventors as well as their technology expertise (as shown by the patents filed by them).[19] I then construct the technological similarity measure as the cosine similarity between the technology classes of patents in the inventors' and firms' respective portfolios. Hence, this measure falls within the range of zero and one, and the closer this similarity measure is to one, the more similar an inventor's technology expertise is to the firm's own technology expertise. I report the results in Table 12.

In Panel A of Table 12, I examine the technological similarity between patents of firms and patents of inventors who are newly hired by firms in the next three years subsequent to year t. I find that the new inventors who flow into assignor firms in the first year after patent transactions have technology expertise that is more similar to the firms' own technology expertise, compared to new inventors hired by the same assignor firms during other periods. This is evidenced by the positive and significant coefficient on *I(Selling Patent)* in Column (1) of Panel A. In Panel B of Table 12, I also

[19] The details of this dataset can be found in Li et al. (2014).

examine the technological similarity between firms' patents and patents of inventors who remain in the firms over the three years subsequent to year t. The positive and significant coefficients on *I(Selling Patent)* in Columns (1) to (3) of Panel B suggest that the inventors who remain in the assignor firms in the three years following patent transactions also share a more similar technological expertise with the firms.[20]

Second, I look at the seller firms' patenting activity following the patent transactions, which includes the number of patents generated by the seller firms and the average technological distance of these patents from the seller firms' patent portfolios. I report the results in Table 13. In Panel A of Table 13, I examine the innovation quantity produced by the seller firms subsequent to the patent transactions. The positive and significant coefficients across different columns suggest that seller firms generate a larger number of patents following the patent transactions, and the effect appears to be most pronounced in the first year following the patent transactions. In Panel B of Table 13 where dependent variables are now the average technological distance of new patents generated in different years to the seller firms' patent portfolios. The negative coefficients in all columns indicate that after the patent transactions, seller firms are creating patents that are closer to their main operations. Together, results in Tables 12 and 13 seem to support the increase in innovation focus channel.

7. Conclusion

In this paper, I analyze the secondary market for patents from the assignor firms' points of view. I study the determinants of assignor firms selling some of their patents and the implications of such transactions for the future financial performance of assignor firms. Overall, I document that at firm level, firms with higher innovation productivity (i.e., more able to innovate) but with lower production

[20] It should be noted that assignor firms do not achieve the increase in their innovation focus simply by reducing the size of their R&D departments. In Table A10 of Appendix B of the Internet Appendix, I examine the inventors' flow of assignor firms following patent transactions. The positive and significant coefficients on I(Selling Patents) in all columns indicate that assignor firms experience an inflow of inventors over the three years subsequent to patent transactions.

efficiency (i.e., less able to efficiently commercialize all of their patents) are more likely to sell some of their patents. At patent level, patents that are less relevant for seller firms' main operations are more likely to be sold in the patent transactions. In addition, patents that are technologically closer to buyer than to seller firms are more likely to be sold in the patent transactions, implying there are gains from trading the patents.

In terms of the economic and financial consequences of patent transactions, I document that seller firms experience a positive and statistically significant improvement in their operating performance in the three years after patent transactions. This improvement in the operating performance of seller firms is associated with an increase in their sales, a decrease in their overhead costs, and an increase in their TFP. Using the American Inventor Protection Act of 1999 as an exogenous shock to the patent transaction incidence, I show that the positive effect of secondary market patent transactions on seller firms' operating performance is causal. I find that the improvement in ROA and operating profitability is more pronounced in seller firms which increase their R&D focus after patent transactions, suggesting that an increase in innovation focus is an important channel driving the results. In addition, I find that inventors who are newly hired by assignor firms or those who choose to remain in assignor firms over the three years following patent transactions have similar technological expertise to the firms, and that seller firms generate more and technologically closer patents after the patent transactions. Together, these results further support the increase in innovation focus channel.

This paper also provides some research avenues for future study. For example, researchers could examine the determinants of patent transactions for private assignor firms and the implications of such transactions for these firms in terms of the likelihood of them receiving external financing (such as venture capital investments) and their future growth. Furthermore, policymakers could explore the economy- or market-wide factors that could remove the information frictions and facilitate the patent reallocations in the secondary market.

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Table 1: Variable Definitions

Panel A: Firm-level Variables	
Total Assets	Natural logarithm of firm i's book assets (compustat item: at) in a given year
Sales	Natural logarithm of firm i's total sales (compustat item: sale) in a given year
R&D	The ratio of firm i's R&D expense (compustat item: xrd) to its book assets (compustat item: at) in a given year
ROA	The ratio of firm i's EBIT (Earnings Before Interest) (compustat item: ebit) to its book assets (compustat item: at) in a given year
Leverage	Firm i's total debt (compustat item: dltt+dlc) scaled by its book assets (compustat item: at) in a given year
Current	Firm i's current assets (compustat item: act) divided by its current liabilities (compustat item: dlc) in a given year
Cash	Firm i's cash holdings (compustat item: che) divided by its book assets (compustat item: at) in a given year
CAPEX	Firm i's capital expenditure (compustat item: capx) scaled by book assets (compustat item: at) in a given year
Operating Profitability	Operating income before depreciation (compustat item: oibdp) of firm i in a given year divided by its book assets (compustat item: at)
COGS	Cost of goods sold (compustat item: cogs) of firm i in a given year divided by its book assets
SG&A	Selling, general and administrative expense (compustat item: xsga) of firm i in a given year divided by its book assets
Panel B: Patent-level Control Variables	
Forward Citations	The natural logarithm of the number of truncation-adjusted lifetime forward citation received by patent i
Claims	The natural logarithm of the number of claims in a patent's application
Patent Scope	The number of technology classes to which a patent belongs
Backward Citations	The natural logarithm of the number of backward citations of a patent filed in a given year
Litigation	A dummy variable equal to 1 if a patent is ever litigated and equal to 0 otherwise

Table 2: Summary Statistics

Panel A reports the summary statistics of firm-level variables. *I(Selling Patent)* is a dummy variable equal to 1 if a firm sells some of its patents in a given year and equal to 0 otherwise. *Num_Pat_3* is the natural logarithm of 1 plus the number of patents filed by a firm in the last three years up to a given year. *Num_Pat* is the natural logarithm of 1 plus the number of patents filed by a firm in a given year. *Num_Pat_Total* is the natural logarithm of 1 plus the total number of patents filed by a firm up to a given year. *Num_Cite_3* is the natural logarithm of 1 plus the number of lifetime citations per patents for patents filed by a firm in the last three years up to a given year. *Num_Cite* is the natural logarithm of 1 plus the number of lifetime citations per patent for patents filed by a firm in a given year. *Num_Cite_Total* is the natural logarithm of 1 plus the total number of lifetime citations received by all patents that a firm files in a given year. *TFP* is a firm's revenue-based total factor productivity in a given year, constructed following the methodology of Olley and Pakes (1996). *Total Assets* is the natural logarithm of a firm's book assets. *R&D* is the ratio of a firm's R&D expense to its book assets. *ROA* is measured as the ratio of a firm's EBIT (Earnings Before Interest) to its book assets. *Leverage* is the ratio of a firm's total debt to its book assets. *Current* is the ratio of a firm's current assets to its current liabilities. *Cash* is a firm's cash holdings divided by its book assets. *CAPEX* is the ratio of a firm's capital expenditure to its book assets. *Sales* is the natural logarithm of a firm's total sales. *COGS* is a firm's cost of goods sold divided by its book assets. *SG&A* is a firm's selling, general and administrative expense scaled by its book assets. Panel B reports the summary statistics of patent-level variables. *Tech_Dist* is the technological distance between a patent and the patent portfolio of the owning firm. *Forward Citations* is the natural logarithm of the number of truncation-adjusted lifetime forward citation received by a patent. *Claims* is the natural logarithm of the number of claims in a patent's application. *Patent Scope* is the number of technology classes to which a patent belongs. *Backward Citations* is the natural logarithm of the number of backward citations of a patent filed in a given year. *Litigation* is a dummy variable equal to 1 if a patent is ever litigated and equal to 0 otherwise.

Variable	Mean	Std. Dev.	1st Quartile	Median	3rd Quartile	Num. of Obs.
Panel A: Firm-level variables						
I(Selling Patent)	0.054	0.226	0	0	0	197,010
Num_Pat_3	0.912	1.509	0	0	1.386	197,010
Num_Pat	0.570	1.164	0	0	0.693	197,010
Num_Pat_Total	1.543	2.027	0	0.693	2.639	197,010
Num_Cite_3	0.001	0.004	0	0	0.001	197,010
Num_Cite	0.000	0.005	0	0	0.000	197,010
Num_Cite_Total	0.007	0.049	0	0	0.001	197,010

TFP	3.359	0.859	2.893	3.495	3.944	161,733
Total Assets	4.526	2.766	2.608	4.379	6.416	186,898
R&D	0.147	0.289	0.014	0.052	0.145	135,839
ROA	-0.197	0.930	-0.119	0.052	0.117	185,824
Leverage	0.309	0.556	0.031	0.194	0.367	186,348
Current	3.040	3.567	1.264	2.018	3.315	184,672
Cash	0.216	0.252	0.030	0.107	0.316	186,813
CAPEX	0.057	0.062	0.017	0.038	0.074	184,338
Sales	4.452	2.920	2.591	4.476	6.488	178,007
COGS	0.744	0.670	0.277	0.595	1.009	186,288
SG&A	0.514	0.845	0.165	0.301	0.522	164,622
Panel B: Patent-level variables						
I(Patent is Sold)	0.187	0.390	0	0	0	1,873,126
Tech_Dist	0.608	0.288	0.391	0.680	0.853	1,873,126
Forward Citations	0.001	0.007	0	0	0	1,873,126
Claims	2.684	0.655	2.303	2.833	3.045	1,873,126
Patent Scope	1.854	1.152	1	2	2	1,873,126
Backward Citations	2.080	1.012	1.386	2.079	2.639	1,873,126
Litigation	0.004	0.065	0	0	0	1,873,126

Table 3: Firm's Innovation Productivity and the Probability of the Firm Selling Patents

The dependent variable *I(Selling Patent)* is an indicator variable equal to 1 if firm i sells a patent in year t. It is equal to 0 otherwise. *Num_Pat_3* is the natural logarithm of 1 plus the number of patents generated by firm i in the last three years prior to year t. *Num_Pat_Total* is the natural logarithm of 1 plus the total number of patents in firm i's patent portfolio until year t. *Num_Pat* is the natural logarithm of 1 plus the number of patents generated by firm i in year t. Firm-level lagged control variables include *Total Assets*, calculated as the natural logarithm of firm i's book assets; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets; *ROA*, measured as the ratio of firm's EBIT (Earnings Before Interest) to its book assets; *Leverage*, calculated as the ratio of firm i's total debt to its book assets; *Current*, calculated as the firm i's current assets divided by its current liabilities; *Cash*, calculated as the firm i's cash holdings divided by its book assets; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets. 3-digit SIC industry and year fixed effects are included. Robust standard errors are clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	I(Selling Patent)					
	(1)	(2)	(3)	(4)	(5)	(6)
Num_Pat_3	0.063***	0.058***				
	(0.002)	(0.002)				
Num_Pat_Total			0.049***	0.045***		
			(0.001)	(0.001)		
Num_Pat					0.08***	0.07***
					(0.002)	(0.002)
Total Assets		0.012***		0.012***		0.013***
		(0.001)		(0.001)		(0.001)
R&D		-0.004		-0.004		0.003
		(0.003)		(0.003)		(0.003)
ROA		-0.008***		-0.011***		-0.007***
		(0.001)		(0.001)		(0.001)
Leverage		0.004***		0.003***		0.004***
		(0.001)		(0.001)		(0.001)
Current		-0.002***		-0.002***		-0.001***
		(0.000)		(0.000)		(0.000)

Cash		-0.048***		-0.035***		-0.042***
		(0.005)		(0.005)		(0.005)
CAPEX		-0.139***		-0.084***		-0.143***
		(0.013)		(0.013)		(0.013)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.193	0.216	0.201	0.222	0.190	0.215
Num. of Obs.	197,010	122,183	197,010	122,183	197,010	122,183

Table 4: Firm's Innovation Quality and the Probability of the Firm Selling Patents

The dependent variable *I(Selling Patent)* is an indicator variable equal to 1 if firm i sells some of its patents in year t, and it is equal to 0 otherwise. *Num_Cite_3* is the natural logarithm of 1 plus the total number of lifetime citations received by firm i's patents filed in three years prior to year t divided by the total number of patents firm i filed in these three years. *Num_Cite* is the natural logarithm of 1 plus the total number of lifetime citations received by firm i's patents filed in year t divided by the total number of patents firm i filed in year t. *Num_Cite_Total* is the natural logarithm of 1 plus the total number of lifetime citations received by firm i's patents filed in year t. Firm-level lagged control variables include *Total Assets*, calculated as the natural logarithm of firm i's book assets; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets; *ROA*, measured as the ratio of firm's EBIT (Earnings Before Interest) to its book assets; *Leverage*, calculated as the ratio of firm i's total debt to its book assets; *Current*, calculated as the firm i's current assets divided by its current liabilities; *Cash*, calculated as the firm i's cash holdings divided by its book assets; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets. 3-digit SIC industry and year fixed effects are included. Robust standard errors are clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	I(Selling Patent)					
	(1)	(2)	(3)	(4)	(5)	(6)
Num_Cite_3	1.651***	0.685**				
	(0.491)	(0.278)				
Num_Cite			1.495***	0.807***		
			(0.449)	(0.280)		
Num_Cite_Total					1.656***	1.214***
					(0.096)	(0.077)
Total Assets		0.039***		0.039***		0.030***
		(0.001)		(0.001)		(0.001)
R&D		0.029***		0.029***		0.024***
		(0.004)		(0.004)		(0.003)
ROA		-0.015***		-0.015***		-0.009***
		(0.001)		(0.001)		(0.001)
Leverage		0.004***		0.004***		0.004***
		(0.001)		(0.001)		(0.001)

Current		-0.002***		-0.002***		-0.002***
		(0.000)		(0.000)		(0.000)
Cash		-0.004		-0.004		-0.009*
		(0.005)		(0.005)		(0.005)
CAPEX		-0.084***		-0.084***		-0.101***
		(0.015)		(0.015)		(0.014)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.037	0.134	0.037	0.134	0.108	0.168
Num. of Obs.	197,010	122,183	197,010	122,183	197,010	122,183

Table 5: Firm-Level Production Efficiency and the Probability of the Firm Selling Patents

The dependent variable *I(Selling Patent)* is an indicator variable equal to 1 if firm i sells a patent in year t, and it is equal to 0 otherwise. *TFP* represents the firm i's revenue-based Total Factor Productivity (TFP) in year t-1. *Num_Pat_3* is the natural logarithm of 1 plus the number of patents filed by firm i in the last three years prior to year t. Firm-level lagged control variables include *Total Assets*, calculated as the natural logarithm of firm i's book assets; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets; *ROA,* measured as the ratio of firm i's EBIT (Earnings Before Interest) to its book assets; *Leverage*, calculated as the ratio of firm i's total debt to its book assets; *Current*, calculated as the firm i's current assets divided by its current liabilities; *Cash*, calculated as the firm i's cash holdings divided by its book assets; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets. 3-digit SIC industry and year fixed effects are included. Robust standard errors are clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	I(Selling Patent)			
	(1)	(2)	(3)	(4)
TFP	-0.027***	-0.051***	-0.011***	-0.051***
	(0.003)	(0.003)	(0.001)	(0.003)
Num_Pat_3			0.106***	
			(0.005)	
Num_Cite_3				3.339***
				(1.451)
TFP × Num_Pat_3			-0.016***	
			(0.001)	
TFP × Num_Cite_3				-0.756***
				(0.377)
Total Assets		0.042***	0.011***	0.041***
		(0.001)	(0.001)	(0.001)
R&D		0.044***	0.002	0.045***
		(0.005)	(0.005)	(0.005)
ROA		-0.000	-0.000	-0.000
		(0.001)	(0.001)	(0.002)
Leverage		0.001	0.005***	0.001
		(0.002)	(0.002)	(0.002)
Current		-0.003***	-0.002***	-0.002***

		(0.000)	(0.000)	(0.000)
Cash		-0.015**	-0.049***	-0.016***
		(0.006)	(0.005)	(0.006)
CAPEX		-0.116***	-0.161***	-0.118***
		(0.017)	(0.015)	(0.017)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.050	0.157	0.233	0.155
Num. of Obs.	152,326	109,450	109,450	109,450

Table 6: Patent's Technological Distance to the Seller and the Probability of the Patent Being Sold in a Patent Transaction

The dependent variable, *I(Patent is Sold),* is an indicator variable equal to 1 if patent i filed in year t is sold by firm j, and it is equal to 0 otherwise. *Tech_Dist* is the technological distance between patent i filed in year t and the patent portfolio of owning firm j (i.e., all the patents held by firm j before patent i). *Patent_Num* is the number of patents in firm j's patent portfolio at the time of patent i's application in year t. Patent-level control variables includes *Forward Citations*, which is the natural logarithm of 1 plus the number of truncation-adjusted lifetime forward citation received by a patent; *Claims,* which is the natural logarithm of the number of claims in a patent's application; *Patent Scope,* which is the number of technology classes to which a patent belongs; *Backward Citations,* which is the natural logarithm of 1 plus the number of backward citations of a patent filed in a given year; and *Litigation,* which equals 1 if a patent is ever litigated and equals 0 otherwise. Owning firm by filing-year fixed effects are included. Robust standard errors are clustered at patent technology class level. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	I(Patent is Sold)		
	(1)	(2)	(3)
Tech_Dist	0.063***	0.066***	-0.071
	(0.014)	(0.014)	(0.057)
Patent_Num			0.055***
			(0.006)
Tech_Dist × Patent_Num			0.018**
			(0.009)
Forward Citations		-0.004	0.036
		(0.074)	(0.065)
Claims		0.004***	0.004***
		(0.001)	(0.001)
Patent Scope		-0.003**	-0.003**
		(0.001)	(0.002)
Backward Citations		0.004***	0.004***
		(0.001)	(0.001)
Litigation		0.129***	0.129***
		(0.014)	(0.014)

Firm × Filing Year FE	Yes	Yes	Yes
Adj. R^2	0.433	0.434	0.434
Num. of Obs.	1,859,106	1,859,106	1,859,106

Table 7: Patent's Relative Technological Distance to the Buyer versus the Seller and the Probability of the Patent Being Sold

The dependent variable *I(Patent is Sold)* is a dummy equal to 1 if patent i filed in year t is sold by seller firm j to buyer firm k and equal to 0 otherwise. *Relative_Tech_Dist* is the technological distance of patent i to the buyer firm k minus the technological distance of patent i to the seller firm j. Patent-level control variables include *Forward Citations*, the natural logarithm of the number of truncation-adjusted lifetime forward citation received by a patent; *Claims,* the natural logarithm of the number of claims in a patent's application; *Patent Scope,* the number of technology classes to which a patent belongs; *Backward Citations*, the natural logarithm of the number of backward citations of a patent filed in a given year; and *Litigation,* which equals 1 if a patent is ever litigated and equals 0 otherwise. Seller, buyer, and filing-year fixed effects are included. Robust standard errors are clustered at patent technology class level. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	I(Patent is Sold)	
	(1)	(2)
Relative_Tech_Dist	-0.082***	-0.052***
	(0.017)	(0.010)
Forward Citations		0.001
		(0.053)
Claims		0.000
		(0.001)
Patent Scope		-0.001
		(0.001)
Backward Citations		0.000
		(0.000)
Litigation		-0.004
		(0.003)
Seller Firm FE	Yes	Yes
Buyer Firm FE	Yes	Yes
Filing Year FE	Yes	Yes
Adj. R^2	0.454	0.492
Num. of Obs.	84,621	82,353

Table 8: Financial Consequences of Patent Transactions: Baseline Results

Return on Assets is defined as firm i's earnings before interest (EBIT) in year t divided by its book assets. *Operating Profitability* is defined as firm i's operating income before depreciation in year t divided by its book assets. *Assignor* is a dummy variable equal to 1 if firm i is the seller firm in a patent transaction. It is equal to 0 otherwise. *Post* is a dummy variable equal to 1 if the observation is within a three-year period after a patent transaction. It is equal to 0 otherwise. Firm-level control variables include *Total Assets*, calculated as the natural logarithm of firm i's book assets in year t; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets in year t; *Leverage*, calculated as the ratio of firm i's total debt to its book assets in year t; *Current*, calculated as the firm i's current assets divided by its current liabilities in year t; *Cash*, calculated as the firm i's cash holdings divided by its book assets in year t; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets in year t. Industry-by-year fixed effects are included in both regressions. Robust standard errors are clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	Return on Assets	Operating Profitability
	(1)	(2)
Assignor × Post	0.034***	0.032***
	(0.006)	(0.007)
Assignor	-0.076***	-0.069***
	(0.008)	(0.008)
Firm-level Controls	Yes	Yes
Industry × Year FE	Yes	Yes
Adj. R^2	0.581	0.580
Num. of Obs.	134,844	134,955

Table 10: Diff-in-Diff Analysis: The Impact of American Inventors Protection Act

Return on Assets is defined as firm i's earnings before interest (EBIT) in year t divided by its book assets. *Operating Profitability* is defined as firm i's operating income before depreciation in year t divided by its book assets. *Assignor* is a dummy variable equal to 1 if a firm is a seller firm in a patent transaction. It is equal to 0 otherwise. *Post* is a dummy variable equal to 1 if the unit of observation is within a three-year period after the year 2000. It is equal to 0 otherwise. Firm-level control variables include *Total Assets*, calculated as the natural logarithm of firm i's book assets in year t; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets in year t; *Leverage*, calculated as the ratio of firm i's total debt to its book assets in year t; *Current*, calculated as the firm i's current assets divided by its current liabilities in year t; *Cash*, calculated as the firm i's cash holdings divided by its book assets in year t; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets in year t. Industry-by-year fixed effects are included in both regressions. Robust standard errors are clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	Return on Assets	Operating Profitability
	(1)	(2)
Assignor × Post	0.044***	0.046***
	(0.015)	(0.014)
Assignor	-0.040***	-0.038***
	(0.013)	(0.012)
Firm-level Controls	Yes	Yes
Industry × Year FE	Yes	Yes
Adj. R^2	0.540	0.533
Num. of Obs.	36,709	36,617

Table 11: Triple Diff-in-Diff Analysis and Assignor Firms' Increase in Focus

Return on Assets is defined as firm i's earnings before interest (EBIT) in year t divided by its book assets. *Operating Profitability* is defined as firm i's operating income before depreciation in year t divided by its book assets. *Assignor* is a dummy variable equal to 1 if firm i is the seller firm in a patent transaction. It is equal to 0 otherwise. *Post* is a dummy variable equal to 1 if the observation is within a three-year period after a patent transaction. It is equal to 0 otherwise. *Focus_Increase* is a dummy variable equal to 1 if the average technological distance of patents filed by firm i in the next three years is smaller than that of patents filed in year t; it is equal to 0 otherwise. Firm-level control variables include *Total Assets*, calculated as the natural logarithm of firm i's book assets in year t; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets in year t; *Leverage*, calculated as the firm i's total debt scaled by its book assets in year t; *Current*, calculated as the firm i's current assets divided by its current liabilities in year t; *Cash*, calculated as the firm i's cash holdings scaled by its book assets in year t; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets in year t. Industry-by-year fixed effects are included. Robust standard errors are clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	Return on Assets	Operating Profitability
	(1)	(2)
Assignor × Post × Focus_Increase	0.048**	0.045**
	(0.021)	(0.021)
Assignor × Post	0.028***	0.027***
	(0.008)	(0.008)
Other Triple DiD Terms	Yes	Yes
Firm-level Controls	Yes	Yes
Industry × Year FE	Yes	Yes
Adj. R^2	0.581	0.580
Num. of Obs.	134,844	134,955

Table 12: Technological Similarity Between Inventors and Assignor Firms Following Patent Transactions

$Tech\_Similarity_{t+1}$ is the technological similarity between patents of inventors who are newly hired by firm i in year t+1 (Panel A), or patents of inventors who remain in firm i in year t+1 (Panel B), and firm i's patents up to year t+1. It is calculated as the cosine similarity between technology classes of patents in inventors' and firms' respective portfolios. *$Tech\_Similarity_{t+2}$* and *$Tech\_Similarity_{t+3}$* are defined similarly. *I(Selling Patent)* is a dummy equal to 1 if firm i sells some of its patents in year t. Firm-level control variables include *Total Assets*, the natural logarithm of firm i's book assets in year t; *R&D*, the ratio of firm i's R&D expense to its book assets in year t; *ROA*, the ratio of a firm's EBIT to its book assets; *Leverage*, the firm i's total debt scaled by its book assets in year t; *Current*, the firm i's current assets divided by its current liabilities in year t; *Cash*, the firm i's cash holdings scaled by its book assets in year t; and *CAPEX*, the ratio of firm i's capital expenditure to its book assets in year t. Firm and year fixed effects are included in both panels. Robust standard errors are clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

Panel A: New Inventors			
	$Tech\_Similarity_{t+1}$	$Tech\_Similarity_{t+2}$	$Tech\_Similarity_{t+3}$
	(1)	(2)	(3)
I(Selling Patent)	0.020**	-0.001	-0.003
	(0.008)	(0.008)	(0.009)
Firm-level Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj. R^2	0.365	0.363	0.362
Num. of Obs.	7,634	7,208	6,737
Panel B: Remaining Inventors			
	$Tech\_Similarity_{t+1}$	$Tech\_Similarity_{t+2}$	$Tech\_Similarity_{t+3}$
	(1)	(2)	(3)
I(Selling Patent)	0.008*	0.017***	0.020***
	(0.004)	(0.005)	(0.005)
Firm-level Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj. R^2	0.502	0.502	0.502
Num. of Obs.	25,494	23,491	21,549

Table 13: Seller Firms' Patenting Activity Following Patent Transactions

Num_Pat_{t+1} is the natural logarithm of 1 plus the number of patents generated by firm i in year t+1. *Avg_Dist_{t+1}* is the average technological distance of all patents filed by firm i in year t+1. The remaining dependent variables are defined similarly. Firm-level control variables include *Total Assets*, calculated as the natural logarithm of firm i's book assets; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets; *ROA*, measured as the ratio of firm's EBIT (Earnings Before Interest) to its book assets; *Leverage*, calculated as the ratio of firm i's total debt to its book assets; *Current*, calculated as the firm i's current assets divided by its current liabilities; *Cash*, calculated as the firm i's cash holdings divided by its book assets; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets. Firm and year fixed effects are included. Robust standard errors are clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

Panel A: Innovation Quantity			
	Num_Pat_{t+1}	Num_Pat_{t+2}	Num_Pat_{t+3}
	(1)	(2)	(3)
I(Selling Patent)	0.161***	0.071***	0.029*
	(0.017)	(0.017)	(0.017)
Firm-level Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj. R^2	0.794	0.798	0.803
Num. of Obs.	166,301	152,509	139,570
Panel B: Technological Distance of Patents			
	Avg_Dist_{t+1}	Avg_Dist_{t+2}	Avg_Dist_{t+3}
	(1)	(2)	(3)
I(Selling Patent)	-0.008***	-0.006**	-0.007**
	(0.003)	(0.003)	(0.003)
Firm-level Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj. R^2	0.608	0.619	0.625
Num. of Obs.	50,254	46,796	43,477

Figure 1: Number and Percentage of Firms Selling Patents (1980-2017)

This figure shows the number and percentage of innovative firms (including both private and public firms) selling their patents in the secondary market from 1980 to 2017. The data is from the USPTO Patent Reassignment Database.

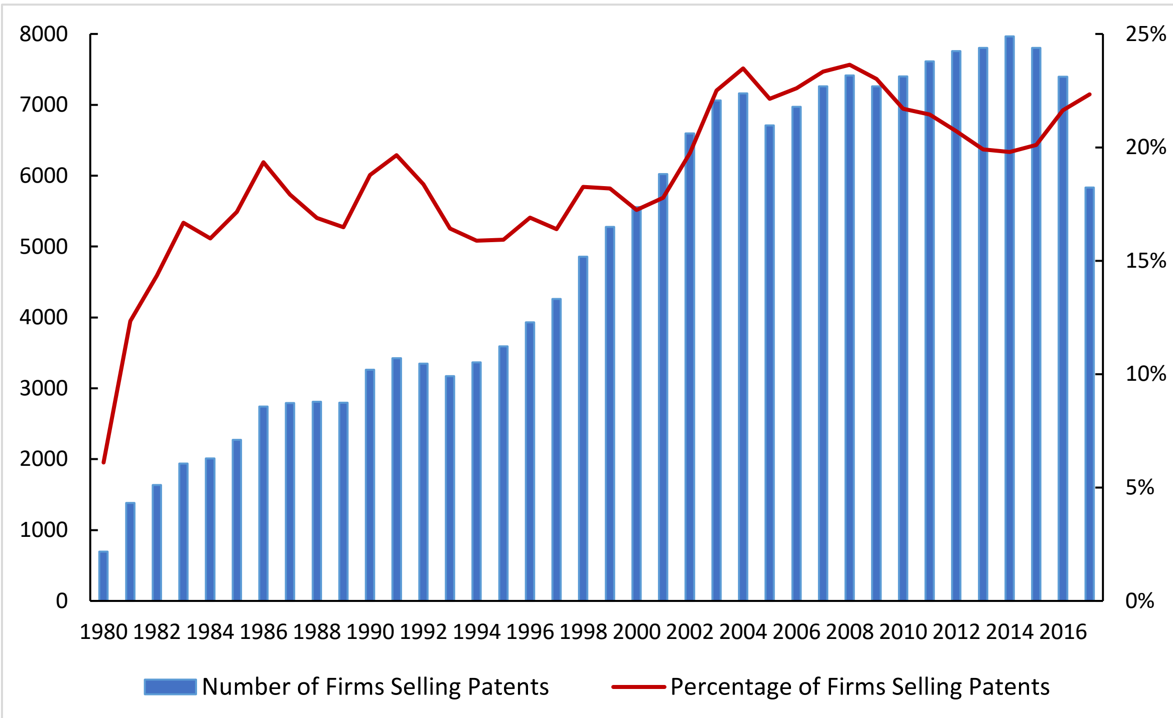


Figure 2: Number of Patents Sold (1980-2017)

This figure shows the number of patents sold in the U.S. patent secondary market from 1980 to 2017. Data is from the USPTO Patent Reassignment Database. This figure only shows the patents sold in secondary market transactions and does not include the change of ownership of patents due to other reasons (mergers & acquisitions, mortgage, security interest etc.).

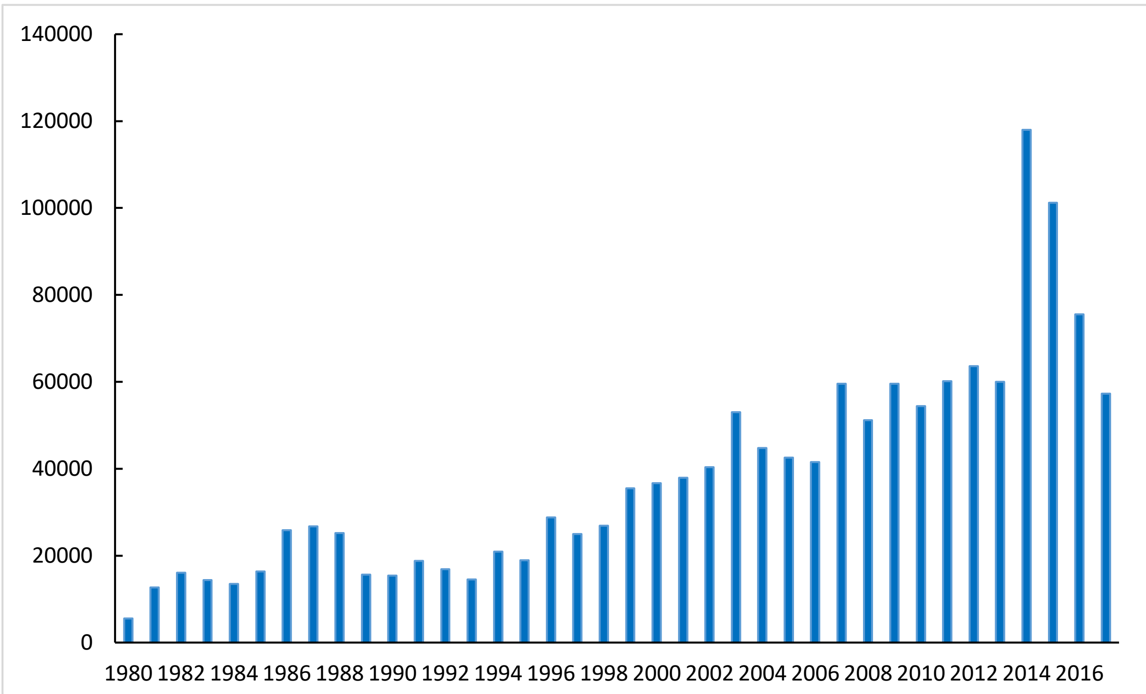


Figure 3: Coefficients Dynamics Around American Inventors Protection Act: The Case of Return on Assets

This figure plots the dynamics of coefficient on the DiD estimator $Assignor_i \times Year_t$ in the regression specification (12). The dependent variable here is $ROA_{i,j,t}$, constructed as EBIT of firm i in industry j in year t divided by its book assets. A vector of firm-level control variables includes: *Total Assets,* calculated as logarithm of firm i's book assets in year t; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets in year t; *Leverage*, calculated as the ratio of firm i's total debt to its book assets in year t; *Current Ratio*, calculated as the firm i's current assets divided by its current liabilities in year t; *Cash*, calculated as the firm i's cash holdings divided by its book assets in year t; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets in year t. Industry-by-year fixed effects are included. Robust standard errors are clustered by firms.

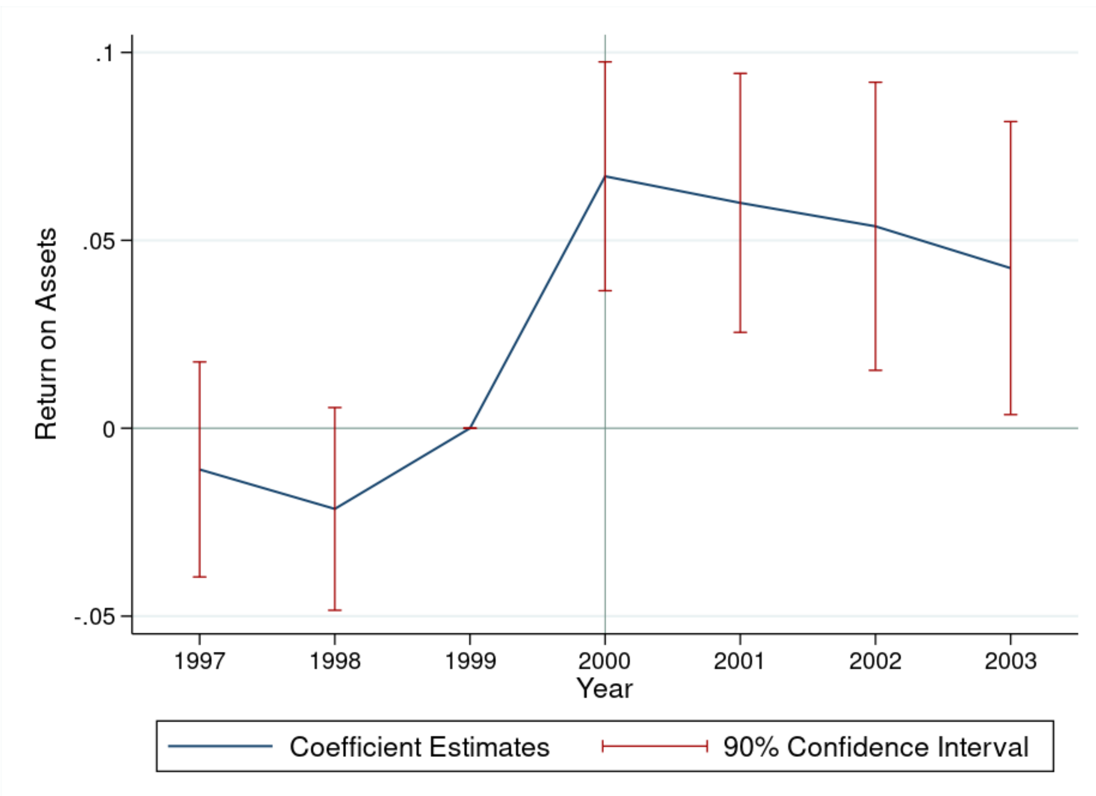
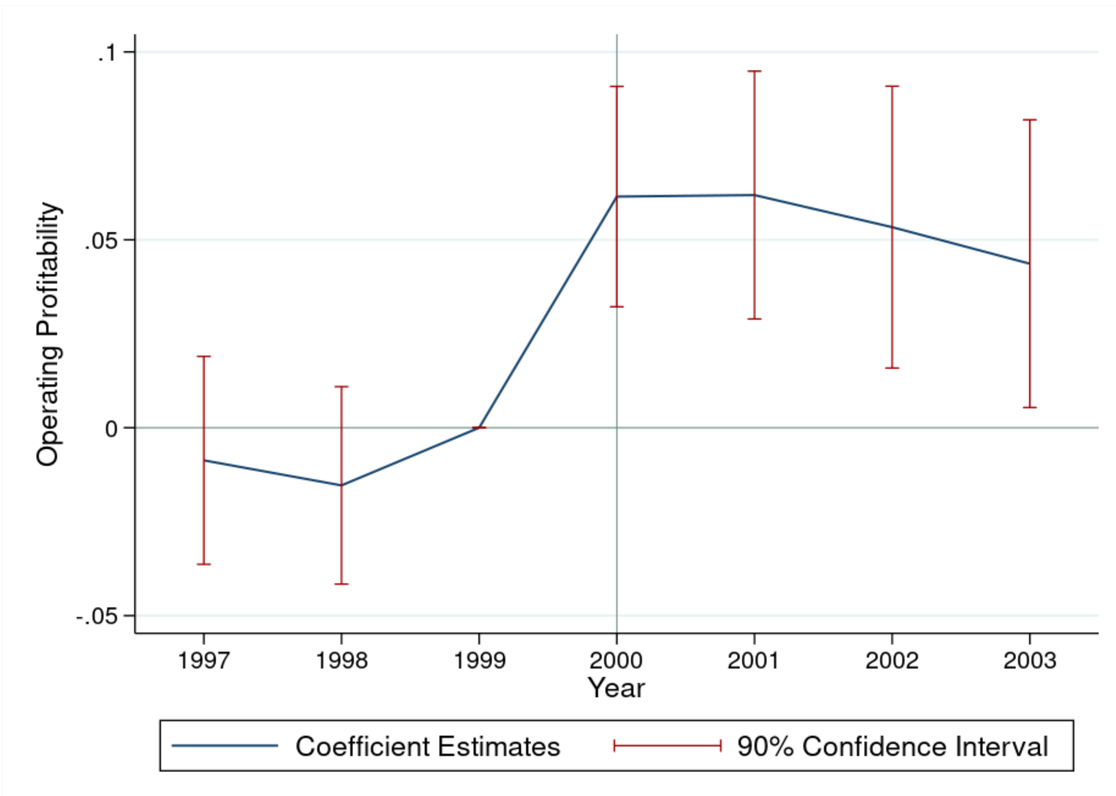


Figure 4: Coefficients Dynamics Around American Inventors Protection Act: The Case of Operating Profitability

This figure plots the dynamics of coefficient on the DiD estimator $Assignor_i \times Year_t$ in the regression specification (12). The dependent variable here is $Operating\ Profitability_{i,j,t}$, constructed as the operating income of firm i in industry j in year t scaled by its book assets. A vector of firm-level control variables includes: *Total Assets,* calculated as logarithm of firm i's book assets in year t; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets in year t; *Leverage*, calculated as the ratio of firm i's total debt to its book assets in year t; *Current Ratio*, calculated as the firm i's current assets divided by its current liabilities in year t; *Cash*, calculated as the firm i's cash holdings divided by its book assets in year t; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets in year t. Industry-by-year fixed effects are included. Robust standard errors are clustered by firms.



Internet Appendix for "Why Do Innovative Firms Sell Patents? An Empirical Analysis of the Causes and Consequences of Secondary Market Patent Transactions"

Appendix A: Descriptive Statistics

This section reports the univariate firm comparison between assignor and non-assignor firms and some descriptive statistics. Table A1 reports the univariate firm comparison. On average, assignor firms have higher innovation productivity than non-assignor firms. For example, assignor firms generate approximately 25 patents per year on average. As a comparison, non-assignor firms only file 0.6 patents per year. This difference is statistically significant at 1% level. Assignor firms also have a higher innovation quality than non-assignor firms, as measured by different citation-based variables used as the proxy for innovation quality. For example, assignor firms on average receive 20.9 citations per patent for all the patents they have filed in the last three years, while this number for non-assignor firms is only 5.39. In addition, assignor firms are also larger (in terms of total assets) and spend more (in absolute terms) in R&D than non-assignor firms. However, the average R&D ratio of assignor firms is lower than that of non-assignor firms, presumably because of the larger size of assignor firms. These two types of firms do not differ much in leverage, short-term liquidity (as measured by the current ratio), and investment opportunities (as measured by capital expenditure).

Table A2 gives some descriptive statistics about the industry distribution of assignor firms and the technology class distribution of patents sold in the patent transactions. Panel A of Table A2 reports the 3-digit SIC industry classification of assignor firms. During the sample period from 1980 to 2017, among all assignor firms, the top five industries to which the assignor firms belong are Drugs (12.11%), Computer Programming and Data Processing Services (9.13%), Medical Instruments and

Supplies (7.19%), Electronic Components and Accessories (5.47%), and Computer and Office Equipment (5.11%). Most of these five industries are R&D intensive. Panel B of Table A2 reports the NBER technology category of patents sold on the secondary market. The top three technology categories are Computer & Communications, Electrical & Electronic, and Chemical. It is interesting to note that, although firms in the drugs industry account for a large part of the assignor firm sample, the number of patents in drugs and chemical category that are traded on the secondary market is relatively small, compared to patents in other NBER technology categories.

Table A1: Univariate Firm Comparison

Number of Patents in Last 3 Years is the number count of patents filed by a firm in the last 3 years up to a given year. *Number of Patents Per Year* is the number count of patents filed by a firm in a given year. *Total Number of Patents* is the total number count of patents filed by a firm up to a given year. *Number of Citations Per Patent in Last 3 Years* is the number of lifetime citations per patents for patents filed by a firm in the last 3 years up to a given year. *Number of Citations Per Patent* is the number of lifetime citations per patent for patents filed by a firm in a given year. *Total Number of Citations* is the total number of lifetime citations received by all patents filed by a firm in a given year. *Total Assets* is a firm's total book assets. *R&D Expense* is a firm's R&D expense in a given year. *R&D* is the ratio of a firm's R&D expense to its book assets. *ROA* is measured as the ratio of a firm's EBIT (Earnings Before Interest) to its book assets. *Leverage* is the ratio of a firm's total debt to its book assets. *Current* is the ratio of a firm's current assets to its current liabilities. *Cash* is measured as a firm's cash holdings divided by its book assets. *CAPEX* is the ratio of a firm's capital expenditure to its book assets. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

Variable	Assignors	Non-assignors	Difference
Number of Patents in Last 3 Years	73.34	1.56	71.78***
Number of Patents Per Year	24.84	0.55	24.29***
Total Number of Patents	422.64	5.80	416.84***
Number of Citations Per Patent in Last 3 Years	20.90	5.39	15.51***
Number of Citations Per Patent	14.27	2.79	11.48***
Total Number of Citations	379.91	10.31	369.60***
Total Assets	4727.10	1732.77	2994.33***
R&D Expense	163.20	25.86	137.35***
R&D	0.15	0.39	-0.24***
ROA	0.06	-0.01	0.07***
Leverage	0.49	0.49	0.00
Current	3.52	3.54	-0.02
Cash	0.20	0.23	-0.03***
CAPEX	0.06	0.06	0.00*
Num. of Obs.	4,842	9,635	

Table A2: Industry and Technology Class Distribution

Panel A: 3-digit SIC Industry Classification of Assignors		
3-Digit SIC Industry	Frequency	Percent
Drugs	593	12.11%
Computer Programming and Data Processing Services	447	9.13%
Medical Instruments and Supplies	352	7.19%
Electronic Components and Accessories	268	5.47%
Computer and Office Equipment	250	5.11%
Communications Equipment	177	3.62%
Measuring and Controlling Devices	174	3.55%
Motor Vehicles and Equipment	111	2.27%
Special Industry Machinery	87	1.78%
General Industrial Machinery	73	1.49%
Construction and Related Machinery	61	1.25%
Refrigeration and Service Machinery	50	1.02%
Toys and Sporting Goods	50	1.02%
Panel B: The NBER Technology Category of the Patents Sold		
NBER Technology Category	Number	Percent
Computers & Communications	216,715	42.72%
Electrical & Electronic	108,385	21.36%
Chemical	62,068	12.23%
Mechanical	48,648	9.59%
Drugs & Medical	30,782	6.07%

Appendix B: Additional Results

This section reports several additional results. I first conduct a robustness test of examining the relationship between a firm's innovation productivity and the probability of the firm selling some of its patents. Different from Table 3, I use alternative measures as proxies for a firm's innovation productivity. In Table A3, the main independent variables are *Num_Pat_3/R&D,* which is the natural logarithm of 1 plus the number of patents generated by firm i in the last three years prior to year t scaled by firm i's R&D ratio in year t. *Num_Pat_Total/R&D,* which is the natural logarithm of 1 plus the total number of patents in firm i's patent portfolio until year t scaled by firm i's R&D ratio in year t. *Num_Pat/R&D,* which is the natural logarithm of 1 plus the number of patents generated by firm i in year t scaled by firm i's R&D ratio in year t.

I then explore the relationship between a patent's value (as represented by its scientific value or its economic value) and the probability of it to be sold in a secondary market patent transaction. The corresponding results are reported in Table A4. The economic value of a patent is measured as the announcement return on owning firm's stock around the grant of the patent (following the methodology of Kogan et al. (2017)). The scientific value of a patent is constructed as the number of forward citations (truncation-adjusted) received by the patent. I show that a patent with higher economic value or higher scientific value is more likely to be sold in a secondary market patent transaction.

I report the buy-and-hold abnormal return (BHAR) of assignor firms' stocks following patent transactions in Table A5. The benchmark portfolios against which the assignor firms' equity is compared include size-matched firms (following the methodology of Loughran and Ritter (1995)) and other market portfolios. Different columns of Table A5 represent different holding periods following patent transactions during which the BHAR is calculated.

I conduct a robustness test of the effect of patent transactions on firms' subsequent operating performance using a matched sample of seller and non-seller firms based on the closest propensity score. For each seller firm, I select one non-seller firm (with replacement) in the same 3-digit SIC industry and transaction year that has the closest propensity score estimated using the number of patents filed by a firm in the transaction year, total assets, R&D ratio, current year's ROA, leverage, current, cash, and capital expenditure. I combine a seller firm and the matched non-seller firm into a cohort, and I then stack all the cohorts of seller and matched non-seller firms to conduct DiD analysis. The results documented in Table A6 are broadly consistent with the empirical patterns shown in Table 8. Overall, compared to non-seller firms that are at least similar in terms of observables, seller firms experience an increase in operating performance (as measured by ROA and operating profitability) following patent transactions.

To delve deeper and gain a better understanding of the sources of increase in ROA, I explore separately the effect of secondary market patent transactions on individual components of ROA, as well as its effect on firm-level total factor productivity (TFP). I use a similar specification as in (10) and report the results in Table A7. I find that seller firms increase their sales in the next three years subsequent to patent transactions. In addition, seller firms experience a decrease in their overhead costs and an increase in their cost of goods sold following the patent transactions. More importantly, I document seller firms also experience a significant improvement in their production efficiency as measured by the TFP following patent sales.

Table A7 reports the results on the validity of American Inventors Protection Act of 1999 used as an exogenous shock to the patent transaction incidence in my setting. In this table, the main independent variable is *I(Year > 2000)*, which is a dummy variable equal to 1 if an observation is after the year 2000, the year in which the patent disclosure requirement is effective. The coefficient on this variable is positive and significant across different specifications, suggesting that following the passage of this Act, assignor firms are more likely to engage in secondary market patent transactions.

In Table A9, to ensure the internal validity of my DiD estimator associated with the American Inventors Protection Act of 1999 documented in Table 10, I conduct a falsification test. Specifically, I falsely assume that the part of the Act related to the expedited disclosure of patent applications was effective three years before it actually did (i.e., the year 2000). Therefore, based on the sample of all assignor and non-assignor firms, I estimate a three-year window around the year 1997 such that the panel ends before the actual year when the part of the Act related to patent application disclosure was in effect. The positive but insignificant coefficients on the DiD estimators suggest that the results documented in Table 10 are likely to be driven by the Act itself instead of some alternative forces.

I examine the inventors' flow of assignor firms in the three years subsequent to patent transactions in Table A10. I find that assignor firms do not achieve the increase in their innovation focus simply by reducing the size of their R&D departments. The positive and statistically significant coefficients on *I(Selling Patent)* in all the columns of Table A10 suggest that assignor firms experience an inflow of inventors over the next three years after patent transactions.

Table A3: Firm's Innovation Productivity and the Probability of the Firm Selling Patents: Robustness Test

This table reports the robustness test of the relationship between a firm's innovation productivity and the probability of the firm selling some of its patents. The dependent variable *I(Selling Patent)* is an indicator variable equal to 1 if firm i sells a patent in year t. It is equal to 0 otherwise. *Num_Pat_3/R&D* is the natural logarithm of 1 plus the number of patents generated by firm i in the last three years prior to year t, scaled by firm i's R&D ratio in year t. *Num_Pat_Total/R&D* is the natural logarithm of 1 plus the total number of patents in firm i's patent portfolio until year t, scaled by firm i's R&D ratio in year t. *Num_Pat/R&D* is the natural logarithm of 1 plus the number of patents generated by firm i in year t, scaled by firm i's R&D ratio in year t. Firm-level lagged control variables include *Total Assets*, calculated as logarithm of firm i's book assets; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets; *ROA* is measured as the ratio of firm's EBIT (Earnings Before Interest) to its book assets; *Leverage*, calculated as the ratio of firm i's total debt to its book assets; *Current*, calculated as the firm i's current assets divided by its current liabilities; *Cash*, calculated as the firm i's cash holdings divided by its book assets; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets. 3-digit SIC industry and year fixed effects are included. Standard errors are robust and clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	I(Selling Patent)					
	(1)	(2)	(3)	(4)	(5)	(6)
Num_Pat_3/R&D	0.00005***	0.00002***				
	(0.00001)	(0.00000)				
Num_Pat_Total/R&D			0.00002***	0.00000***		
			(0.00000)	(0.00000)		
Num_Pat/R&D					0.00008***	0.00004***
					(0.00002)	(0.00001)
Total Assets		0.041***		0.041***		0.040***
		(0.002)		(0.002)		(0.002)
R&D		0.038***		0.038***		0.037***
		(0.004)		(0.004)		(0.004)
ROA		-0.014***		-0.015***		-0.014***
		(0.002)		(0.002)		(0.002)

Leverage		0.003*		0.003*		0.003*
		(0.002)		(0.002)		(0.002)
Current		-0.002***		-0.002***		-0.002***
		(0.000)		(0.000)		(0.000)
Cash		-0.008		-0.008		-0.008
		(0.006)		(0.006)		(0.006)
CAPEX		-0.087***		-0.087***		-0.087***
		(0.016)		(0.017)		(0.016)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.051	0.140	0.047	0.139	0. 052	0.141
Num. of Obs.	128,162	112,511	128,162	112,511	128,162	112,511

Table A4: Patent's Value and the Probability of a Patent Sold

I(Patent is Sold) is an indicator variable equal to 1 if patent i filed in year t is sold by firm j. *Eco_Value* is the economic value of patent i to the owning firm j filed in year t, measured as the stock return on firm j upon grant of patent i. *Forward Citations* is the natural logarithm of the truncation-adjusted total number of forward lifetime citations received by patent i filed in year t. Patent-level control variables includes *Claims,* the natural logarithm of the number of claims in a patent's application; *Patent Scope,* measured as the number of technology classes to which a patent belongs; *Backward Citations,* the natural logarithm of the number of backward citations of a patent filed in a given year; and *Litigation,* which equals 1 if a patent is ever litigated and equals 0 otherwise. Owning firm by filing-year fixed effects are included. Robust standard errors are clustered at patent technology class level. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	I(Patent is Sold)		
	(1)	(2)	(3)
Eco_Value	0.004**		0.004**
	(0.002)		(0.002)
Forward Citations		0.181***	0.180***
		(0.061)	(0.061)
Claims	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)
Patent Scope	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Backward Citations	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)
Litigation	0.128***	0.128***	0.128***
	(0.014)	(0.014)	(0.014)
Firm × Filing-Year FE	Yes	Yes	Yes
R^2	0.432	0.432	0.432
Num. of Obs.	1,859,106	1,859,106	1,859,106

Table A5: Patent Transactions and Assignor Firms' Long-Run Stock Return

The dependent variable BHAR is the long-run buy-and-hold abnormal return of seller firm i of date t on which a patent transaction takes place. The columns represent different durations for which the BHAR is constructed. The rows represent different benchmark portfolios against which the BHAR is compared. Standard errors are robust. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	Long-Run Buy-and-Hold Abnormal Returns (BHAR)					
	1 Quarter BHAR [1, 63]	2 Quarters BHAR [1, 126]	3 Quarters BHAR [1, 189]	1 Year BHAR [1, 252]	2 Years BHAR [1, 504]	3 Years BHAR [1, 756]
Size-matched Firms	0.018** (0.009)	0.038*** (0.012)	0.052*** (0.015)	0.072*** (0.021)	0.068** (0.029)	0.261** (0.117)
CRSP Value-weighted Index	0.106* (0.061)	0.115** (0.050)	0.121*** (0.043)	0.127*** (0.048)	0.13*** (0.050)	0.124** (0.060)
Standard & Poor's 500	0.112* (0.061)	0.128** (0.050)	0.139*** (0.043)	0.15*** (0.047)	0.176*** (0.050)	0.193*** (0.070)
Nasdaq Composite Index	0.103* (0.061)	0.112** (0.050)	0.115*** (0.043)	0.117** (0.048)	0.113** (0.050)	0.105* (0.060)

Table A6: Financial Consequences of Patent Transactions: Robustness Test

This table reports the result of a robustness test of financial consequences of patent transactions using a matched sample of seller and non-seller firms based on the closest propensity score. I match each seller firm with one non-seller firm (with replacement) in the same 3-digit SIC industry and transaction year that has the closest propensity score estimated using number of patents filed by a firm in the transaction year, total assets, R&D ratio, current year's ROA, leverage, current, cash, and capital expenditure. I combine a seller firm and the matched non-seller firm into a cohort, and then I stack all the cohorts of seller and matched non-seller firms to conduct DiD analysis. *Return on Assets* is defined as firm i's earnings before interest (EBIT) in year t divided by its book assets. *Operating Profitability* is defined as firm i's operating income before depreciation in year t divided by its book assets. *Assignor* is a dummy variable equal to 1 if firm i is the seller firm in a patent transaction. It is equal to 0 otherwise. *Post* is a dummy variable equal to 1 if the observation is within a three-year period after a patent transaction. It is equal to 0 otherwise. Firm-level control variables include *Total Assets*, which is calculated as logarithm of firm i's book assets in year t; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets in year t; *Leverage*, calculated as the ratio of firm i's total debt to its book assets in year t; *Current*, calculated as the firm i's current assets divided by its current liabilities in year t; *Cash*, calculated as the firm i's cash holdings divided by its book assets in year t; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets in year t. Cohort-by-year fixed effects are included in both regressions. Standard errors are robust and clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	Return on Assets	Operating Profitability
	(1)	(2)
Assignor × Post	0.067**	0.062**
	(0.031)	(0.030)
Assignor	0.062	0.074
	(0.055)	(0.054)
Firm-level Controls	Yes	Yes
Cohort × Year FE	Yes	Yes
Adj. R^2	0.962	0.964
Num. of Obs.	9,020	9,000

Table A7: Financial Consequences of Patent Transactions: Decomposition of ROA and Change in TFP

Sales is defined as the natural logarithm of firm i's total sales in year t. *SG&A* is defined as firm i's selling, general and administrative expense in year t divided by its book assets. *COGS* is constructed as firm i's cost of goods sold in year t scaled by its book assets. *TFP* is firm i's revenue-based total factor productivity in year t, constructed following the methodology of Olley and Pakes (1996). Firm-level control variables include *Total Assets*, calculated as the natural logarithm of firm i's book assets in year t; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets in year t; *Leverage*, calculated as the ratio of firm i's total debt to its book assets in year t; *Current*, calculated as the firm i's current assets divided by its current liabilities in year t; *Cash*, calculated as the firm i's cash holdings divided by its book assets in year t; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets in year t. Industry-by-year fixed effects are included in all regressions. Robust standard errors are clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	Sales	SG&A	COGS	TFP
	(1)	(2)	(3)	(4)
Assignor × Post	0.041***	-0.030***	0.013**	0.120***
	(0.010)	(0.007)	(0.006)	(0.013)
Assignor	0.002	0.111***	0.020**	-0.237***
	(0.014)	(0.009)	(0.010)	(0.019)
Firm-level Controls	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.910	0.577	0.284	0.318
Num. of Obs.	128,057	119,725	135,154	115,218

Table A8: American Inventors Protection Act of 1999 and Patent Transaction Incidence

The dependent variable *I(Selling Patent)* is an indicator variable equal to 1 if firm i sells a patent in year t. It is equal to 0 otherwise. *I(Year >2000)* is a dummy variable equal to 1 if the unit of observation is after year 2000 and equal to 0 otherwise. Firm-level control variables include *Total Assets*, calculated as logarithm of firm i's book assets; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets; *ROA*, measured as the ratio of firm i's EBIT (Earnings Before Interest) to its book assets; *Leverage*, calculated as the ratio of firm i's total debt to its book assets; *Current*, calculated as the firm i's current assets divided by its current liabilities; *Cash*, calculated as the firm i's cash holdings divided by its book assets; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets. Year trend is included in all regressions. 3-digit SIC industry and firm fixed effects are included in different regressions separately. Standard errors are robust and clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	I(Selling Patent)			
	(1)	(2)	(3)	(4)
I(Year > 2000)	0.010***	0.006**	0.008***	0.007**
	(0.002)	(0.002)	(0.003)	(0.003)
Year Trend	Yes	Yes	Yes	Yes
Firm Controls	No	Yes	No	Yes
Industry FE	Yes	Yes	No	No
Firm FE	No	No	Yes	Yes
Adj. R^2	0.028	0.093	0.248	0.244
Num. of Obs.	197,010	186,309	197,010	183,718

Table A9: Diff-in-Diff Analysis of the Impact of American Inventors Protection Act: Falsification Test

In this falsification test, to ensure the internal validity of my DiD estimator associated with the American Inventors Protection Act of 1999 in Table 10, I falsely assume that the Act related to patent application disclosure enacted three years before it actually did (i.e., year 2000). I thus estimate a three-year window around year 1997 on the sample of all assignor and non-assignor firms. *Return on Assets* is defined as firm i's earnings before interest (EBIT) in year t divided by its book assets. *Operating Profitability* is defined as firm i's operating income before depreciation in year t divided by its book assets. *Assignor* is a dummy variable equal to 1 if a firm is a seller firm in a patent transaction. It is equal to 0 otherwise. *Post* is a dummy variable equal to 1 if the unit of observation is within a three-year period after year 1997. It is equal to 0 otherwise. Firm-level control variables include *Total Assets*, calculated as the natural logarithm of firm i's book assets in year t; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets in year t; *Leverage*, calculated as the ratio of firm i's total debt to its book assets in year t; *Current*, calculated as the firm i's current assets divided by its current liabilities in year t; *Cash*, calculated as the firm i's cash holdings divided by its book assets in year t; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets in year t. Industry-by-year fixed effects are included in both regressions. Robust standard errors are clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	Return on Assets	Operating Profitability
	(1)	(2)
Assignor × Post	0.093	0.090
	(0.137)	(0.137)
Assignor	0.013	0.017
	(0.029)	(0.029)
Firm-level Controls	Yes	Yes
Industry × Year FE	Yes	Yes
Adj. R^2	0.422	0.421
Num. of Obs.	20,143	20,123

Table A10: Inventor Flows of Assignor Firms Following Patent Transactions

Inventor_Flow$_{t+1}$ is the number of flow of inventors of a firm in year t+1. If this measure is positive (negative), it indicates that the firm experiences an inflow (outflow) of inventors in year t+1. *Inventor_Flow$_{t+2}$* and *Inventor_Flow$_{t+3}$* are defined similarly. *I(Selling Patent)* is an indicator variable equal to 1 if firm i sells some of its patents in year t. It is equal to 0 otherwise. Firm-level control variables include *Total Assets*, calculated as the natural logarithm of firm i's book assets in year t; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets in year t; *ROA*, measured as the ratio of a firm's EBIT (Earnings Before Interest) to its book assets; *Leverage*, calculated as the firm i's total debt scaled by its book assets in year t; *Current*, calculated as the firm i's current assets divided by its current liabilities in year t; *Cash*, calculated as the firm i's cash holdings scaled by its book assets in year t; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets in year t. Firm and year fixed effects are included. Standard errors are robust and clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	Inventor_Flow$_{t+1}$	Inventor_Flow$_{t+2}$	Inventor_Flow$_{t+3}$
	(1)	(2)	(3)
I(Selling Patent)	5.787**	6.548**	7.333***
	(2.660)	(3.183)	(3.454)
Firm-level Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj. R^2	0.562	0.558	0.561
Num. of Obs.	49,041	46,678	44,118

Chapter 2: Venture Capital and Value Creation in the Product Market: Evidence from the Nielsen Retail Scanner Data

1 Introduction

Entrepreneurial firms comprise a majority of the business establishments in the U.S. and contribute to a great degree of job creation and economic growth. According to the data provided by the U.S. Census Bureau, as of 2018, small firms accounted for 99.7% of all employer firms (i.e., firms with paid employees). A report released by the Small Business Administration (SBA) in 2018 shows that small firms contributed 43.5% of the U.S. GDP by 2014.[1] In addition, from 2000 to 2019, small businesses have contributed 10.5 million net new job creation, which accounts for a 65.1% of overall net job creation since 2000.[2] In this paper, we focus on a special type of entrepreneurial firms, i.e., firms that are backed by venture capitalists (VCs), and study how VCs help to create value for these firms in the product market.

The role of venture capitalists (VCs) in creating value for the startups backed by them is well documented in the literature. [3] However, due to the data availability of private firms, the existing literature is limited in terms of examining what aspects of value VCs could provide to the startups. Abundant papers in this strand of literature use publicly available data (e.g., data on firms' exit and innovation output) and argue that VCs create value for entrepreneurial firms along these dimensions. However, as firms' growth ultimately hinges on how they conduct operations and generate revenue in the product market, VCs could as well play an important role in this process.[4] This paper aims to fill this gap in the literature.

The central research question of this paper is whether and how VCs create value for

[1]The full article of this report is available at https://cdn.advocacy.sba.gov/wp-content/uploads/2018/12/21060437/Small-Business-GDP-1998-2014.pdf.

[2]The report by the SBA is available at https://cdn.advocacy.sba.gov/wp-content/uploads/2020/11/05122043/Small-Business-FAQ-2020.pdf.

[3]For example, Barry et al. (1990), Kortum and Lerner (2000), Chemmanur et al. (2014), and Bernstein et al. (2016)

[4]For example, Levitt et al. (1965) and Argente et al. (2018), among others, have argued that firms could exploit their existing products or introduce new products to achieve revenue growth

startups in the product market. By constructing a novel dataset based on the Nielsen Retail Scanner Data that comprehensively covers the universe of firms in the consumer goods industry as well as the VentureXpert Database, we are able to analyze the product market performance of VC-backed entrepreneurial firms in detail for the first time in the literature. The Nielsen Retail Scanner Data, provided by the Kilts Center for Marketing at the University of Chicago Booth School of Business, contains granular information about individual products (e.g., prices, quantity sold, stores, geographic locations and etc). We then aggregate the product-level information to the firm level. This detailed information allows us to examine firms' product market performance in various dimensions. Further, we merge Nielsen data with the VentureXpert Database. VentureXpert is a leading provider of data on VC investments and portfolio companies, and it is frequently used by previous studies. By merging these two databases, we can identify VC-backed entrepreneurial firms and hence compare their product market performance with that of non-VC-backed private firms.

Our baseline findings can be summarized as follows. We find that in the five years following the first VC financing, VC-backed entrepreneurial firms on average experience higher sales and seize larger market share than non-VC-backed private firms. Controlling for both firm and state-by-year fixed effects, this increase in sales is statistically significant and large in magnitude: the sales of VC-backed startups have more than doubled after they receive the VC investment. To understand what factors drive the growth in sales, we further decompose the sales into the average price of products and the quantity of products sold. We find that VC-backed entrepreneurial firms achieve the growth in sales and market share by lowering the prices of their products and thus increasing the quantity of products sold.[5] In addition, compared to non-VC-backed firms, VC-backed startups also enlarge

[5] One might question the representativeness of the decrease in the average price of products in our firm-level baseline findings, since this measure is averaged across all products within a firm. If a firm operates several different product lines, this measure may lose certain specificity. To address this concern, we also repeat our baseline analysis at the firm-product-line level, where the unit of observation is firm-product-line-year, and we document similar empirical patterns.

their product portfolios and operate more product lines. We show that this increase is driven by the introduction of new products and new product lines. Further, we find that after receiving their first VC investment, VC-backed firms expand their products to more stores and geographic locations.

The fact that our baseline results are robust to the inclusion of firm and state-by-year fixed effects provides first proof of identification. However, there still remain several endogeneity concerns facing our baseline specifications. One prominent concern is the selection versus treatment effect of venture capitalists frequently studied in the existing literature. In other words, is the outperformance of VC-backed startups compared to non-VC-backed counterparts mostly driven by VCs' ability to choose better firms (i.e., selection/screening)? Or is it because VCs have a superior ability to better create value for these startups (i.e., treatment)?[6] Therefore, to address this endogeneity concern, we conduct the Instrumental Variable (IV) analysis based on a sample of matched VC-backed and non-VC-backed firms. We instrument the supply of VC financing with a proxy for the weighted return of VC limited partners' investment. This instrumental variable is first pioneered by Samila and Sorenson (2011) and is later used by many studies. The instrument is particularly suitable for our setting, since it allows us to disentangle the selection versus treatment effect of VCs and enables us to answer our research question of whether VCs indeed create value for startups in the product market (in addition to the selection effect that may exist). The central assumption here is that, after controlling for all other factors, the IV will affect startups' product market performance only through the supply of VC financing, and it is not likely to be correlated with underlying firm characteristics. We will discuss in detail the exclusion restriction and the relevance of IV in Section 5.

Overall, the results from our IV analysis show that the effect of VCs on startups' product

[6] In fact, we conduct an analysis to examine which type of entrepreneurial firms is more likely to be selected by VC investors. We show the results in our Online Appendix. We find that in our setting, VC investors appear to prefer those with higher growth potential, pointing to the existence of selection effect to some extent.

market performance is likely causal. The first-stage results of our IV analysis show that this instrument is relevant for the likelihood of entrepreneurial firms obtaining VC financing. Controlling for all other factors that could potentially affect VC investment, we find that the coefficient of regressing VC financing dummy on the weighted limited partner return is positive and statistically significant at 1% level. This indicates that the higher the past returns of limited partners, the more likely it is for an entrepreneurial firm in a state to receive an investment from VC. In the second stage of our IV analysis, we find that the results we document in our baseline specification continue to hold: the fitted value of the VC financing dummy obtained in the first stage positively predicts the subsequent 5-year average of sales, market share, number of products, number of product lines, as well as geographic availability of products of entrepreneurial firms.

Having established that VCs indeed create value in the product market for the entrepreneurial firms backed by them, we then address our second research question of how VCs create value for these entrepreneurial firms in the product market and examine several potential channels. The first channel we examine is the market share. If an entrepreneurial firm develops several popular products and possesses a larger market share than its competitors do, the entrepreneurial firm may be advised by its VC investors to adopt a different marketing strategy from those VC-backed entrepreneurial firms that possess a smaller market share. If this channel is valid, we would expect to see heterogeneous value creation effects of VCs for entrepreneurial firms with different market shares.

To examine this potential channel, we divide VC-backed entrepreneurial firms into two sub-samples based on their nationwide market share (calculated using all the firms in the same product department and year) when they first received their VC financing. We then combine these two sub-samples separately with all non-VC-backed private firms and run our baseline specifications again. We find that the value creation effect of VCs is more pronounced in the sub-sample where VC-backed entrepreneurial firms possess a larger market share. Specifically, we find that for VC-backed entrepreneurial firms in this sub-sample, they outperform their non-VC-backed counterparts in terms of sales, size of product portfolios, number of product lines, and geographical availability of their products. They achieve the growth in sales by lowering the average price of their products and hence gaining more market share following their first VC financing. The empirical patterns we document for this particular sub-sample are very similar to those documented in the baseline results. However, when we look at the sub-sample of VC-backed firms where they possess a smaller market share, we find that for VC-backed firms in this sub-sample, interestingly, the geographic availability of their products has declined compared to non-VC-backed firms subsequent to their first VC financing. This seems to suggest that VCs direct these firms to adopt a marketing strategy that is more geographically concentrated. The VC-backed firms in this sub-sample also experience a decline in the size of their product portfolios and the number of product lines they operate. However, this strategy may not work well in terms of sales: following their first VC financing, the VC-backed firms in this sub-sample experience a decrease in sales compared to their non-VC-backed counterparts, and we find that the decrease in sales is mostly driven by a decline in their quantity of products sold.

The second potential channel we examine is VCs' monitoring of startup companies. As Gorman and Sahlman (1989) and Bernstein et al. (2016), among others, have argued, it is usually the lead VC of a startup who takes on the monitoring role, while other members in the VC syndicate play a more passive role of providing capital. We proxy for the monitoring intensity of VC investors using the distance between the headquarters of VC-backed entrepreneurial firms and that of their lead VC investors. We hypothesize that the longer the distance between an entrepreneurial firm and its lead VC investor, the more difficult the lead VC is to monitor the entrepreneurial firm's operation intensively.

To examine this potential channel, we first calculate the distance between a startup and its lead VC investor as the spherical distance between the centroid of the ZIP code of the startup's headquarter and that of its lead VC's headquarter. we then divide VC-backed firms in our sample into two sub-samples based on their relative distance to their lead VC investors. We combine these two sub-samples of VC-backed firms separately with all non-VC-backed firms and run the baseline regressions again.

We document that in the short-distance sub-sample where the monitoring intensity of lead VCs is presumably higher, the results are very similar to our baseline findings, and the magnitude of most coefficients is slightly larger. In other words, for the VC-backed entrepreneurial firms with higher monitoring intensity from their lead VC investors, they outperform the non-VC-backed counterparts in terms of sales, nationwide market share, number of products, number of product lines, and geographic availability of their products subsequent to receiving first VC investment. On the other hand, in the long-distance sub-sample where the monitoring intensity of lead VCs is presumably lower, the value creation effect of VCs appears to be smaller. The significance of the coefficient disappears when the dependent variable is nationwide market share. Furthermore, in terms of the size of product portfolios, the number of product lines, and the geographic availability of products, the coefficients are smaller in magnitude and less statistically significant compared to those documented in the short-distance sub-sample. Overall, putting these pieces of evidence together, we argue that, apart from providing capital to their portfolio companies, VCs also create value in the product market by directing firms' marketing strategy and monitoring their operations.

The rest of this paper is organized as follows. We review the existing literature and discuss our contribution to the literature in Section 2. We discuss in detail the various databases used in our study and the sample selection procedure in Section 3. We present our firm-level baseline results in Section 4. We then discuss the results of IV analysis in Section 5. We further explore the potential mechanisms underlying our results in Section 6. Section 7 concludes.

2 Relation to the Existing Literature

There are two papers closely related to our study. Using survey data on silicon-valley high-tech startups, Hellmann and Puri (2000) document that venture capital is associated with a significant reduction in the time bringing a product to market. This effect is stronger for innovator firms. On the other hand, Chemmanur et al. (2011) document that the overall efficiency of VC-backed firms is higher than that of non-VC-backed firms at every point in time and that both screening and monitoring of VCs contribute to the difference in overall efficiency. By utilizing the rich information contained in the Nielsen Retail Scanner Data combined with the VentureXpert dataset, we build on the above two papers and contribute to the literature by documenting whether and how VCs create value for startups in the various dimensions of product market.

Our study contributes to the broader literature on entrepreneurial financing. There have been many papers studying the effect of venture capital on the performance of entrepreneurial firms in terms of their corporate innovation, subsequent valuation, successful exit, and long-term performance. Gorman and Sahlman (1989) document that, based on survey evidence, VCs are associated with raising funds for startups, providing strategic consulting and recruiting management team members. Kortum and Lerner (2000) show that increases in venture capital funding at the industry level are associated with higher innovation output, as measured by the number of patented innovations. They show that this effect is likely to be causal. In another paper, using survey data, Hellmann and Puri (2002) document that venture capital is related to the professionalization of entrepreneur firms. In addition, VC-backed entrepreneur firms are more likely to experience management turnover with the founder being replaced with an outside CEO. Chemmanur et al. (2014) show that corporate venture capitalists (CVCs) have a better ability of nurturing the innovation of entrepreneur firms than independent venture capitalists (IVCs), possibly due to the technological fit between CVCs' parent firms and entrepreneurs. Bernstein et al. (2016) show that VCs' on-site monitoring and involvement have an causal impact on the innovation output of startups. On the other hand, Hochberg et al. (2007) and González-Uribe (2020) argue the importance of networks in VC investments. Hochberg et al. (2007) document that startups securing funding from better-networked VCs are more likely to obtain subsequent financing and are more likely to successfully exit via initial public offerings (IPOs) or mergers and acquisitions (M&As). González-Uribe (2020) show that venture capitalists foster the exchange of innovation resources among their portfolio companies. This points to a different source of value addition provided by VCs: VCs internalize the resources within their networks and thus result in a better performance of startups. However, while the existing literature on the value addition effect of VCs is abundant, due to the data availability for private firms, the research on how VCs create value for startups in the product market is limited. Our study contributes to this strand of literature by utilizing a granular product market dataset and analyze VCs' value creation in the product market.

Our study also contributes to the strand of literature on firms' product market performance. Firms' revenue growth crucially depends on either developing current product lines or introducing novel products (Levitt et al. (1965) and Argente et al. (2018)). Existing literature studies the impact of different financial institutions on firm's product market performance. For instance, Chevalier (1995a) and Chevalier (1995b) study the pricing and market expansion behavior of supermarket leveraged buyouts and their competitors. Fracassi et al. (2020) argue that following a private equity buyout of firms that manufacture products, target firms experience a significant increase in their sales by launching more products and expanding geographically. Aslan and Kumar (2016) find that hedge fund activism has significant product market spillover effects on the industry rivals of target firms. The impact on rivals' performance is associated with improvements in factor productivity, capital allocation efficiency, and product differentiation following intervention. On the other hand, the product market also plays a vital role in the US economy. Product creation and destruction are key factors in explaining firms' business cycle fluctuations and long-run growth (e.g., Shleifer (1986), Caballero and Hammour (1996), Broda and Weinstein (2010), and Argente et al. (2019)). Product market innovation is also related to firms' R&D effort (Argente et al. (2020)). Moreover, by structurally estimating a model of financing and investment to quantify the effects of the product life cycle channel, Hajda and Nikolov (2020) find that capital investment and product introductions act as complements, and that product dynamics induce stronger precautionary savings motives. Our contribution to this strand of literature is we focus on whether and how VCs create value in the product market for entrepreneurial firms, an important component of the U.S. economy.

3 Data Sources and Sample Selection

3.1 Nielsen Retail Scanner Data

To measure startups' product market performance, we utilize the Nielsen Retail Scanner Data from the Kilts Center for Marketing at the University of Chicago Booth School of Business. This database tracks weekly purchases of more than two million unique products from 2006 to 2019 at the participating grocery, drug, mass merchandiser, and other stores in the U.S. Specifically, this database contains information about the price, size, and units sold (among other variables) of every product in a specific store at a weekly frequency. Thus, product-week-store uniquely identifies all the observations of the Nielsen Retail Scanner Data. To allow tractability, we link each unique product to its parent firm and construct all variables at an annual frequency. As a result, the unit of observation is firm-year in our study.

Each product in the Nielsen Retail Scanner Data is uniquely identified by a Universal Product Code (UPC). Nielsen first categorizes each product into one of the 1,311 product modules. Each one of the 1,311 product modules is then classified into one of the 117 product groups, which then belongs to one of the 10 product departments. In other words, individual products constitute the most granular level of observation in the Nielsen Retail Scanner Data, while the product department provides the most comprehensive classification. Apart from granularity, Nielsen Retail Scanner Data also has broad coverage of the purchase information in the U.S. It collects weekly purchase information on 2,463,853 unique UPCs from 60,600 unique stores, 2,763 counties, 882 3-digit ZIP Code regions, 139 retail chains, 209 Designated Market Areas (DMAs), and 49 states.[7] Thus, this dataset provides a thorough insight into the product market across different states in the U.S. and the product portfolios of individual firms.

To link the product to its parent company (i.e., the company which produces the product), we utilize the structure of 12-digit UPCs. The first 6 to 10 digits of a UPC represent the company prefix (GCP code), which is issued by GS1 US. The 12th digit is calculated based on a MOD 10 check digit algorithm, and the rest of the UPC are item reference numbers.[8] With the GCP codes, we are able to identify all of the parent companies that have products covered by the Nielsen Retail Scanner Data. We obtain all the GCP codes from the GS1 Company Database (GEPIR) provided by the Product Open Data (POD) and then merge them with the first 6 to 10 digits of all the UPCs in the Nielsen data. By doing so, we successfully identify 3,768,901 unique UPCs in the whole Nielsen data with 62,387 parent companies.[9] We also collect the address information of these parent firms from GEPIR. Table 1 gives an overview of the overall Nielsen Retail Scanner Data.

[Insert Table 1 here.]

[7] According to Nielsen, a DMA region is a group of counties and zip codes that form an exclusive geographic area in which the home market television stations hold a dominance of total hours viewed. For more information, see https://www.nielsen.com/us/en/contact-us/intl-campaigns/dma-maps/.

[8] MOD 10 algorithm is also known as the Luhn algorithm. See https://en.wikipedia.org/wiki/Luhn_algorithm for more information.

[9] Overall, there are 4,547,517 unique UPCs in the Nielsen Retail Scanner Data as of December 2019. So the match rate of our study is approximately 83% (i.e., 3,768,901/4,547,517). This is comparable to other studies using this dataset (e.g., Hajda and Nikolov (2020) and Fracassi et al. (2020)). Since not all UPCs have transaction information, Nielsen Retail Scanner Data ultimately collects weekly purchase data for 2,463,853 unique UPCs.

3.2 Venture Capital Data

We gather data on VC firms and their portfolio companies (i.e., VC-backed entrepreneurial firms) from VentureXpert through Thomson ONE. VentureXpert is a leading database used extensively by previous studies examining venture capital. This database contains detailed information about the names and geographic locations of portfolio companies. We download the round-by-round financing data of startups and merge it with the Nielsen Retail Scanner Data. VentureXpert also provides information about the locations of VC firms. We use this particular piece of information to explore the monitoring channel in Section 6. Further, this database covers the first investment date, the total amount invested per round, the date of each investment round, etc. Since the Nielsen Retail Scanner Data starts covering purchase information from January 2006 and the latest version of this database ends in the year 2019, we limit our sample to VC-backed firms which receive their first-round investment between 2006 and 2019.

3.3 Overall Sample

To measure VC-backed companies' product market performance, we match VentureXpert with the Nielsen Data based on the company names. Since each company name may have a slightly different version in those two datasets (for example, the same firm in VentureXpert could have a name as "ABC Corporation" but at the same time appear in the Retail Scanner Data as "ABC Corp."), we employ some matching procedures to merge these two databases. We illustrate the detailed matching steps in Section A of the online appendix.

As a result, our final sample contains 261 VC-backed firms, which receive the first VC financing between 2006 and 2019. Combining with 42,377 non-VC-backed private firms in the Retail Scanner Data that have at least one purchase information during this period, we have 42,638 firms with 336,038 firm-year observations for our firm-level analysis. Table 2 shows the summary statistics of the variables used in our study.

[Insert Table 2 here.]

4 Baseline Results

We now present and discuss our firm-level baseline results of whether VCs create value for startups in the product market. The empirical specification we use to examine this research question is as follows, where the unit of observation is firm-year:

$$Y_{i,s,t} = \alpha + \beta VC_i \times Post_t + \eta_i + \delta_{s\times t} + \epsilon_{i,s,t} \tag{1}$$

We focus on four sets of outcome variables in this paper: sales and market share of a startup, size of the startup's product portfolios, number of product lines operated by the startup, and the geographic expansion of the startup's products. Hence, the dependent variable $Y_{i,s,t}$ in Eq. 1 denotes different aforementioned outcome variables of firm i in year t located in state s. The main independent variable of interest is the interaction term $VC_i \times Post_t$. VC_i is a dummy equal to 1 if firm i is backed by VC investors. It is equal to 0 otherwise. $Post_t$ is a dummy variable equal to 1 if the observation is within 5 years after the first VC investment.[10] For VC-backed firms, we drop observations that are more than 5 years prior to and after the first VC investment, so we are essentially estimating a 5-year panel around the year of their first VC investment. We include firm and state-by-year fixed effects to absorb any firm-specific unobservables and those varying by state-year. We cluster the standard errors at state level.

[10]Hence this dummy variable is equal to 0 for all non-VC-backed firms.

4.1 Sales and Market Share

We first examine the effect of VC financing on entrepreneurial firms' sales and market share. We report the results in Table 3.

[Insert Table 3 here.]

Column (1) of Table 3 reports the result when the dependent variable is the sales of an entrepreneurial firm in a given year. The positive coefficient on the interaction term suggests that compared to non-VC-backed firms, VC-backed startups experience a significant increase in sales over the 5 years following their first VC financing. The effect of VC financing on entrepreneurial firms' sales is both statistically significant and large in magnitude. It indicates that during the five years after the first VC investment, VC-backed startups on average have more than doubled their sales than non-VC-backed firms. Column (2) reports the result when the dependent variable is the nationwide market share (in percentage terms) of an entrepreneurial firm of a given product department in a given year. We also document a positive and statistically significant coefficient on the interaction term. The coefficient is also economically significant: over the 5 years after receiving the first VC financing, VC-backed firms seize 0.009% more nationwide market share than non-VC-backed firms, or about 43% of the sample mean.

So how exactly do VC-backed startups achieve the growth in sales? To explore what factors contribute to the overall growth in sales of VC-backed firms, we decompose the sales figures into the average price of firms' products and the average quantities of products sold in a given year. Columns (3) and (4) of Table 3 present the results. We find that, surprisingly, the coefficient on the interaction term when the dependent variable is the average price of firms' products is negative, while it is positive when the dependent variable is the quantity of products sold. These results together suggest that VC-backed firms achieve the growth in sales and seize more nationwide market share by lowering the average price of their products and thus increasing the quantity of products sold.

4.2 Size of Product Portfolios and Product Lines

In this subsection, we first examine the effect of VC financing on the size of firms' product portfolios. We then study if VC investors also help the firms backed by them to develop and operate more product lines. We report the results regarding the size of product portfolios in Table 4.

[Insert Table 4 here.]

In Column (1) of Table 4, we first examine the effect of VC financing on the overall size of firms' product portfolios. We find that, during the 5 years following the first VC investment, VC-backed startups on average increase the number of their products by more than 50% compared to non-VC-backed firms. To figure out what drives the overall increase in the size of VC-backed startups' product portfolios, we examine the number of new products introduced by firms in Column (2). We document a positive and statistically significant coefficient on the interaction term $VC \times Post$. This suggests that the source of the increase in the size of VC-backed startups' product portfolios is their introduction of new products over the 5 years after receiving their first VC investment.

[Insert Table 5 here.]

We now study if VC investors also help create value for firms backed by them in terms of developing and operating more product lines. We report the results in Table 5. In Column (1) of Table 5 where the dependent variable is the number of product lines a firm has in a given year, we find a positive coefficient on the interaction term, which is also statistically significant at 1% level. This indicates that VC-backed startups develop and operate more product lines than non-VC-backed firms after receiving the first VC investment.

We want to examine if the aforementioned effect is due to the fact that VC-backed firms introduce more new product lines than their non-VC-backed counterparts. Therefore, in Column (2) of Table 5, we regress a dummy variable denoting the introduction of new product lines on the interaction term $VC \times Post$. This dummy variable is equal to 1 if an entrepreneurial firm introduces at least one new product line in a given year. We decide to use a dummy variable instead of the actual number of new product lines a firm has in a given year, because we observe the actual number of new product lines is scarce, in the sense that firms below the 75th quartile do not introduce any new product line in a given year. As a result, when we regress the new product line dummy on the interaction term in Column (2), we find a positive coefficient. This suggests that, compared to non-VC-backed firms, VC-backed startups are more likely to introduce at least one new product line over the 5 years following the first VC financing.

4.3 Products' Geographic Expansion

In addition to enlarging their product portfolios and developing a larger number of product lines, VCs could also help firms to expand their products to more stores and geographic locations in order to achieve long-term growth. In this subsection, we examine the effect of VC financing on the geographic availability of firms' products. We report the results in Table 6.

[Insert Table 6 here.]

In Column (1) of Table 6, we regress the number of stores in which a firm's products are sold in a given year on the main independent variable of interest, $VC \times Post$. This statistically significant coefficient indicates that VC-backed startups sell their products in 142% more stores than non-VC-backed firms in the five years following their first VC financing. We also construct different measures of the geographic availability of a firm's products. We use the number of counties, number of retail chains, and number of 3-digit ZIP code regions where a firm's products are sold in a given year to capture the geographic availability. The corresponding results are reported in Columns (2) to (4) of Table 6. The positive and significant coefficients on our main independent variable of interest across the spectrum indicate that, compared to their non-VC-backed counterparts, VC-backed entrepreneurial firms expand their products to more counties, retail chains, and 3-digit ZIP code regions after receiving the first VC investment. As a robustness check, we also construct several alternative measures of products' geographic availability based on the data Nielsen provides us. The results are reported in the Online Appendix A.2 and are consistent with our baseline findings.

5 Matched-Sample Instrumental Variable (IV) Analysis

Our baseline results show that there is a positive association between VC financing and startups' product market performance, as measured by higher sales and larger market share, a larger number of products and product lines, and greater geographic availability of products. However, there still remain several endogeneity concerns facing our baseline specification. One prominent concern is the selection versus treatment effect of VC investors frequently studied in the existing literature. In other words, is the outperformance of VC-backed startups relative to non-VC-backed counterparts due to VCs' ability to select better firms (hence the outperformance is related to underlying startups' characteristics)? Or is this because VCs have the ability to better nurture the entrepreneurial firms backed by them?

The literature argues that both effects could exist during VCs' investment in entrepreneurial firms. We confirm in our Online Appendix A.1 that there seems to be a certain degree of selection effect when VCs choose to invest in firms. In Online Appendix A.1 we regress a VC financing dummy on a set of startup-level characteristics in a given year. The dependent variable, *VC Financing*, is equal to 1 for VC-backed firms in the year of the first VC investment, and it is equal to 0 for VC-backed firms for all the years prior to the first VC financing.[11] This variable is equal to 0 for all the non-VC-backed

[11] We drop all the observations of VC-backed firms after the year of their first VC financing, since we want

firms. We find that while sales and geographic availability (as measured by the number of counties where a firm's products are sold) are negatively associated with the probability of an entrepreneurial firm receiving VC financing in a given year, the growth rate of a firm's size of product portfolio and that of the geographic availability of a firm's products positively predicts such probability. This suggestive evidence indicates that in our sample, VC investors appear to select firms with better growth potential. Hence, the positive value creation effect of VCs we documented in the baseline results may be driven by VCs' ability to select better firms with growth potential, rather than driven by their ability to better nurture the startups backed by them.

Therefore, to address the endogeneity concern, we conduct an Instrumental Variable (IV) analysis based on a sample of matched VC-backed and non-VC-backed firms. The key assumption we are making here is that based on a sample of similar VC-backed and non-VC-backed firms, controlling for all the factors that could affect the probability of receiving VC financing, the instrument will affect outcome variables only through the supply of VC financing (instead of the underlying firm characteristics).

5.1 Matching

In this subsection, we discuss in detail how we match VC-backed firms to their non-VC-backed counterparts. We conduct the matching here because we want to ensure that VC-backed firms and matched non-VC-backed firms are comparable. Then, we can utilize a seemingly exogenous shock to the supply of VC financing (discussed in detail in Section 5.2) to examine the causal effect of VC financing on startups' product market performance, after controlling for firm characteristics that could potentially affect the probability of receiving VC financing.

For each VC-backed startup (i.e., a treated firm), we select one non-VC-backed firm

to investigate what factors drive the selection of entrepreneurial firms by VC investors prior to the actual VC investment.

(i.e., a control firm) that appears in the same year of the first VC financing of this treated firm and belongs to the same product group as this treated firm. We use the nearest-neighbor propensity-score matching based on four variables: firms' total sales, the total number of products in firms' product portfolios, the total number of stores in which firms' products are sold, and the growth in firm's sales over the previous year. All of these four variables are measured in the year of the first VC financing of a treated firm. We investigate the matching quality by examining the difference between VC and non-VC-backed firms along some of the product market dimensions. We report the results in Table 7. The nearest-neighbor propensity-score matching appears to deliver a balanced sample: the VC-backed firms and matched non-VC-backed counterparts are similar not only in the variables used in the matching process but also in those that are not used in our propensity-score matching procedure.

[Insert Table 7 here.]

After matching each treated VC-backed firm with one control counterpart, we combine these two firms into an individual cohort. Then we combine all cohorts and use them to conduct the subsequent IV analysis. This matching procedure leads to a cross-sectional dataset, where the dependent variable is a firm's next 5-year average of different product market variables, and the main independent variable of interest is a dummy distinguishing VC-backed firms from their matched non-VC-backed counterparts. We will discuss in detail the IV specifications and variable constructions in Section 5.2.

5.2 Instrumental Variable (IV) Analysis

In this subsection, we discuss our IV specifications and the corresponding results. The specifications for our IV analysis are outlined in Eq. 2 and 3, where Eq. 2 denotes the first stage and Eq. 3 denotes the second stage.

$$VC_i = \alpha_1 + \beta_1 Limited\_Partner\_Return_{s,t} + \gamma_1 X_i + \eta_s + \delta_c + \lambda_t + \epsilon_i \quad (2)$$

$$Y_i = \alpha_2 + \beta_2 \widehat{VC}_i + \gamma_2 X_i + \eta_s + \delta_c + \lambda_t + \epsilon_i \quad (3)$$

In the first-stage specification, the dependent endogenous variable is VC_i. It is a dummy variable equal to 1 if entrepreneurial firm i located in state s that belongs to cohort c is backed by VC investors, where the subscript t denotes the year when it receives its first VC investment. It is equal to 0 for matched non-VC-backed firms. We instrument this endogenous variable with $Limited\_Partner\_Return_{s,t}$, which is constructed at the state-year level. In both first-stage and second-stage specifications we include a vector of startup-level characteristics measured in the year of VC financing (consistent with the set of variables in Table A.1).[12] We include state, cohort, and year fixed effects to absorb any state-specific, cohort-specific, and time-varying unobservables. Then, in the second stage, we use the predicted probability of a firm receiving VC financing from the first stage as the main independent variable of interest, so that we can examine the causal link between VC financing and entrepreneurial firms' product market performance. The dependent variables in the second stage are the subsequent 5-year average of product-market-related variables we study in the baseline (i.e., sales, market share, number of products, number of product lines, and geographic availability of products). These outcome variables are measured in the year t when entrepreneurial firm i located in state s that belongs to cohort c receives its first VC investment. We use two-stage-least-squares (2SLS) estimations to identify the coefficient β_2, which is our main parameter of interest.

We instrument the endogenous variable VC_i with $Limited\_Partner\_Return_{s,t}$. We construct this instrument following Samila and Sorenson (2011). The definition of this

[12] For controlled non-VC-backed firms, we measure these control variables in the same year when their matched treated firms receive their first VC investment.

instrument is illustrated in Eq. 4.

$$Limited\_Partner\_Return_{s,t} = \sum_{j} \sum_{\tau=t-3}^{t-1} \frac{CER_{\tau} lnLP_{j\tau}}{1 + dist_{sj}} \tag{4}$$

where this instrument is constructed for each startup located in state s in year t. The CER_{τ} in the numerator represents the return on the college and university endowments in a given year τ. We use the return on the college and university endowments, since they are an important type of limited partners in the venture capital industry. We obtain such data from National Association of College and University Business Officers (NACUBO). $lnLP_{j\tau}$ in the numerator denotes the natural logarithm of 1 plus the number of limited partners in a state j that had invested in venture capital at least 10 years prior to the given year τ. Similar to the construction in Samila and Sorenson (2011), we require a 10-year lag to account for any potential endogeneity arising from limited partners' investment in venture capital as a response to changes in local economic conditions. In addition, $dist_{sj}$ in the denominator denotes the distance (in kilometers) between state s of a startup and state j of limited partners. The weighting distance in the denominator accounts for limited partners' propensity to invest in VC firms located close to them.

The argument about the validity of this IV in our setting is as follows. First, the variation in returns on the college and university endowments (an important class of the limited partners) is likely to affect the supply of VC funds. The rationale behind this is that limited partners of VCs oftentimes adopt an investment strategy, which allocates a fixed ratio of their funds to alternative assets (such as VCs). Therefore, if limited partners of VCs earn a higher return on their investment portfolios in previous years, they will invest more amount into alternative assets such as VCs so that they can maintain their pre-determined asset allocation. In addition, we also empirically show that this IV significantly predicts the probability of an entrepreneurial firm receiving VC financing in the first stage of our 2SLS regressions. Hence, the above argument validates the relevance condition of the IV in our setting.

Second, we argue that the return on the *national* college and university endowments in the previous 3 years is not very much likely to be driven by the underlying characteristics of *local* firms today; rather, it is more likely to be correlated to today's supply of VC funds. Furthermore, as documented in the existing literature (e.g., Cumming and Dai (2010)), both limited partners and VCs are more inclined to invest locally. Put together, the instrument we use in this paper is more likely to affect entrepreneurial firms' product market performance through the channel of the supply of VC funds instead of the underlying firm characteristics. Therefore, the instrument is likely to satisfy the exclusion restriction, and we can thus disentangle the selection effect from the treatment effect to study the causal value creation of VC investors in the product market.

Table 8 to 11 reports the results of IV analysis. In Table 8 where the dependent variables are the subsequent 5-year average of sales and market share, we document positive and statistically significant coefficients on the VC dummy, as shown in Columns (2) and (3). This indicates the causal value creation effect of VCs on startups' sales and market share. We show the first-stage results in Column (1), where we regress the VC dummy on the $Limited\_Partner\_Return$. We find a positive and statistically significant coefficient on our IV. This suggests that when limited partners enjoy a higher return in previous years, entrepreneurial firms within a state are more likely to receive VC financing. This is consistent with our argument earlier. In addition, the Kleibergen-Paap rk Wald statistic (Kleibergen and Paap, 2006), which tests directly whether the instrument predicts a sufficient amount of variation in the endogenous variable to identify our equations, has a value of 20.406. This is greater than the critical value proposed by Stock and Yogo (2005) for the IV estimates to have no more than 10% of the bias of OLS estimates. Collectively, these pieces of evidence show that the IV used in this paper is relevant for our setting.

[Insert Table 8 here.]

Similarly, we run the IV specifications 2 and 3 but replace the outcome variables with the 5-year average number of products and product lines of a firm. In Table 9 where the dependent variable is the 5-year average number of products of an entrepreneurial firm, the coefficient on the VC dummy in Column (2) is positive and statistically significant at 1% level. In Table 10 where the dependent variable is replaced with the 5-year average number of product lines an entrepreneurial firm develops and operates, we also document a positive and significant coefficient on the VC dummy in the second stage, as shown in Column (2) of Table 10. Together, these results show that VC financing has a positive causal effect on the size of entrepreneurial firms' product portfolios and the number of product lines they operate.

[Insert Table 9 here.]

[Insert Table 10 here.]

Lastly, Table 11 presents the IV analysis results when the dependent variables include different measures of the geographic availability of firms' products. In Column (1) of Table 11 where we show the first-stage results of the IV analysis, we continue to find a positive and statistically significant coefficient on the instrument. Columns (2) to (5) display results with different outcome variables for the geographic availability of firms' products. The positive and significant coefficients on the VC dummy across the spectrum indicate that VC investors help startups backed by them to causally expand their products to more stores, counties, retail chains, and 3-digit ZIP code areas than their matched non-VC-backed counterparts.

[Insert Table 11 here.]

6 Mechanisms

Having established that VCs causally create value for startups backed by them in the product market (in addition to the selection effect that may exist), we want to investigate how VC investors help to create value. In this section, we examine through which mechanisms VCs create value for startups in the product market. First, we study whether VCs help direct startups' marketing strategy (and the heterogeneous value creation effects resulting from such strategy) when startups face different competition environments (as measured by relative market shares of firms). Second, we examine whether VCs' monitoring of startups' operations plays a key role in firms' product market performance.

6.1 Market Share Channel

How do VCs add value to startups that operate in different competition environments? In this subsection, we explore this question by splitting VC-backed firms into two groups based on their relative market share (calculated as the nationwide market share in a given product department and year) when they first receive their VC investment. Then, we combine these two sub-samples of VC-backed firms separately with all the non-VC-backed firms and repeat our baseline specification.

[Insert Table 12 here.]

We report the results on the market share channel in Table 12. We first focus on VC-backed firms that have a relatively higher market share. Column (1) of Table 12 reports the coefficient on the interaction term when the sample for regressions includes VC-backed firms with relatively larger nationwide market share and all the non-VC-backed firms. The empirical patterns we document for this particular sub-sample are very similar to those documented in the baseline results. In other words, for VC-backed startups with a larger market share when they first receive their VC financing, they outperform their non-VC-backed counterparts in the subsequent 5 years in terms of sales, size of product portfolios, number of product lines, and geographical availability of their products. They achieve the growth in sales and grab an even larger market share by lowering the average price of their products following the first VC financing.

However, when we look at the sub-sample of VC-backed firms where they have a relatively smaller market share, we find that for VC-backed firms in this sub-sample, interestingly, the geographic availability of their products has decreased compared to non-VC-backed firms, as shown in Column (5) of Table 12. This seems to suggest that VCs direct these firms to adopt a marketing strategy that is more geographically concentrated and focuses more on local markets. The VC-backed firms in this sub-sample also experience a decline in the size of their product portfolios and the number of product lines they operate compared to non-VC-backed firms. However, this strategy may have led to poorer performance of VC-backed firms in terms of sales: following their first VC financing, the VC-backed firms in this sub-sample experience a decrease in their sales compared to non-VC-backed counterparts, and we find that the decrease in sales is mostly driven by a decline in their quantity of products sold. Overall, we document heterogeneous value creation effects of VCs for startups with different market share, and we show that the value creation effect of VCs is more pronounced in the sub-sample where VC-backed entrepreneurial firms possess a larger market share.

6.2 Monitoring Channel

The involvement of VC firms ("monitoring") plays a vital role in the portfolio companies' performance. Existing literature documents that the VC monitoring intensity contributes to firms' success and is sensitive to geographic proximity (e.g., Lerner (1995), Chen et al. (2010), Tian (2011) and Bernstein et al. (2016)). In this section, we study the impact of VCs' monitoring on portfolio companies' product market performance. It has been studied in the literature that the cost of VCs' monitoring of startups' operations is less when they locate more proximate to each other due to less travel time (e.g., Giroud (2013) and Bernstein et al. (2016)). Hence, we use the geographic distance (in kilometers) between VC firms and startups backed by them as a proxy for monitoring intensity.

However, for a specific VC deal, oftentimes there are multiple investors. In these cases, one of the investors usually takes the role of lead VC and syndicates their investments with other follower investors. Gorman and Sahlman (1989) document that the lead investor is more actively involved in monitoring the portfolio company. Thus, to capture the monitoring intensity of VC investors, we calculate the distance between the centroid of the ZIP code of the headquarter of the lead investor in a deal and that of the corresponding startup. We assume that the longer the distance, the more time needed to travel from a VC firm to the corresponding startup, and thus higher the monitoring cost.

To investigate the monitoring channel, we split the sample of VC-backed firms into two sub-samples based on the relative distance between their headquarters and their lead investors' headquarters. "Short Distance" sub-sample represents the group of VC-backed firms with distance below the median (and thus lower monitoring cost), while "Long Distance" is those with distance above the median (and thus higher monitoring cost). We then combine these two sub-samples of VC-backed firms separately with all the non-VC-backed firms separately and repeat our baseline specification.

[Insert Table 13 here.]

Table 13 reports the results regarding the monitoring channel. Column (1) of Table 13 shows the coefficients on the interaction term when the sample for regressions includes VC-backed firms with a relatively shorter distance and all the non-VC-backed firms. We find that for the sub-sample of VC-backed firms with a relatively shorter distance to their lead VCs (and hence the monitoring intensity of lead VCs is presumably higher), the empirical patterns documented in Column (1) are quite consistent with our baseline findings. Specifically, we find that compared to non-VC-backed counterparts, the VC-backed startups in this sub-sample increase their sales and seize a larger nationwide market share following the first VC financing. VC-backed startups in this sub-sample achieve this growth in sales and market share by lowering the average price of their products. In addition, compared to non-VC backed counterparts, the VC-backed startups in this sub-sample witness an increase in their number of products, number of product lines, and geographic availability of their products over the 5 years after the first VC investment.

On the other hand, when we examine the long-distance sub-sample where the monitoring intensity of lead VCs is presumably lower, the value creation effect of VCs appears to be smaller. For example, for this sub-sample of VC-backed startups, the significance of the coefficient on the interaction term disappears when the dependent variable is nationwide market share. Furthermore, in terms of the size of product portfolios, the number of product lines, and the geographic availability of products, the coefficients are smaller in magnitude and less statistically significant compared to those documented in the short-distance sub-sample. Overall, putting these pieces of evidence together, we argue that the monitoring of VC investors is likely to be one of the potential mechanisms driving our results.

7 Conclusion

This paper studies whether and how venture capitalists (VCs) create value in the product market for the entrepreneurial firms backed by them. By constructing a novel dataset based on the Nielsen Retail Scanner and the VentureXpert databases, we show that over the five years following the first VC financing, VC-backed entrepreneurial firms on average have more than doubled their sales and seized a larger market share compared to non-VC-backed private firms. This increase is driven by a decrease in the average price of their products and hence an increase in the quantity of their products sold. In addition, compared to non-VC-backed firms, VC-backed startups also enlarge the size of their product portfolios by introducing new products and operate a larger number of product lines following their first VC financing. Further, after receiving the first VC investment, VC-backed startups also expand their products to more stores, counties, retail chains, and 3-digit ZIP code regions than their non-VC-backed counterparts. We use an IV analysis based on a sample of matched VC-backed and non-VC-backed firms to establish the causal link between VC financing and startups' product market performance. We use an exogenous shock to the supply of VC funds as an instrument (which is less likely to be correlated to underlying firm characteristics) and show that the results we document in our baseline setting are causal.

We document several mechanisms through which VCs create value for startups in the product market. First, we document the heterogeneous effects of VC value creation for startups with different market share. We show that the value creation effect of VCs is more pronounced for firms with higher market share, and that VC-backed firms with different relative market share seem to adopt different marketing strategy. Second, we document that VCs' value creation effect is stronger for entrepreneurial firms located closer to lead VCs. To sum up, we argue that, on top of providing capital, VCs also create value for their portfolio companies in the product market by directing their marketing strategy and monitoring their operations.

One limitation of our study is that our results only speak for the firms producing consumer goods that are sold in stores. For startups in the high-tech industry that provide virtual goods and services and are more likely to be targets of VC investments, the product market may entail different things. So a possible future research avenue is that researchers could look into the latter type of firms and determine how to measure their product-market-related variable, and then see how different financial intermediaries could add value to their product market performance. Nevertheless, the product market plays a critical role in the whole economy, and our sample covers the majority of products that appear in our daily lives, so our study helps shed new light on how VCs create value for entrepreneurial firms and how this value creation effect is manifested in the economy.

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Table 1: Overview of the Nielsen Retail Scanner Data

This table shows an overview of the Nielsen Retail Scanner Data. *Products* are uniquely identified by each Universal Product Code (UPC). *Parent Firms* represents the firms that produce the products in this dataset. *Product Departments*, *Product Groups*, and *Product Modules* are the hierarchical structure of each product provided by Nielsen. Each product belongs to one of 1311 product modules (in our paper we view each product module as a distinct product line), and each one of these 1311 product modules belongs to one of 117 product groups. Finally, each one of these 117 product groups belongs to one of the 10 product departments. *Stores*, *Counties*, *3-digit ZIP Codes*, *Designated Market Areas (DMAs)*, *Retail Chains*, and *States* show the availability of products in different geographic locations, as measured by stores, counties, retail chains, 3-digit ZIP code regions, Designated Market Areas (DMAs), and states in the U.S.

Variable	Num. of Obs.
Products (UPCs)	2,463,853
Parent Firms	62,387
Product Departments	10
Product Groups	117
Product Modules	1,311
Stores	60,600
Counties	2,763
Retail Chains	139
3-digit ZIP Codes	882
Designated Market Areas (DMAs)	209
States	49

Table 2: Summary Statistics

This table contains the summary statistics of the variables used in our study. *Sales* is the natural logarithm of the sales of firm i across all the stores in a given year t. *Price* is the average price of all products of firm i in a given year. It is calculated by dividing the total sales of firm i's products across all the stores in a given year t by the total quantity of its products sold. *Quantity* is the natural logarithm of the total units of products sold by firm i across all the stores in a given year t. *Market Share* is the nationwide market share of firm i in a given year and department (in percentage terms). *Number of Products* is the natural logarithm of the number of unique products firm i sells across all the stores in a given year t. *Number of New Products* is the natural logarithm of 1 plus the number of new products introduced by firm i in a given year t. We add 1 to avoid losing any observation where firm i does not introduce any new product in a given year. *Number of Product Lines* is the natural logarithm of the number of unique product lines firm i operates in a given year t. Each product line is identified by its unique product module code provided by Nielsen. *New Product Lines* is a dummy variable equal to 1 if firm i introduces any new product line in a given year t; it is equal to 0 otherwise. *Number of Stores* is the natural logarithm of the number of unique stores where products of firm i are sold in a given year t. *Number of Counties* is the natural logarithm of the number of counties where products of firm i are sold in a given year t. *Number of Chains* is the natural logarithm of the number of retail chains where products of firm i are sold in a given year t. *Number of ZIPs* is the natural logarithm of the number of 3-digit ZIP code regions where products of firm i are sold in a given year t.

Variable	Mean	Std. Dev.	1st Quartile	Median	3rd Quartile	Num. of Obs.
Sales	10.076	4.073	7.426	10.492	12.973	336,038
Price	15.236	19.540	5.810	10.749	18.599	336,038
Quantity	7.768	3.772	5.136	8.007	10.452	336,038
Market Share	0.021	0.097	0.000	0.000	0.002	336,038
Number of Products	1.747	1.482	0.693	1.609	2.708	336,038
Number of New Products	0.756	1.047	0.000	0.000	1.099	336,038
Number of Product Lines	0.680	0.842	0.000	0.693	1.099	336,038
New Product Line	0.122	0.328	0.000	0.000	0.000	336,038
Number of Stores	4.627	2.759	2.485	4.673	6.681	336,038
Number of Counties	3.608	2.303	1.792	3.555	5.493	336,038
Number of Chains	1.647	1.339	0.693	1.386	2.565	336,038
Number of ZIPs	3.422	2.110	1.609	3.367	5.226	336,038

Table 3: VC Financing on Startups' Sales and Market Share: Firm-Level Baseline Results

This table reports the OLS coefficient estimates from regressing the sales, the average price of products, the quantities of products sold, and the nationwide market share of firm i in a given year t on *VC* $\times$ *Post*. *VC* is a dummy variable equal to 1 if firm i is a VC-backed entrepreneurial firm, and it is equal to 0 otherwise. *Post* is a dummy variable equal to 1 if the year t is within 5 years after firm i receiving its first VC investment; it is equal to 0 otherwise. *Sales* is the natural logarithm of the sales of firm i across all the stores in a given year t. *Market Share* is the nationwide market share of firm i in a given year and department (in percentage terms). *Price* is the average price of all products of firm i in a given year. It is calculated by dividing the sales of firm i's products across all the stores in a given year t by the total quantity of its products sold. *Quantity* is the natural logarithm of the total units of products sold by firm i across all the stores in a given year t. Firm and state-by-year fixed effects are included. Robust standard errors are reported in parentheses and are clustered by state. ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively.

	Sales	Market Share	Prices	Quantity
	(1)	(2)	(3)	(4)
VC $\times$ Post	1.110***	0.009*	-1.021*	1.120***
	(0.162)	(0.005)	(0.598)	(0.161)
Firm FE	Yes	Yes	Yes	Yes
State $\times$ Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.725	0.890	0.713	0.737
No. of Obs.	332,795	332,795	332,795	332,795

Table 4: VC Financing on Size of Startups' Product Portfolios: Firm-Level Baseline Results

This table reports the OLS coefficient estimates from regressing the number of products and the number of new products of firm i in a given year t on *VC* $\times$ *Post*. *VC* is a dummy variable equal to 1 if firm i is a VC-backed entrepreneurial firm, and it is equal to 0 otherwise. *Post* is a dummy variable equal to 1 if the year t is within 5 years after firm i receiving its first VC investment; it is equal to 0 otherwise. *Number of Products* is the natural logarithm of the number of unique products firm i sells across all the stores in a given year t. *Number of New Products* is the natural logarithm of 1 plus the number of new products introduced by firm i in a given year t. We add 1 to avoid losing any observation where firm i does not introduce any new product in a given year. Firm and state-by-year fixed effects are included. Robust standard errors are reported in parentheses and are clustered by state. ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively.

	Number of Products	Number of New Products
	(1)	(2)
VC $\times$ Post	0.407***	0.095**
	(0.071)	(0.048)
Firm FE	Yes	Yes
State $\times$ Year FE	Yes	Yes
Adjusted R^2	0.842	0.632
No. Obs	332,795	332,795

Table 5: VC Financing on Startups' Number of Product Lines: Firm-Level Baseline Results

This table reports the OLS coefficient estimates from regressing the number of product lines of firm i in a given year t, and a dummy variable indicating that firm i introduces a new product line in year t, on *VC* $\times$ *Post*. *VC* is a dummy variable equal to 1 if firm i is a VC-backed entrepreneurial firm, and it is equal to 0 otherwise. *Post* is a dummy variable equal to 1 if the year t is within 5 years after firm i receiving its first VC investment; it is equal to 0 otherwise. *Number of Product Lines* is the natural logarithm of the number of unique product lines firm i operates in a given year t. Each product line is identified by its unique product module code provided by Nielsen. *New Product Lines* is a dummy variable equal to 1 if firm i introduces any new product line in a given year t; it is equal to 0 otherwise. Firm and state-by-year fixed effects are included. Robust standard errors are reported in parentheses and are clustered by state. ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively.

	Number of Product Lines	New Product Line
	(1)	(2)
VC $\times$ Post	0.137***	0.027*
	(0.031)	(0.015)
Firm FE	Yes	Yes
State $\times$ Year FE	Yes	Yes
Adjusted R^2	0.829	0.174
No. Obs	332,795	332,795

Table 6: VC Financing on Geographic Expansion of Startups' Products: Firm-Level Baseline Results

This table reports the OLS coefficient estimates from regressing the number of stores, the number of counties, the number of chains, and the number of 3-digit ZIP code regions where firm i's products are sold in a given year t on *VC* $\times$ *Post*. *VC* is a dummy variable equal to 1 if firm i is a VC-backed entrepreneurial firm, and it is equal to 0 otherwise. *Post* is a dummy variable equal to 1 if the year t is within 5 years after firm i receiving its first VC investment; it is equal to 0 otherwise. *Number of Stores* is the natural logarithm of the number of unique stores where products of firm i are sold in a given year t. *Number of Counties* is the natural logarithm of the number of counties where products of firm i are sold in a given year t. *Number of Chains* is the natural logarithm of the number of retail chains where products of firm i are sold in a given year t. *Number of ZIPs* is the natural logarithm of the number of 3-digit ZIP code regions where products of firm i are sold in a given year t. Firm and state-by-year fixed effects are included. Robust standard errors are reported in parentheses and are clustered by state. ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively.

	Number of Stores	Number of Counties	Number of Chains	Number of ZIPs
	(1)	(2)	(3)	(4)
VC $\times$ Post	0.885***	0.741***	0.530***	0.661***
	(0.129)	(0.113)	(0.065)	(0.108)
Firm FE	Yes	Yes	Yes	Yes
State $\times$ Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.736	0.743	0.805	0.733
No. Obs	332,795	332,795	332,795	332,795

Table 7: Matched Sample of VC-backed and Non-VC-backed Firms: Matching Quality

This table reports the difference and the p-value of its statistical significance along some of the variables related to product market. *Total Sales* is the total sales of firm i (in USD millions) in a given year t. *Total Products* is the total number of products firm i sells across all the stores in a given year t. *Total Stores* is the total number of stores where firm i's products are sold in a given year t. *Sales Growth* is the one-year growth in sales of firm i prior to a given year t. *Total Product Lines* is the total number of product lines firm i owns in a given year t. *Total Counties* is the total number of counties where firm i's products are sold in a given year t. *Total Chains* is the total number of chains where firm i's products are sold in a given year t. *Total ZIPs* is the total number of 3-digit ZIP code areas where firm i's products are sold in a given year t.

	Mean		Difference	*P*-Value
	VC-backed Firms	Non-VC-backed Firms		(diff != 0)
	(1)	(2)	(3)	(4)
Total Sales	10.301	11.274	-0.974	0.904
Total Products	24.190	21.027	3.163	0.611
Total Stores	2867.687	3112.61	-244.923	0.719
Sales Growth	3.717	2.749	0.968	0.607
Total Product Lines	3.102	3.253	-0.151	0.744
Total Counties	464.490	436.466	28.024	0.694
Total Chains	22.932	18.479	4.453	0.172
Total ZIPs	294.497	242.459	52.038	0.139

Table 8: VC Financing on Startups' Sales and Market Share: IV Analysis

This table reports the 2SLS coefficient estimates from regressing the 5-year average of sales and nationwide market share of firm i on *VC* for a cross-sectional matched-sample of VC- and non-VC-backed firms. Each VC-backed firm is matched with a non-VC-backed firm in the same year of receiving its first VC financing and same industry (as measured by the product group). This matching procedure is based on the closest propensity score estimated using sales, sales growth, number of products, and number of stores in which a firm's products are sold. *VC* is a dummy variable equal to 1 if firm i is a VC-backed entrepreneurial firm, and it is equal to 0 otherwise. For VC-backed firms, *Sales_5y_Avg* is the 5-year average of sales of firm i following its first VC investment. For matched non-VC-backed firms, this measure is the 5-year average of sales of firm j following the year when its matched counterpart receives its first VC investment. For VC-backed firms, *Market_Share_5y_Avg* is the 5-year average of nationwide market share of firm i following its first VC investment (in percentage terms). For matched non-VC-backed firms, this measure is the 5-year average of nationwide market share of firm j following the year when its matched counterpart receives its first VC investment. *Limited Partner Returns* is the instrument variable for *VC*. It is a proxy for the return of VC limited partners' investment weighted by geographic proximity. The details of how to construct this IV are in Eq. 4. State, cohort, and year fixed effects are included. Robust standard errors are reported in parentheses and are clustered by state. ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively.

	VC	Sales_5y_Avg	Market_Share_5y_Avg
	(1)	(2)	(3)
Limited Partner Returns	1.024***		
	(0.227)		
VC		2.196**	0.116**
		(1.026)	(0.055)
Firm-level Controls	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
No. of Obs.	216	216	216
Kleibergen-Paap rk Wald F statistic	20.406		

Table 9: VC Financing on Size of Startups' Product Portfolios: IV Analysis

This table reports the 2SLS coefficient estimates from regressing the 5-year average number of products of firm i on *VC* for a cross-sectional matched-sample of VC- and non-VC-backed firms. Each VC-backed firm is matched with a non-VC-backed firm in the same year of receiving its first VC financing and same industry (as measured by the product group). This matching procedure is based on the closest propensity score estimated using sales, sales growth, number of products, and number of stores in which a firm's products are sold. *VC* is a dummy variable equal to 1 if firm i is a VC-backed entrepreneurial firm, and it is equal to 0 otherwise. For VC-backed firms, *Products_5y_Avg* is the 5-year average number of products of firm i following its first VC investment. For matched non-VC-backed firms, this measure is the 5-year average number of products of firm j following the year when its matched counterpart receives its first VC investment. *Limited Partner Returns* is the instrument variable for *VC*. It is a proxy for the return of VC limited partners' investment weighted by geographic proximity. The details of how to construct this IV are in Eq. 4. State, cohort, and year fixed effects are included. Robust standard errors are reported in parentheses and are clustered by state. ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively.

	VC	Products_5y_Avg
	(1)	(2)
Limited Partner Returns	1.024***	
	(0.227)	
VC		0.845***
		(0.282)
Firm-level Controls	Yes	Yes
State FE	Yes	Yes
Cohort FE	Yes	Yes
Year FE	Yes	Yes
No. of Obs.	216	216
Kleibergen-Paap rk Wald F statistic	20.406	

Table 10: VC Financing on Startups' Number of Product Lines: IV Analysis

This table reports the 2SLS coefficient estimates from regressing the 5-year average number of product lines of firm i on *VC* for a cross-sectional matched-sample of VC- and non-VC-backed firms. Each VC-backed firm is matched with a non-VC-backed firm in the same year of receiving its first VC financing and same industry (as measured by the product group). This matching procedure is based on the closest propensity score estimated using sales, sales growth, number of products, and number of stores in which a firm's products are sold. *VC* is a dummy variable equal to 1 if firm i is a VC-backed entrepreneurial firm, and it is equal to 0 otherwise. For VC-backed firms, *Product_Line_5y_Avg* is the 5-year average number of product lines of firm i following its first VC investment. For matched non-VC-backed firms, this measure is the 5-year average number of product lines of firm j following the year when its matched counterpart receives its first VC investment. *Limited Partner Returns* is the instrument variable for *VC*. It is a proxy for the return of VC limited partners' investment weighted by geographic proximity. The details of how to construct this IV are in Eq. 4. State, cohort, and year fixed effects are included. Robust standard errors are reported in parentheses and are clustered by state. ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively.

	VC	Product_Line_5y_Avg
	(1)	(2)
Limited Partner Returns	1.024***	
	(0.227)	
VC		0.398**
		(0.191)
Firm-level Controls	Yes	Yes
State FE	Yes	Yes
Cohort FE	Yes	Yes
Year FE	Yes	Yes
No. of Obs.	216	216
Kleibergen-Paap rk Wald F statistic	20.406	

Table 11: VC Financing on Geographic Expansion of Startups' Products: IV Analysis

This table reports the 2SLS coefficient estimates from regressing the 5-year average number of stores, counties, retail chains, and 3-digit ZIP code regions where the products of firm i are sold on *VC* for a cross-sectional matched-sample of VC- and non-VC-backed firms. Each VC-backed firm is matched with a non-VC-backed firm in the same year of receiving its first VC financing and same industry (as measured by the product group). This matching procedure is based on the closest propensity score estimated using sales, sales growth, number of products, and number of stores in which a firm's products are sold. *VC* is a dummy variable equal to 1 if firm i is a VC-backed entrepreneurial firm, and it is equal to 0 otherwise. For VC-backed firms, *Store_5y_Avg* is the 5-year average number of stores where the products of firm i are sold following its first VC investment. For matched non-VC-backed firms, this measure is the 5-year average number of stores where the products of firm j are sold following the year when its matched counterpart receives its first VC investment. *County_5y_Avg*, *Chain_5y_Avg*, and *ZIPs_5y_Avg* are defined similarly. *Limited Partner Returns* is the instrument variable for *VC*. It is a proxy for the return of VC limited partners' investment weighted by geographic proximity. The details of how to construct this IV are in Eq. 4. State, cohort, and year fixed effects are included. Robust standard errors are reported in parentheses and are clustered by state. ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively.

	VC	Store_5y_Avg	County_5y_Avg	Chain_5y_Avg	ZIPs_5y_Avg
	(1)	(2)	(3)	(4)	(5)
Limited Partner Returns	1.024*** (0.227)				
VC		2.653** (0.975)	1.878** (0.747)	0.520* (0.304)	1.675** (0.686)
Firm-level Controls	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
No. of Obs.	216	216	216	216	216
Kleibergen-Paap rk Wald F statistic	20.406				

Table 12: Channel of VC Value Creation: Market Share

This table reports the OLS coefficient estimates of the test for the market share channel. The specification is similar to Eq. 1. *Large Market Share* denotes the sub-sample of VC-backed firms with a larger nationwide market share when they receive their first VC investment. *Small Market Share* denotes the sub-sample of VC-backed firms with a smaller nationwide market share when they receive their first VC investment. We combine the two sub-samples of VC-backed firms separately with all the non-VC-backed firms and run the regressions. We control for firm and state-by-year fixed effects in all regressions. All outcome variables are defined the same as in the baseline results. Robust standard errors are reported and are clustered by state. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

	Large Market Share				Small Market Share			
	VC × Post	S.E.	Adj. R^2	No. Obs	VC × Post	S.E.	Adj. R^2	No. Obs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sales	1.391***	0.133	0.725	332,518	-1.128*	0.627	0.725	331,383
Price	-1.180*	0.665	0.713	332,518	0.245	1.156	0.713	331,383
Quantity	1.405***	0.134	0.737	332,518	-1.142*	0.585	0.737	331,383
Market Share	0.010*	0.005	0.890	332,518	-0.000	0.000	0.890	331,383
No. Products	0.511***	0.061	0.842	332,518	-0.422*	0.221	0.842	331,383
No. New Products	0.115**	0.052	0.632	332,518	-0.067	0.092	0.632	331,383
No. Product Lines	0.179***	0.030	0.829	332,518	-0.197**	0.092	0.829	331,383
New Product Lines	0.032*	0.017	0.174	332,518	-0.011	0.021	0.174	331,383
No. Stores	1.121***	0.123	0.736	332,518	-0.992**	0.392	0.736	331,383
No. Counties	0.948***	0.103	0.743	332,518	-0.897**	0.365	0.743	331,383
No. Chains	0.640***	0.055	0.805	332,518	-0.340**	0.133	0.805	331,383
No. ZIPs	0.858***	0.099	0.733	332,518	-0.905**	0.342	0.733	331,383

Table 13: Channel of VC Value Creation: Monitoring

This table reports the OLS coefficient estimates of the test for the VC monitoring channel. The specification is similar to Eq. 1. *Short Distance* denotes the sub-sample of VC-backed firms with a shorter distance between their headquarters and their lead VC investors' headquarters. *Long Distance* denotes the sub-sample of VC-backed firms with a longer distance between their headquarters and their lead VC investors' headquarters. The distance is calculated as the spherical distance between the centroid of the ZIP code of an entrepreneurial firm's headquarter and that of the corresponding lead VC investor's headquarter. We combine the two sub-samples of VC-backed firms separately with all the non-VC-backed firms and run the regressions. We control for firm and state-by-year fixed effects in all regressions. All outcome variables are defined the same as in the baseline results. Robust standard errors are reported and are clustered by state. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

	Short Distance				Long Distance			
	VC $\times$ Post	S.E.	Adj. R^2	No. Obs	VC $\times$ Post	S.E.	Adj. R^2	No. Obs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sales	1.173***	0.197	0.725	332,417	0.921***	0.250	0.725	331,484
Price	-1.318*	0.781	0.713	332,417	-0.143	0.827	0.713	331,484
Quantity	1.201***	0.188	0.737	332,417	0.880***	0.266	0.736	331,484
Market Share	0.011*	0.006	0.890	332,417	0.005	0.008	0.890	331,484
No. Products	0.456***	0.081	0.842	332,417	0.261**	0.099	0.842	331,484
No. New Products	0.098*	0.056	0.632	332,417	0.084	0.103	0.632	331,484
No. Product Lines	0.148***	0.033	0.829	332,417	0.105	0.063	0.829	331,484
New Product Lines	0.024	0.019	0.174	332,417	0.035	0.046	0.174	331,484
No. Stores	0.956***	0.154	0.736	332,417	0.674**	0.277	0.736	331,484
No. Counties	0.774***	0.124	0.743	332,417	0.645**	0.292	0.743	331,484
No. Chains	0.578***	0.058	0.805	332,417	0.389**	0.148	0.805	331,484
No. ZIPs	0.712***	0.122	0.733	332,417	0.511**	0.251	0.733	331,484

Appendix to

"Venture Capital and Value Creation in the Product Market: Evidence from the Nielsen Retail Scanner Data"

A Matching Firm Names

By connecting the company prefix (GCP code) with the GS1 Company Database (GEPIR) provided by the Product Open Data (POD), we identify 3,768,901 unique UPCs in the whole Nielsen Data with 62,387 parent companies. To find parent firms that are VC-backed portfolio companies, we merge the 62,387 parent companies ("Parent Firm Sample") with all VC-backed firms in the VentureXpert dataset. Since the Nielsen Data covers information from January 2006 and December 2019, we drop the portfolio companies which receive their first VC financing before 2006. This section illustrates how we merge the company names in the two datasets and finalize our sample. We employ the following matching procedure:

1. Merge the two datasets using original company names

We use the portfolio companies' names in the VentureXpert as the baseline group and merge them with the Parent Firm Sample using the original company names. By doing so, we successfully find 23 firms.

2. Merge the unmatched companies using standardized names

We first standardize the company names for the rest of the unmatched companies in both datasets. Specifically, we follow the name-standardization algorithm provided by the NBER Patent Data Project to standardize the company names.[13] This standardization process removes the punctuation, standardizes the suffix (i.e., changing both "Corporation" and "Corp" into "CORP"), and capitalizes the company names. After merging the two datasets, we identify 151 VC-backed firms in the Parent Firm Sample.

3. Merge the unmatched companies using stemmed names

For the remaining unmatched company names, we employ a similar algorithm as before to create stemmed names (e.g., keeping the main body of a capitalized name and removing its suffix) and merge two samples based on the stemmed names. We find 142 matched

[13] For detailed descriptions of the NBER name-standardization algorithm, see the name standardization routines on NBER Data Project website: https://sites.google.com/site/patentdataproject/Home/posts/namestandardizationroutinesuploaded.

firms from this procedure.

4. Use Python algorithm "fuzzymatcher" to conduct the last-round matching

This algorithm forms all pairwise combinations of every remaining firm between two samples and then selects the firm pair with the highest fuzzy-name matching score as a potential match. We follow the same procedure as before to merge the two samples (by using original names, standardized names, and stemmed names, respectively). Finally, we manually check the matched sample provided by this algorithm based on information from Google, Capital IQ, and Nexis Uni. With the help of this python algorithm, we find 47 VC-backed portfolio companies which have products in the Nielsen Data.

As a result, we find 363 VC-backed firms which have products in the Nielsen database. Since not all the firms have their products' weekly transaction information, after tracking the purchasing data at the Nielsen Retail Scanner Data, our final sample contains 252 VC-backed firms, which receive their first VC investment from January 2006 to December 2019, and 46,749 non-VC-backed private firms.

B Other Measures of Geographic Expansion

In Section 4.3, we find that in the five years following the first VC financing, VC-backed firms expand their products to more stores, counties, retail chains, and 3-digit ZIP code regions than non-VC-backed firms. There are two concerns associated with the findings: 1) the increase in the number of stores to which VC-backed firms' products are sold could be partly due to one retail chain (e.g., Walmart) opening more stores; 2) the significant increase of the products' geographic availability can also be driven by the nationwide expansion of stores or retail chains. To eliminate these two concerns, in this section, we employ other measures of the geographic expansion of firms' products. The results are reported in Table A.2.

The dependent variables in Table A.2 include the number of Designated Market Areas

(DMA) and states where a firm's products are sold. The positive and statistically significant coefficients on the interaction term suggest that VC-backed firms expand their products to 78% more DMAs and 53% more states than non-VC-backed firms over the 5 years following the first VC investment. Overall, the baseline results regarding the geographic availability of products are robust to different measures.

[Insert Table A.2 here.]

Table A.1: Selection into VC Financing

This table reports the OLS coefficient estimates from regressing VC financing dummy on a set of startup-level characteristics. *VC Financing* is a dummy variable equal to 1 for firms in the year when they first receive the VC investment. We drop the observations of VC-backed firms after they receive the first VC financing. This dummy variable is equal to 0 otherwise. *Sales* is the natural logarithm of the sales of firm i across all the stores in a given year t. *Number of Products* is the natural logarithm of the number of unique products firm i sells across all the stores in a given year t. *Number of Product Lines* is the natural logarithm of the number of unique product lines firm i operates in a given year t. Each product line is identified by its unique product module code provided by Nielsen. *Number of Stores* is the natural logarithm of the number of unique stores where products of firm i are sold in a given year t. *Number of Counties* is the natural logarithm of the number of counties where products of firm i are sold in a given year t. *Number of Chains* is the natural logarithm of the number of retail chains where products of firm i are sold in a given year t. *Number of ZIPs* is the natural logarithm of the number of 3-digit ZIP code regions where products of firm i are sold in a given year t. *Sales_Growth* is the growth in firm i's total sales from year t-1 to year t. *Products_Growth* is the growth in firm i's total number of products from year t-1 to year t. *Product_Lines_Growth* is the growth in firm i's total number of product lines from year t-1 to year t. *Stores_Growth* is the growth in the total number of stores where firm i's products are sold from year t-1 to year t. *Counties_Growth* is the growth in the total number of counties where firm i's products are sold from year t-1 to year t. *Chains_Growth* is the growth in the total number of retail chains where firm i's products are sold from year t-1 to year t. *ZIPs_Growth* is the growth in the total number of 3-digit ZIP code areas where firm i's products are sold from year t-1 to year t. State-by-year fixed effects are included. Robust standard errors are reported in parentheses and are clustered by state. ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively.

	VC Financing
Sales	-0.00004**
	(0.00002)
Number of Products	0.00000
	(0.00004)
Number of Product Lines	-0.00012
	(0.00008)
Number of Stores	0.00001
	(0.00008)
Number of Counties	-0.00032**
	(0.00014)
Number of Chains	0.00014
	(0.00009)
Number of ZIPs	0.00045***
	(0.00016)

Continued on next page

Table A.1 – *Continued from previous page*

Sales_Growth	-0.00000
	(0.00000)
Products_Growth	0.00031**
	(0.00014)
Product_Lines_Growth	-0.00022
	(0.00020)
Stores_Growth	-0.00005
	(0.00003)
Counties_Growth	0.00006
	(0.00005)
Chains_Growth	0.00038***
	(0.00013)
ZIPs_Growth	0.00006
	(0.00009)
State $\times$ Year FE	Yes
Adjusted R^2	0.0003
No. Obs	282,015

Table A.2: VC Financing on Geographic Expansion of Startups' Products: Alternative Measures

This table reports the OLS coefficient estimates from regressing different measures of products' geographic availability on *VC* $\times$ *Post*. *VC* is a dummy variable equal to 1 if firm i is a VC-backed entrepreneurial firm, and it is equal to 0 otherwise. *Post* is a dummy variable equal to 1 if the year t is within 5 years after firm i receiving its first VC investment; it is equal to 0 otherwise. *Number of DMAs* is the natural logarithm of the number of DMAs where products of firm i are sold in a given year t. *Number of States* is the natural logarithm of the number of states where products of firm i are sold in a given year t. Firm and state-by-year fixed effects are included. Robust standard errors are reported in parentheses and are clustered by state. ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively.

	Number of DMAs	Number of States
	(1)	(2)
VC × Post	0.578***	0.423***
	(0.090)	(0.067)
Firm FE	Yes	Yes
State × Year FE	Yes	Yes
Adjusted R^2	0.750	0.757
No. Obs	332,795	332,795

Chapter 3: The Dynamics of Venture Capital Syndicates: The Effect of Prior Collaboration among VCs on Value Addition to Entrepreneurial Firms

1 Introduction

It is now well known that venture capitalists (VCs) add considerable value to entrepreneurial firms through a variety of channels (see, e.g.,Chemmanur et al. (2011) or Chemmanur et al. (2014)) and further, often invest in entrepreneurial firms as part of teams called "syndicates." There has also been considerable research on the rationale for VC syndication, both theoretically (see, e.g., Casamatta and Haritchabalet (2007)) and empirically (see, e.g., Brander et al. (2002)). However, there is relatively less research on how venture capitalists choose other VCs to form syndicates with and on the composition of VC syndicates that are conducive to adding value to entrepreneurial firms most efficiently. In this paper, we hypothesize that the ability of VC syndicates to add value to entrepreneurial firms is the greatest when at least some members of the VC syndicate have co-invested together previously and even greater when the prior co-investment has been particularly successful (i.e., led to a very successful exit such as an IPO rather than to a less successful exit such as an acquisition or an unsuccessful exit). This is because each VC may face some information asymmetry about the ability of other VCs to add value to entrepreneurial firms as part of a VC syndicate and about the complementarity of the VC's skills with those of another VC (it is reasonable to expect each VC to have some private information about its own value addition skills and deficiencies). In this paper, we argue that, when two VCs co-invest together, this may allow them to learn about each others' value-addition skills and about the complementarity (if any) between each others' value-addition skills. Further, if each VC views the syndication process as a repeated game, this would increase its incentive to co-operate with other VCs forming part of the syndicate for any given entrepreneurial firm: i.e., the repeated nature of the syndication process may reduce the potential for conflicts among VCs forming the syndicate financing a given entrepreneurial firm.

The above arguments generate a number of research questions that we examine empirically in this paper for the first time in the literature. First, does prior collaboration between an entrepreneurial firm's lead VC and some syndicate members result in greater short-run value addition to the firm compared to a situation where there has been no such prior collaboration? We use the sales growth and employment growth of an entrepreneurial firm in the three years immediately after VC investment and the probability of a patented innovation being generated by an entrepreneurial firm and the quality of innovations generated in the three years subsequent to VC investment as measures of short-run value addition. Second, does prior collaboration between an entrepreneurial firm's lead VC and some syndicate members result in greater long-run value addition to the firm compared to a situation where there has been no such prior collaboration? As is standard in the literature, we make use of the probability of a successful exit (an IPOs or an acquisition) by the entrepreneurial firm as the measure of long-run value addition by a VC syndicate. Third, do VC syndicates where the lead VC and some syndicate members have collaborated very successfully (i.e., led to an IPO exit) in the past result in greater short-run and long-run value addition compared to value addition by those syndicates where there has been prior collaboration between the lead VC and some syndicate members but the collaboration has not been as successful? We are motivated to ask this question, since prior collaborative success suggests greater complementarity between the skills of the VCs involved and therefore their ability to add greater value in future syndicates for entrepreneurial firms.

Fourth, if indeed prior collaboration reduces information asymmetry among VCs about each other's value addition skills and reduces the potential for conflicts among syndicate members, one would expect VCs characterized by prior collaboration among syndicate members to be characterized by greater uniformity in the composition of their VC syndicates across financing rounds (when investing in a given entrepreneurial firm). This is because, in such syndicates characterized by lower information asymmetry across VCs and a smaller potential for conflict among them, there would be less of a need to replace VCs (and potentially bring in new VCs to join the syndicate) across financing rounds. This is therefore the next research question that we address here. Fifth, if VCs are aware that syndicates with other VCs with whom they have collaborated previously indeed leads to greater value addition, then we would expect such VCs to syndicate more often with prior collaborators. Further, if prior collaboration that resulted in greater success leads to even greater value addition than prior collaboration alone, then we would expect VCs to form syndicates with such successful prior collaborators with a greater frequency than syndicates with VCs where the previous collaboration was not as successful. This is the last research question that we address here.

To answer the above research questions, we utilize multiple data sources to compile data on private firms used in our study. The main source from which we collect information about the sample of VC-backed startups is VentureXpert via Thomson One, which is a leading data provider on venture capital investments, funded companies, investing firms, and funds. From VentureXpert we collect round-by-round VC financing information. By collecting such information, we are able to see the identity of the VC investors participating in different rounds of financing for different startup companies. We can thus determine if any pairs of VC investors have co-invested in the past before they invest together in the current focal startup. In this paper, we mainly focus on three sets of outcome variables, which are exit, employment and sales growth, and innovation of startup companies. First, we collect data on startups' exit choices (i.e., IPO or M&A) from Thomson Reuters SDC Platinum New Issues and M&A Database. Second, we collect information on the level of startups' employment and sales from the National Establishment Time Series (NETS) database, based on which we calculate startups' employment and sales growth over the 3 years following their first VC financing. Third, the source from which we collect data on startups' innovation output is USPTO PatentsView database.

Our baseline results can be summarized as follows. First, in terms of the successful exit, we find that startups backed by VC investors who have co-invested in the past are more likely to experience successful exits, as measured by IPOs or M&As. In addition, we also examine the effect of VC investors' past collaboration on the probability of startups going public, since existing literature has argued that from both startups' and VCs' perspectives, going public is a stronger measure of successful exit than being acquired by another company. For startups that choose to exit via IPOs, it indicates that they, as stand-alone firms, are more likely to have a strong edge in the product market and can fend for themselves (Bayar and Chemmanur (2011)). From VCs' point of view, going public could also be a more desirable exit choice compared to the acquisition of their portfolio companies by others, as Sahlman (1990a) finds that VC investors earn the majority of their financial returns from portfolio companies that eventually go public. We find that startups backed by VC investors who have collaborated in the past are also more likely to experience more successful exits, as measured by IPOs alone. The effect of VC investors' past collaboration on the probability of startups' successful exits (as measured by IPO or M&A) is both statistically and economically significant: startups backed by VCs who share prior co-investment experience are 4.45% more likely to exit successfully than those backed by VCs with no prior co-investment experience, or about 10% of the unconditional sample mean.

Second, regarding the employment and sales growth, we document that startups backed by VC investors who have co-invested in the past have higher employment and sales growth over the 3 years after receiving their first VC investment. We find that the effect of VCs' past collaboration on startups' 3-year growth in employment and sales is both statistically and economically significant as well: startups backed by VCs who have co-invested previously are associated with an 8.66% higher employment growth and a 13.17% higher sales growth than those backed by VCs who do not have prior collaboration. The magnitude of these coefficients is equivalent to 6.2% and 7.8% of the unconditional sample mean, respectively.

Third, in terms of startups' innovation output, we find that startups backed by VC investors who have co-invested previously are more likely to obtain at least one patent (that is eventually granted) during the 3 years subsequent to their first VC financing. Further, these startups also generate patents of higher quality (as measured by the number of citations per patent of a firm) during the same period compared to their counterparts. We show that startups backed by VCs who share prior co-investment experience are 4% more likely to obtain at least one new patent and are associated with a 4% larger number of citations per patent for patents filed (and eventually granted) within the 3 years after the first VC investment. This translates to 20% and 28% of their unconditional sample mean, respectively.

Our baseline results suggest that there is a positive relationship between VC investors' past collaboration and the future success of startups backed by them, as measured by startups' successful exits, employment and sales growth, and innovation output. However, there are several endogeneity concerns facing our baseline specifications. One such concern is the selection versus treatment effect of VC investors frequently studied in the entrepreneurial financing literature. Specifically, is the outperformance of startups backed by VCs with past collaboration experience due to these VC investors' ability to select better firms (i.e., selection/screening effect)? Or is it because these VCs have the ability to better create value for startups backed by them (i.e., treatment effect)? To disentangle the selection effect from the treatment effect, we conduct an Instrumental Variable (IV) analysis.

In this paper, we construct our IV as the number of pairs between the lead VC of a startup and any other syndicate members from the first round of financing that has a distance less than 50 miles between the MSAs of their headquarters.[1] Then we use this IV to instrument for the endogenous variable of the past collaboration between the lead VC and any other syndicate members from the first round of the startup. We argue that our IV is likely to satisfy the relevance condition and exclusion restriction. In terms of the relevance of our IV, we argue that VC investors are more likely to co-invest with each other when they are located closer, since it is more likely for VCs located closer to each other to share investment opportunities and develop investment networks. We also empirically show in the first stage of the IV analysis that our IV is relevant. In terms of the exclusion restriction, we argue that the geographic proximity between lead VC and syndicate members of a startup is likely to affect the startup's performance only through the likelihood of VC investors sharing past collaboration experience rather than through the underlying startups' characteristics. Therefore, by utilizing the IV to instrument for the endogenous variable of past collaboration, we are able to disentangle the selection effect from the treatment effect and to examine if VCs having prior co-investment experience indeed create value for the startup that they currently invest in. The results from our IV analysis show that VCs that have collaborated in the past indeed add value to startups backed by them. We show that the past collaboration of VCs causally leads to startups having greater chances of successful exits, enjoying larger employment and sales growth, having a higher probability of filing for new patents, and achieving higher innovation quality.

Next, we discuss several potential mechanisms that could drive our results. The first potential mechanism through which VCs' past collaboration creates value for startups is the reduction in information asymmetry and potential conflicts between VCs. If two VC investors have collaborated with each other and co-invested in some startups together before, they are more likely to know each other very well (i.e., the extent of information asymmetry is lower), and the potential conflicts between them is likely to be lower. As a result, they are more likely to form a more stable/uniform syndicate for the startup that they currently invest in. If the VC syndicate is more stable across different financing rounds of a startup, the startup is likely to face less financing uncertainty and hence could achieve higher growth in the long term. We find that the past collaboration between the lead VC and any other syndicate members of a startup positively and significantly predicts the

[1] In Section 5.5, we also construct several alternative IVs using different distance cutoff points. The results are robust to different distance cutoff points

stability of VC syndicate across different financing rounds of the startup, which lends support to this potential mechanism.

The second potential mechanism we conjecture is the complementary skills and coordination efficiency between VCs. We test this mechanism by examining the past success achieved by VC pairs. In this paper, we define that a VC pair achieves past success if they have successfully brought a previous startup they co-invested into IPO, since we mentioned above that IPO is probably a more successful exit than M&A from both a startup's and its VC investors' points of view.[2] We conjecture that if a VC pair was able to help a previous startup that they co-invested in to go public, it could be the case that the VC pair has some complementary capabilities and can co-ordinate efficiently, such that together they could create greater value for future startups than others can. It is also possible that from this past success experience has the VC pair learned valuable know-how, which they could lever into the current startup they are co-investing in. In any circumstance, if past success is indeed one of the channels driving our results, we would expect to find that the future success of startups (as measured by the successful exit, employment and sales growth, as well as innovation output) is more pronounced in the sub-sample where their VC investors share some previous successful experience. We find that this is indeed the case. We show that conditional on the sub-sample of startups whose VC investors from the first round have collaborated in the past, past success of their VC investors positively and significantly predicts the probability of startups' successful exits, the 3-year employment and sales growth of startups, the probability of startups applying for new patents over the 3 years following the first VC investment, and startups' innovation quality during the 3 years subsequent to their first VC financing.

The rest of this paper is organized as follows. Section 2 discusses the existing literature related to our paper and our contribution to the literature. Section 3 develops several testable hypotheses for our empirical analysis. Section 4 discusses the data sources used in our study and the sample selection procedure. Section 5 presents our main empirical tests and results on the effect of past VC collaboration on value addition by VC syndicates. Section 6 examines several potential mechanisms through which the past collaboration among VCs in a syndicate allows them to create greater value for entrepreneurial firms. Section 7 concludes.

[2] In an untabulated analysis, we also define the past success of a VC pair as a startup backed by them going public or being acquired by another firm. The results remain quite consistent with what we document in this paper.

2 Related literature

Our paper contributes to two strands in the existing literature. The first strand is the broad literature analyzing the value-adding role of VC investors in their portfolio companies. The theoretical literature includes papers on the optimal contracting and the advising role of VC (e.g., Sahlman (1990b), Berglöf (1994), Admati and Pfleiderer (1994), Hellmann (1998), and Ueda (2004), Casamatta (2003), Schmidt (2003)). The empirical literature includes papers on the monitoring and value-adding role of VC (e.g., Lerner (1995), Kaplan and Strömberg (2004), Hellmann and Puri (2002), Bernstein, Giroud, and Townsend (2016), Chemmanur, Krishnan, and Nandy (2011), Chemmanur, Loutskina, and Tian (2014), González-Uribe (2020)).[3] We extend the above literature by studying the role of past collaboration between VCs in improving the post-investment performance of startups.

The second strand is the theoretical and empirical literature on VC syndication formation. Casamatta and Haritchabalet (2007) theoretically argue that the rationale for the lead VC to form syndication is to gather information while preventing competition from syndicate members. Cestone, White, and Lerner (2007) also theoretically analyze how an optimally designed contract of cash flow rights among VC syndicate members helps induce truthful information revelation (see also Bachmann and Schindele (2006)). Brander, Amit, and Antweiler (2002) show theoretically and empirically that VC syndication helps improve more on VC's post-investment treatment effects than VC's pre-investment screening abilities. Unlike the above papers, Admati and Pfleiderer (1994) focus on optimal contracting in sequential syndication within the same startup for lead VCs to resolve informational asymmetries between outside investors (i.e., syndicate members in the future rounds) and startups. In a similar vein, Bayar, Chemmanur, and Tian (2020) theoretically and empirically show that firms financed by a stable set of VCs across various financing rounds are more likely to have a successful exit outcome. However, unlike Admati and Pfleiderer (1994) and Bayar, Chemmanur, and Tian (2020), we focus on the collaboration experience between VCs across deals invested in different companies. Other papers have examined which characters drive the outcomes of the syndication. Hochberg et al. (2007) analyze the role of networks and show that the portfolio companies of better-networked VCs are more likely to have successful exits such as IPO

[3] See Da Rin, Hellmann, and Puri (2013) for a detailed literature review on venture capital financing.

or acquisitions. Bottazzi et al. (2016) theoretically and empirically examine the effect of trust in cross-country VC investment and suggest that syndication is more valuable in low-trust deals. More recently, Bubna, Das, and Prabhala (2020) show that VCs with similar ages and functional styles are more likely to form syndication and subsequently have a better effect on startups in terms of better exit outcomes and greater innovation.[4]. Overall, our paper contributes to this literature by analyzing the dynamics of VC syndicates in investment deals across different startups for the first time in the literature.[5]

3 Theory and Hypothesis Development

We posit that there may be two advantages if venture capitalists constituting a syndicate may have had a prior collaboration (in terms of serving together previously in a VC syndicate investing in an entrepreneurial firm in the past). First, the VCs may know each others' skills and abilities better; in other words, each VC may have a larger amount of information (i.e., have a lower extent of information asymmetry) about the other VCs in the syndicate. Second, if two VCs believe that they are playing a sequential game in terms of being part of the same VC syndicate , then they have more of an incentive to co-operate with each other in terms of value creation for the entrepreneurial firm they are investing in (in other words, there will be fewer conflicts among VCs serving in the VC syndicate investing in an entrepreneurial firm).

Both of the above effects will lead to greater efficiency in value addition by VCs in a syndicate if some of the VCs in a syndicate have had a prior collaboration in terms of investing together in an entrepreneurial firm in the past compared to a situation where there has been no such previous collaboration. This is the first hypothesis that we test here **(H1)**. We will use the following measures of value creation in our empirical analysis: probability of successful exit; employment growth in the entrepreneurial firms subsequent to VC investment; sales growth in the entrepreneurial firms subsequent to VC investment; probability of having successful innovation output; and finally, the

[4]There are also several papers in the areas of management and strategy that study the prior collaboration between VCs. For example, Bellavitis et al. (2020) document a U-shaped relationship between the number of prior co-investments between VCs and the probability of a startup exiting successfully through an initial public offering or a M&A. In a different paper, Wang et al. (2022) find a slightly different result that as the number of past collaboration among a group of VCs increases, a startup backed by this group of VCs is more likely to exit by a M&A, while a lower number of past collaboration among VCs is associated with a higher probability of a startup exiting by IPOs.

[5]Our paper is also broadly related to the literature on team and alliance formation (see, e.g., Pichler and Wilhelm (2001), Robinson (2008)).

quality of firms' innovation output.

We now turn to an empirical analysis of the mechanisms through which VCs who have collaborated with each others in the previous VC syndicates are able to create greater value for entrepreneurial firms. If, as we have mentioned earlier, prior collaboration allows VCs to learn about each others' ability to add value to entrepreneurial firms, and also allows the minimization of conflicts among the VCs constituting a VC syndicate, we would expect there to be a greater degree of uniformity of syndicate membership across financing rounds (since, when VCs have more information about each other and have fewer conflicts among them, there is less of a need to remove a VC from a syndicate and bring in a new VC instead). This is the second hypothesis that we test here **(H2)**.

Even when VCs have collaborated with each other in the past, there may be considerable variation in the extent of the success of their past collaboration. In some cases, the entrepreneurial firms whose syndicate that two VCs have previously collaborated on may have had an extremely successful exit; namely, an IPO; in other cases, the entrepreneurial firms may have had a less successful exit, namely, an acquisition, or worse, an unsuccessful exit. The success of previous VC collaborations is important since this may indicate the collaborating VCs' ability to complement each other and co-ordinate with each other efficiently without conflicts in creating value for entrepreneurial firms that they invest in.[6] This leads to the testable hypothesis that VC syndicates containing VCs who have very successfully collaborated in the past (i.e., their collaboration resulted in an IPO) are ale to create greater value than VC syndicates where the VCs have collaborated in the past without as much success. This is the next hypothesis we test here **(H3)**.

We now turn to the characteristics of other VCs with whom a VC prefers to form a syndicate. If a VC is aware that forming a syndicate with another VC with whom they have collaborated previously enables greater value addition, then that VC has a greater propensity to form a syndicate with such a VC **(H4)**. Further, if a VC believes that (as we hypothesized above) syndicating with a VC with whom they have had a successful collaboration (i.e., a collaboration which led to an IPO outcome) enables greater value creation, then we would expect to see a higher probability of such a syndicate

[6]Even if two VCs' prior collaboration was not particularly successful, having a past collaboration reduces the information asymmetry across the two VCs involved. Therefore, analyzing whether the prior collaboration was very successful or not allows us to dig deeper into the mechanism through which prior collaboration allows VCs to add value to entrepreneurial firms more efficiently.

formation relative to the probability of forming a syndicate with a VC with whom that VC's prior collaboration was not as successful **(H5)**. These are the last two hypotheses we test here.

4 Data and Sample Selection

4.1 Data Sources

The main source from which we collect information about the VC-backed entrepreneurial firms is VentureXpert via Thomson One. VentureXpert is a leading provider of data on venture capital investments, funded companies, investing firms, and funds, and it is frequently used by previous studies. From VentureXpert we collect round-by-round VC financing information. By collecting such information, we can see the identity of the VC investors participating in different rounds of financing for different startup companies. Hence we are able to determine if any pairs of VC investors have co-invested in the past before they invest together in the current focal startup. Among other variables, in particular, we collect information about the investment amount of individual VC firms in different rounds of a startup company, as well as the geographic locations (specifically, MSAs) of VC firms' headquarters. We collect information about the investment amount to determine the lead VC investor of a startup company. We then use this information to construct, for each startup, pairs between lead VC and any other syndicate members from the first round and examine if any of these pairs have collaborated in the past to invest in a startup company. We collect information about the geographic locations of VC firms' headquarters, which we later use to construct the Instrumental Variable (IV) used in our analysis. We will discuss the IV analysis in detail in Section 5.4.

We focus on three sets of outcome variables of startups in this paper, which are exit, employment and sales growth, and innovation. First, the data source from which we collect startup companies' exit is Thomson Reuters SDC Platinum New Issues and M&A Database. We merge firms in the Thomson Reuters SDC database with VentureXpert startup companies based on matching of their standardized names. Second, we collect the data on startups' employment and sales from the National Establishment Time Series (NETS) database, from which we can then calculate startups' employment and sales growth over the 3 years following their first VC financing. We merge firms in the NETS database with VentureXpert startup companies using fuzzy name match and location. Lastly, we obtain the data on startups' innovation output from USPTO PatentsView. To examine startups' filings of new patents during 3 years following their first VC financing, we first obtain application information of utility patents (that are eventually granted) from "application" dataset of USPTO PatentsView Bulk Download Database. We then use the patent-assignee crosswalk file provided by USPTO to aggregate the above information to the firm level. We use the "application" dataset (instead of the dataset of granted patents) because it is usually in the year of a company filing for a patent that the company has possessed the technology embedded in the patent. To examine startups' innovation quality, following the existing literature in corporate innovation, we use the number of citations per patent constructed at the firm level as a proxy. We obtain the citation information of utility patents from "uspatentcitation" dataset and then aggregate this information to the firm level as well.

As frequently discussed in the innovation literature (e.g., Hall, Jaffe, and Trajtenberg (2001)), there are two types of truncation problems associated with patent data. The first type of truncation problem is related to patent count. A patent filed by a company will appear in the USPTO patent database only after it is granted. Based on the data from USPTO, the time lag between the filing and grant of a patent is 2 years on average. Therefore, toward the end of our sample period, the number of patents filed by a firm in a given year is likely to be reduced compared to earlier years of our sample period, since it will take time for these later patents to be granted before they appear in the USPTO patent application dataset. The second type of truncation problem is associated with the number of citations received by a given patent. Patents filed and granted in earlier years of the sample period are expected to receive a larger number of citations than patents filed in later years. To mitigate these two types of truncation problems, we follow a similar methodology to that in Hall, Jaffe, and Trajtenberg (2001) and Seru (2014). Specifically, we scale a patent (number of citations received by a patent) by the total number of patents (total number of citations received by all the patents) filed in the same year and technology class. We then aggregate these class-adjusted measures to firm level and use them to construct the innovation-related outcome variables used in our analysis.

4.2 Sample Selection

We start by selecting startup companies that receive their first VC investment between 1980 and 2019 from VentureXpert. We focus on startup companies with their headquarters located in the United States. We first drop VC firms with unknown identity (i.e., VC firm names that contain ”undisclosed”), since we need the identity of VC firms to determine if any pairs of VC firms have co-invested together in the past. Further, following Bayar, Chemmanur, and Tian (2020), we drop investing firms with their types being “Angel Group” or “Individuals”, since these firms are not the main focus of our study. This initial screening procedure leads to a sample of 49,970 startup companies.

Building on the previous sample, we focus on startups that have at least two VC investors investing in the first round, since this will allow us to determine if any *pair* of VC investors has collaborated in the past to invest in a startup company. Throughout our analysis, we focus on the pairs between lead VC investor of a startup and any other syndicate members from the first-round financing of the startup. We choose to study the past collaboration of VC pairs in the first round, because first-round financing is often assumed to be important for a startup to kick off its business and continue to grow subsequently. In addition, we focus on the pairs between lead VC investor of a startup and any other syndicate members, since it is argued by the existing literature that the lead VC investor often takes on the job of monitoring and overseeing a startup’s operation and hence plays a bigger role in the startup’s growth. It should be noted that, when we determine if a pair between the lead VC investor of a startup and a syndicate member has co-invested in the past, we use all the previously available round-by-round financing data prior to their investment in the current focal startup. Overall, this leads to a final cross-sectional sample with 19,393 startup companies. We report the summary statistics in Table 1. We winsorize all of the continuous variables at 2.5% and 97.5% level.

5 Empirical Tests and Results

5.1 Past VC Collaboration and Successful Startup Exit

In this subsection, we study whether the past collaboration experience between the lead VC and any of its syndicate members leads to better exit outcomes for the startups after they have invested together in the first round. We use two measures to define a successful exit by a startup. Our first measure is *IPO or M&A*, which is a dummy variable that equals one if a startup exits via IPO or Mergers & Acquisitions (M&A) by the end of our sample period (2019) and zero otherwise. Our second measure is *IPO*, which is a dummy variable that equals one if a startup exits via IPO and zero otherwise. More specifically, we study the relationship between VC past collaboration and startup exits by estimating the following regression:

$$y_{i,t} = \alpha + \beta \textit{Past Collaboration}_{i,t} + \gamma Z_{i,t} + \textit{Industry}_j + \textit{Year}_t + \epsilon_{i,t}, \tag{1}$$

where $y_{i,t}$ represents our measures of startup exit: *IPO or M&A*, and *IPO*. Our key independent variable is *Past Collaboration*, which is also a dummy variable that equals one if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round and zero otherwise. $Z_{i,t}$ represents a set of variables that we use to control for startup, lead VC, and investment deal characteristics, which includes *Startup_Age*, *Emp*, *VC_Age*, and *First_Round_Inv*. *Startup_Age* measures the age of a startup and is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* count the number of employees of a startup at the time when it receives its first VC investment. *VC_Age* measures the age of the lead VC investor in an investment deal and is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in millions) received by a startup in the first round. $\textit{Industry}_j$ and $\textit{Year}_t$ represent the 2-digit SIC industry and year fixed effects included in our regressions. Standard errors are also clustered at the industry and year levels.

The results of our regressions are reported in Table 2. Columns (1) - (3) of Table 2 show that the coefficient estimates of *Past Collaboration* are positive and significant across three different specifications when using *IPO or M&A* as our dependent variable. These results suggest that the past collaboration experience between lead VC and any of its syndicate members is associated with a higher probability of exiting successfully via IPO or M&A by their portfolio companies. Further, Columns (4) - (6) of Table 2 show that the coefficient estimates of *Past Collaboration* remain positive and significant after we switch our dependent variable from *IPO or M&A* to *IPO*. In other words, our main findings still hold even if we use a stricter definition of successful exits by counting IPO exits only. The magnitudes of these coefficients also indicate their economic significance. For example, the past collaboration experience between the lead VC and its syndicate members increases their startup's probability of exiting through IPO by a magnitude of 2.4% (i.e., a 21% increase compared to the average probability of exiting via IPOs). Overall, the above findings show that the past collaboration experience between the lead VC and any of its syndicate members contributes to a significantly higher probability of exiting successfully via IPO or M&A by their portfolio companies.

5.2 Past VC Collaboration, Startup Employment Growth, and Startup Sales Growth

In this subsection, we study whether the past collaboration experience between the lead VC and any of its syndicate members is associated with higher employment and sales growth of the startups after they have invested together in the first round. We use the 3-year employment growth (in percentage terms) of a startup starting from the year when it receives its first VC investment to measure post-investment employment growth ($\Delta\%$*Emp_3y*). Similarly, we use the 3-year sales growth (in percentage terms) of a startup starting from the year when it receives its first VC investment to measure post-investment sales growth ($\Delta\%$*Sales_3y*). To study the relationship between VC past collaboration and startup employment and sales growth, we also estimate Equation 1 by replacing $y_{i,t}$ with our measures of employment and sales growth: $\Delta\%$*Emp_3y* and $\Delta\%$*Sales_3y*.

The results of our regressions are reported in Tables 3 and 4 . Table 3 shows that the coefficient estimates of *Past Collaboration* are positive and significant across three different specifications, suggesting that startups invested by lead VCs who have past collaboration experience with any of their syndicate members have been growing faster in terms of employment in the three years after receiving their first VC investment. Similarly, Table 4 shows that the coefficient estimates of *Past Collaboration* are also positive and significant, suggesting a similar positive effect of that the past collaboration experience between lead VC and any of its syndicate members on the post-investment sales growth of startups. Economically, the past collaboration experience between the lead VC and its syndicate members increases their startup's 3-year employment growth rate by 58% (i.e., a 41% increase compared to the average 3-year employment growth rate) and their startup's 3-year sales growth rate by 104% (i.e., a 61% increase compared to the average 3-year sales growth rate).

5.3 Past VC Collaboration and Startup Innovation Productivity

In this subsection, we study whether the past collaboration experience between the lead VC and any of its syndicate members is associated with higher innovation productivity of the startups after they have invested together in the first round. Our first measure of a startup's innovation productivity is a dummy variable, *New_Pat_1_3*, which equals one if a startup files any new patents (that are eventually granted) over a three-year window after it receives its first VC investment and zero otherwise. We also measure the average quality of any new patents produced by startups with the average number of citations per patent. More specifically, *CPP_1_3* is the average number of citations per patent of a startup produced over a three-year window after it receives its first VC investment. To study the relationship between VC past collaboration and startup innovation productivity, we also estimate Equation 1 by replacing $y_{i,t}$ with our measures of startup innovation productivity: *New_Pat_1_3* and *CPP_1_3*.

The results of our regressions are reported in Tables 5 and 6 . Table 5 shows that the coefficient estimates of *Past Collaboration* are positive and significant across three different specifications, suggesting that startups invested by lead VCs who have past collaboration experience with any of their syndicate members are more likely to produce new patents in the three years after receiving their first VC investment. The results are also economically significant. For example, the past collaboration experience between the lead VC and its syndicate members leads to a 4% higher probability of producing new patents for their startups over a 3-year period after receiving the first-round VC investment (i.e., a 21% increase compared to the average probability of producing any new patents over the same period). Further, Table 6 shows that the coefficient estimates of *Past Collaboration* are also positive and significant, suggesting that the new patents produced by these startups are, on average higher quality. Put together, the baseline results from Section 5.1 to 5.3 support the prediction of our testable hypothesis **H1**.

5.4 Identification

So far, we have shown that VC past collaboration is positively correlated with startup successful exits and performances. However, an OLS regression is unable to distinguish whether the effect is due to selection, high-quality VCs are more likely to select high-quality startups at the same time, or treatment, the past collaboration of VCs enables VCs to add value to startups. In this section, we use an instrumental variable (IV) approach to establish the causal link that the past collaboration of VC syndicate members has a positive impact on startups. That is, the positive correlation we have shown in the baseline regressions is not only due to the joint selection of VCs but also the value addition from VCs that have collaborated in the past.

We construct an IV for the past collaboration of VC syndicate members by counting the number of pairs between lead VC and other syndicate members in the first round that have a distance of less than 50 miles between the MSAs of the VC headquarters. We then use the IV and conduct a two-stage-least-square (2SLS) estimation. The first stage of the estimation is based on the following equations:

$$\textit{Past Collaboration}_{i,t} = \alpha + \beta \textit{Dist\_Less\_50} + \gamma Z_{i,t} + \textit{Industry}_j + \textit{Year}_t + \epsilon_{i,t}, \tag{2}$$

and the second stage of the estimation as:

$$y_{i,t} = \alpha + \beta Past\hat{Collaboration}_{i,t} + \gamma Z_{i,t} + \textit{Industry}_j + \textit{Year}_t + \epsilon_{i,t}, \tag{3}$$

where i represents a startup, t is the year that the startup receives the first round of financing. Other variables are defined the same as in our baseline regressions.

Geographical distance between VCs is likely to satisfy the identification assumptions for the IV approach. Regarding the correlation assumption, VCs are more likely to collaborate with each other when they are close. Figure 1 shows that about 35% of the pairs between lead VC and other syndicate members have a distance less than 100 miles. As shown later in this section, the first-stage estimations all have a F-stat greater than 10, passing the critical value required by Stock and Yogo (2005). In terms of the exclusion restriction of the IV approach, we argue that the geographical distance between VCs is likely to affect startup performances only through the likelihood of having a past collaboration.

First, we show the results of our IV analysis of the impact of VC past collaboration on the successful exits of entrepreneurial firms. Table 7 shows the result. In the first stage of the analysis, we instrument the past collaboration variable in the first round of financing (*Past Collaboration*) using the the geographical distance between lead VCs and other syndicate members (*Dist_Less_50*). In the second stage of the analysis, we regress the variables that represent successful exits on the predicted value of *Past Collaboration* from the first stage. Columns (1) and (3) shows the first-stage results. Consistent with our earlier discussion about the IV, we find that a positive correlation between the number of geographically close pairs between the lead VC and the syndicate members and their past collaboration. The Kleibergen-Paap rk Wald statistic (Kleibergen and Paap, 2006), which tests directly whether the IV predicts a sufficient amount of the variation in the endogenous variables to identify our equations, has a value of 159.16 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. Therefore, we empirically show that our IV is relevant. Columns (2) and (4) report the second-stage results of the IV analysis, where the dependent variables are the dummy variables for having an successful exit such as IPO or M&A (*IPO or M&A* and *IPO*). The coefficient estimates are both positive and statistically significant at the 5% significance level, suggesting a causal impact of having past collaboration on the successful exits of startups.

We then perform the IV analysis and examine the relationship between VCs' past collaboration and the employment growth and sales growth of startups. Table 8 presents the results when the dependent variable of the second-stage regression is the 3-year employment growth of a startup. The first-stage coefficient estimate on the IV, *Dist_Less_50* is positive and statistically significant at a 5% significance level. The F-stat of the first-stage regression is 61.52, suggesting the first-stage regressions passes the critical value required by Stock and Yogo (2005). Column (2) of Table 8 shows a positive and significant coefficient estimate on the predicted *Past Collaboration*. Table 9 repeats the analysis and we substitute the dependent variable with the 3-year sales growth of a startup. Again, we find a strong first-stage result and a positive coefficient estimate on *Past Collaboration* that is statistically significant at 1% significance level. The above two tables suggests that the positive relationship between VCs' past collaboration and Startups' employment and sales growths is not merely due to better VCs are more likely to investment in higher quality startups but also there are causal impact of VCs' past collaboration on startups' performances.

Finally, we examine the relationship between VCs' past collaboration and innovation outcome of startups using the IV approach. Table 10 presents the results when the dependent variable of the second-stage regression is the dummy variable indicating whether a startup files any new patents that are eventually granted within three years of receiving the first round of financing. Table 10 Column (2) shows a positive and significant coefficient estimate on the predicted *Past Collaboration*, suggesting that VCs' past collaboration has a positive impact on startups' innovation outcome. Table 11 shows the results of the analysis when we use the number of citation per patent for a startup within three years of receiving its first round of financing. Table 11 Column (2) again shows a positive coefficient estimate on *Past Collaboration* that is statistically significant at 1% significance level. The above two tables suggest that VCs' past collaboration has a positive and significant impact on startups' innovation outcome and the quality of patents.

5.5 Robustness Tests

We perform a battery of tests to check the robustness of our main findings. First, we replace our main dummy independent variable, *Past Collaboration*, with a continuous measure of VCs' past collaboration, *Num of Collaboration*. This continuous measure is costructed as the natural logarithm of 1 plus the average number of past collaboration (i.e., number of previous co-investments) between the lead VC investor of a startup and any other syndicate members from the first round. We then repeat our baseline specifications and report the corresponding results in Tables A.1, A.2, and A.3. We find that overall the empirical patterns documented in these tables are very similar to those documented in our baseline results, except that the coefficient on *Num of Collaboration* is not significant at 10% level (but still positive and very close to 10% significance level) when the dependent variable is entrepreneurial firms' 3-year employment growth subsequent to VC investment.

Second, we exclude startups located in three cities, San Francisco, New York, and Boston, with strong VC presences (Chen et al., 2010) and repeat our analyses in Sections 5.1, 5.2, and 5.3. Tables A.4, A.5, and A.6 report the regression results regarding the successful exit, employment and sales growth, and innovation, respectively. All coefficients of our key variable (i.e., *Past Collaboration*) remain largely unchanged both in terms of magnitudes and statistical significance, indicating that our main findings are not mainly driven by startups in the above three cities.

Third, we use different cutoffs of geographical distance (i.e., 25 miles, 100 miles, 150 miles, and 200 miles) to define the geographical proximity between a lead VC and a syndicate member. For example, *Dist_Less_25* is the number of pairs between the lead VC of a startup and any other syndicate members from the first round that has a distance of less than 25 miles between the MSAs of their headquarters. We repeat our IV analyses in Sections 5.4 using these alternative instrumental variables and report the IV results in Tables A1-A5. More specifically, Panel A of each table reports the first-stage regression results with these alternative instrumental variables, whereas Panel B of each table reports the second-stage regression results. We continue to find that the past collaboration experience between the lead VC and any other syndicate members affects startup performance positively and significantly. More importantly, both the magnitude and statistical significance of the coefficient estimate for *Past Collaboration*) are quite stable across different IVs, indicating that our results are not sensitive to the choice of distance cutoffs. Overall, our main findings in both the baseline analyses and the IV analyses are robust to these alternative specifications.

6 Potential Channels for More Efficient Value Creation

6.1 Reduction in Information Asymmetry and Potential Conflicts Between VCs

After establishing that the past collaboration experience between VC pairs indeed creates value for startup companies in terms of successful exit, higher employment and sales growth, and higher innovation capacity, we now explore through which channels the past collaboration experience between VC pairs drives the above effects.

The first potential channel we examine is the reduction in information asymmetry and potential conflicts between VCs. If two VC investors have collaborated with each other and co-invested some startups before, they are more likely to know each other very well (hence the degree of information asymmetry between them is presumably lower), and the potential conflicts between them is likely to be lower. As a result, they are more likely to form a more stable/uniform syndicate for the startup that they currently invest in. If the VC syndicate is more stable across different financing rounds of a startup, the startup is likely to face less financing uncertainty and hence could achieve a higher growth in the long term. Therefore, we hypothesize that a startup backed by VC investors who have collaborated in the past is more likely to have a stable VC syndicate across different financing rounds.

We follow Bayar, Chemmanur, and Tian (2020) and construct a proxy for the stability of VC syndicate across different financing rounds of a startup. We construct the *VC_Comp* as follows:

$$VC\_Comp = (\sum_{i=1}^{N}\sum_{r=1}^{R} VC_{i,r})/(Num\_VC \times Num\_Rounds) \tag{4}$$

$VC_{i,r}$ in the numerator denotes VC i investing in round r. To construct the numerator, we count the number of rounds in which each VC investor participates, and we then aggregate this across all the VC investors in different rounds. Num_VC in the denominator is the number of VC investors of a startup across all rounds of financing, while Num_Rounds represents the number of rounds of financing a startup receives.[7] The VC_Comp measures the degree of overlap of VC syndicate members of a startup company across all financing rounds. Hence, higher this measure, more stable/uniform a VC syndicate across different financing rounds of a startup company.

To empirically test this channel, we run the following specification. We include the same set of control variables and fixed effects as in Eq. 1. The main right-hand side variable of interest is *Past Collaboration*$_{i,t}$. If the stability of VC composition is one of the channels through which the past collaboration between VCs creates value for startups, we would expect to find β to be positive and significant.

$$\textit{VC\_Comp}_{i,t} = \alpha + \beta \textit{Past Collaboration}_{i,t} + \gamma Z_{i,t} + \textit{Industry}_j + \textit{Year}_t + \epsilon_{i,t}, \tag{5}$$

Table 12 reports the results associated with Eq. 5. In Column (1) of Table 12 where we run a univariate regression of VC composition's stability on the *Past Collaboration* dummy, we document a positive coefficient, which is also statistically significant at 5% level. This suggests that, for a

[7] When constructing this measure, we drop two types of startup companies. The first type of startup companies only has one round of financing. We drop this type because these firms will have $VC\_Comp = 1$. However we cannot tell if the VC composition is stable or not across rounds. The second type of startup companies we drop has multiple rounds of financing, but there is only one VC investor in each round. In this case, the VC_Comp will be equal to $\frac{1}{R}$, where R denotes the total number of financing rounds. If startup A has two rounds of financing and a single (yet different) VC investor in each round, while startup B has five rounds of financing and a single investor in each round, this measure will be 1/2 for A and 1/5 for B. There is no overlap of syndicate members across different rounds for both startups. Yet, the measure for these two companies is different.

startup that is backed by VC investors who have collectively invested in the past, the VC syndicate of this startup is more stable across different financing rounds. When we include industry and year fixed effects in Column (2) and all the company, VC-firm, and deal control variables in Column (3), the results remain, which is consistent with our hypothesis. In other words, these results together indicate that the past collaboration experience between VC pairs affects the future success of startups through the channel of VC composition's stability. This is consistent with the prediction of our testable hypothesis **H2**.

6.2 Complementary Skills and Coordination Efficiency

In this subsection, we explore another potential channel through which the past collaboration experience between VC pairs creates value for portfolio companies, which is the complementary skills and coordination efficiency between VCs. We use the past success experience between VC pairs as a proxy for them. We define that a VC pair achieves past success if they have successfully brought a previous startup they co-invested into IPO. We use IPO as the proxy for VC pairs' past success because we argue that, from both startups' and VCs' perspectives, going public is a stronger measure of successful exit than being acquired by another company. For startups that choose to go public, it indicates that they, as stand-alone firms, are more likely to have a strong edge in the product market and can fend for themselves (Bayar and Chemmanur (2011)). From VCs' point of view, going public could also be a more desirable exit choice compared to acquisition of their portfolio companies by others, as Sahlman (1990a) finds that VC investors earn the majority of their financial returns from portfolio companies that eventually go public.[8]

We hypothesize that the complementary skills and coordination efficiency (as proxied by the past success experience) between VC pairs is a potential channel through which the past collaboration between VC pairs affects the future success of startups. The argument is as follows. If a VC pair was able to help a previous startup they co-invested to go public, it could be the case that the VC pair has some complementary capabilities and can coordinate efficiently, such that together they could create greater value for future startups than others can. It is also possible that from this past success the VC pair has learned valuable experience, which they could lever into the current

[8] In an untabulated analysis, we also define the past success of a VC pair as a startup backed by them going public or being acquired by another firm. The results remain consistent with what we show here in this subsection.

startup they are co-investing. In any circumstance, if the past success is indeed one of the channels driving the results, we would expect to find that the future success of startups (as measured by exit, employment and sales growth, as well as innovation) is more pronounced in the sub-sample where VC investors share some successful experience in the past.

To empirically examine this channel, we use the following specification.

$$Y_{i,t} = \alpha + \beta \textit{Past Success}_{i,t} + \gamma Z_{i,t} + \textit{Industry}_j + \textit{Year}_t + \epsilon_{i,t}, \tag{6}$$

The dependent variable $Y_{i,t}$ denotes three sets of outcome variables we examine in our baseline results, which include successful exit, 3-year employment and sales growth, and innovation of startup i receiving its first VC investment in year t. The main independent variable of interest is *Past Success*$_{i,t}$. It is a dummy variable equal to one if the lead VC of startup i has past success experience with any syndicate member from the first round. It is equal to zero otherwise. We run the above specification for the sub-sample of startups that are backed by VCs with past collaboration experience (i.e., startups with *Past Collaboration* $= 1$). In other words, we would like to see the effect of *Past Success*$_{i,t}$ on future success of startups, conditional on VC investors having past collaboration experience. If the past success channel is valid, we would expect to find β to be positive and significant.

We report the corresponding results in Tables 13 to 15. Table 13 shows the results when the dependent variables represent successful exit of startups. In Column (1) where the successful exit of startups is measured by IPO or M&A, we find that the coefficient on *Past Success* is positive and statistically significant at 1% level. This indicates that, conditional on the sub-sample of startups with their VC investors collaborating in the past, the past success between lead VC investors and any syndicate members is still associated with higher probability of startups' exit. When we replace the dependent variable with IPO dummy in Column (2), the inference remains consistent. In Tables 14 and 15 where we regress the 3-year employment and sales growth or innovation output of startups on the *Past Success* variable, we document similar patterns: conditional on the sub-sample of startups with their VC investors having co-invested in the past, the past success between lead VC investors and any syndicate members is associated with higher employment and sales growth, higher probability of startups filing for new patents, and higher innovation quality of startups.

Overall, these results together suggest that the effect of past collaboration of VCs on future success of startups is more concentrated in startups whose VC investors share the past success experience. This indicates that the complementary skills and coordination efficiency between VCs (as measured by past success of VC pairs) is indeed another channel driving our main results, which is consistent with the prediction of our testable hypothesis **H3**.

7 Conclusion

In this paper, we analyze the effect of the composition of venture capital (VC) syndicates on value creation to the entrepreneurial firms that they invest in. We hypothesize that VCs may learn about each other's skills at value creation when they co-invest together in an entrepreneurial firms, allowing for more efficient value creation when they co-invest in subsequent syndicates. Further, if VCs view syndication as a repeated game, this may generate incentives to co-operate to a greater extent with each other when investing together in a syndicate, reducing the probability of conflicts among VCs. We empirically analyze the implications of these hypotheses and find the following. First, prior collaboration between a lead VC and any of the VCs in a syndicate leads to greater short-term value creation, as evidenced by greater sales growth, employment growth, probability of a patented innovation, and the quality of innovations generated during the three years subsequent to VC syndicate investment. Second, prior collaboration between the lead VC and at least one of the members of the syndicate leads to greater long-term value creation, as evidenced by the higher probability of a successful exit (IPO or acquisition). Third, if the prior collaboration is very successful (leading to an IPO exit resulting from the previous collaboration), then there is even greater value creation by the VC syndicate compared to the case where the prior collaboration was less successful. Finally, consistent with prior collaboration allowing VCs to learn about each other's value creation skills and reducing potential conflicts among the VCs forming a syndicate, syndicates with prior collaboration between the lead VC and at least one syndicate member are characterized by more uniform syndicate compositions across financing rounds.

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Figure 1: Distribution of Distance Between Lead VC Investors and VC Syndicate Members

This graph plots the distribution of distance between lead VC investors and VC syndicate members from the first round of all startup companies. This measure is calculated as the distance between the MSAs of VC investors' headquarters. The unit of distance is in miles.

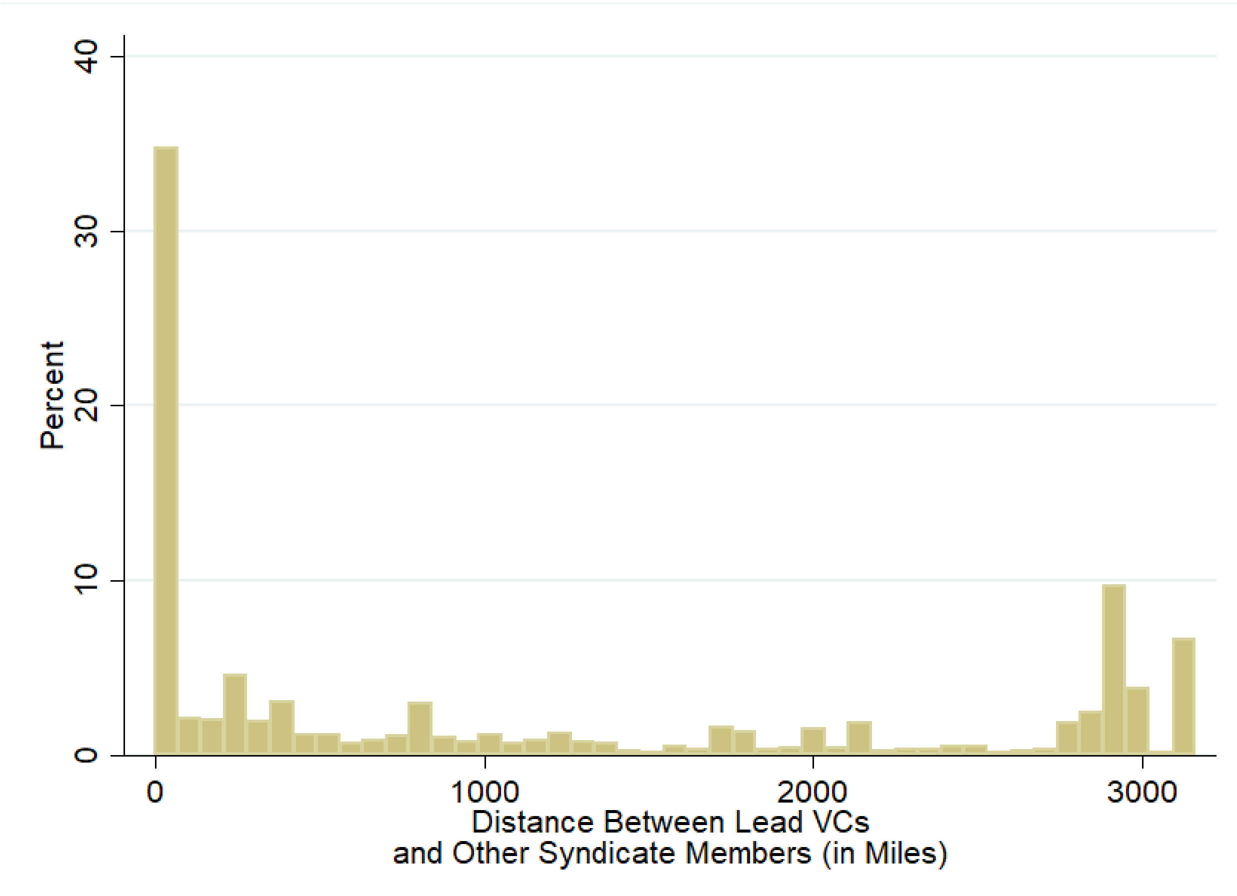

Table 1: Summary Statistics

This table reports the summary statistics of the variables used in our study. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *IPO or M&A* is a dummy variable equal to 1 if a startup exits via IPO or Mergers & Acquisitions (M&A); it is equal to 0 otherwise. *IPO* is a dummy variable equal to 1 if a startup exits via IPO only; it is equal to 0 otherwise. $\Delta\%$*Emp_3y* is the 3-year employment growth (in decimal term) of a startup starting from the year when it receives its first VC investment. $\Delta\%$*Sales_3y* is the 3-year sales growth (in decimal term) of a startup starting from the year when it receives its first VC investment. *New_Pat_1_3* is an indicator variable equal to 1 if a startup files any new patents (that are eventually granted) from the year when it receives its first VC investment to 3 years after; it is equal to 0 otherwise. *CPP_1_3* is the average number of citations per patent of a startup from the year when it receives its first VC investment to 3 years after. It is constructed as the truncation-adjusted number of citations received by all the patents filed within this 3-year period divided by the truncation-adjusted number of patents filed during the same period. *Startup_Age* is the age of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. *Dist_Less_50* is the number of pairs between lead VC and any other syndicate members from the first round that has a distance less than 50 miles between the MSAs of their headquarters.

Variables	N	Mean	Min.	P25	Median	P75	Max.	S.D.
Past Collaboration	19,393	0.273	0.000	0.000	0.000	1.000	1.000	0.446
IPO or M&A	19,393	0.458	0.000	0.000	0.000	1.000	1.000	0.498
IPO	19,393	0.116	0.000	0.000	0.000	0.000	1.000	0.320
$\Delta\%$Emp_3y	5,009	1.396	-1.000	0.000	0.060	1.231	13.667	3.151
$\Delta\%$Sales_3y	5,008	1.698	-1.000	-0.053	0.136	1.264	19.000	4.159
New_Pat_1_3	19,393	0.193	0.000	0.000	0.000	0.000	1.000	0.395
CPP_1_3	19,393	0.142	0.000	0.000	0.000	0.000	1.481	0.368
Startup_Age	16,361	3.476	0.000	1.000	2.000	4.000	160.000	7.448
Emp	10,340	20.381	0.000	0.000	3.000	11.000	25,167.000	281.851
VC_Age	19,393	13.654	0.000	4.000	9.000	18.000	159.000	15.786
First_Round_Inv	18,482	9.377	0.001	2.000	4.500	9.900	2,250.000	27.832
Dist_Less_50	19,393	0.564	0.000	0.000	0.000	1.000	11.000	0.914

Table 2: Past VC Collaboration and Successful Startup Exit

This table reports the results of OLS regression of startups' exits on their VC investors' past collaboration. *IPO or M&A* is a dummy variable equal to 1 if a startup exits via IPO or Mergers & Acquisitions (M&A); it is equal to 0 otherwise. *IPO* is a dummy variable equal to 1 if a startup exits via IPO only; it is equal to 0 otherwise. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are excluded in columns (1) and (4) and are included in other specifications. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	IPO or M&A			IPO		
	(1)	(2)	(3)	(4)	(5)	(6)
Past Collaboration	0.0835***	0.0419***	0.0445***	0.0348***	0.0191**	0.0240***
	(0.0142)	(0.0084)	(0.0083)	(0.0083)	(0.0074)	(0.0066)
Startup_Age			-0.0016**			-0.0004
			(0.0007)			(0.0003)
Emp			0.0000			0.0000***
			(0.0000)			(0.0000)
VC_Age			0.0006*			0.0003
			(0.0003)			(0.0002)
First_Round_Inv			0.0012***			0.0010**
			(0.0004)			(0.0004)
Industry FE	No	Yes	Yes	No	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
Adjusted R^2	0.0055	0.2382	0.1891	0.0021	0.1546	0.1322
Number of Obs.	17,360	17,358	8,196	17,360	17,358	8,196

Table 3: Past VC Collaboration and Startup Employment Growth

This table reports the results of OLS regression of startups' employment growth on their VC investors' past collaboration. $\Delta\%$*Emp_3y* is the 3-year employment growth (in decimal term) of a startup starting from the year when it receives its first VC investment. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are excluded in column (1) and are included in other specifications. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	$\Delta\%$Emp_3y		
	(1)	(2)	(3)
Past Collaboration	0.0989***	0.1012***	0.0866***
	(0.0099)	(0.0146)	(0.0217)
Startup_Age			-0.0187***
			(0.0050)
Emp			-0.0004**
			(0.0002)
VC_Age			0.0049*
			(0.0025)
First_Round_Inv			0.0075*
			(0.0043)
Industry FE	No	Yes	Yes
Year FE	No	Yes	Yes
Adjusted R^2	0.0000	0.0177	0.0268
Number of Obs.	4,744	4,734	4,111

Table 4: Past VC Collaboration and Startup Sales Growth

This table reports the results of OLS regression of startups' sales growth on their VC investors' past collaboration. *$\Delta\%$Sales_3y* is the 3-year sales growth (in decimal term) of a startup starting from the year when it receives its first VC investment. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are excluded in column (1) and are included in other specifications. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	$\Delta\%$Sales_3y		
	(1)	(2)	(3)
Past Collaboration	0.1049*	0.1212	0.1317***
	(0.0535)	(0.0816)	(0.0359)
Startup_Age			-0.0186**
			(0.0083)
Emp			-0.0005***
			(0.0002)
VC_Age			0.0080***
			(0.0028)
First_Round_Inv			0.0122**
			(0.0059)
Industry FE	No	Yes	Yes
Year FE	No	Yes	Yes
Adjusted R^2	0.0001	0.0157	0.0242
Number of Obs.	4,743	4,733	4,110

Table 5: Past VC Collaboration and Probability of Startup Successful Innovation

This table reports the results of OLS regression of startups' filing of new patents on their VC investors' past collaboration. *New_Pat_1_3* is an indicator variable equal to 1 if a startup files any new patents (that are eventually granted) from the year when it receives its first VC investment to 3 years after; it is equal to 0 otherwise. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are excluded in column (1) and are included in other specifications. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	New_Pat_1_3		
	(1)	(2)	(3)
Past Collaboration	0.0665***	0.0473***	0.0400***
	(0.0113)	(0.0077)	(0.0073)
Startup_Age			-0.0046***
			(0.0005)
Emp			0.0000
			(0.0000)
VC_Age			0.0010***
			(0.0003)
First_Round_Inv			0.0005**
			(0.0002)
Industry FE	No	Yes	Yes
Year FE	No	Yes	Yes
Adjusted R^2	0.0054	0.1398	0.1463
Number of Obs.	17,360	17,358	8,196

Table 6: Past VC Collaboration and Startup Innovation Quality

This table reports the results of OLS regression of startups' innovation quality (as measured by the number of citations per patent) on their VC investors' past collaboration. *CPP_1_3* is the average number of citations per patent of a startup from the year when it receives its first VC investment to 3 years after. It is constructed as the truncation-adjusted number of citations received by all the patents filed within this 3-year period divided by the truncation-adjusted number of patents filed during the same period. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are excluded in column (1) and are included in other specifications. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	CPP_1_3		
	(1)	(2)	(3)
Past Collaboration	0.0626***	0.0463***	0.0400***
	(0.0131)	(0.0101)	(0.0108)
Startup_Age			-0.0045***
			(0.0006)
Emp			-0.0000
			(0.0000)
VC_Age			0.0006**
			(0.0003)
First_Round_Inv			0.0004**
			(0.0002)
Industry FE	No	Yes	Yes
Year FE	No	Yes	Yes
Adjusted R^2	0.0054	0.1047	0.1113
Number of Obs.	17,360	17,358	8,196

Table 7: IV Analysis: Past VC Collaboration and Successful Startup Exit

This table reports the results of IV regression of startups' exits on their VC investors' past collaboration. We instrument the *Past Collaboration* with *Dist_Less_50*, which is constructed, for each startup, as the number of pairs between lead VC and any other syndicate members from the first round that has a distance less than 50 miles between the MSAs of their headquarters. *IPO or M&A* is a dummy variable equal to 1 if a startup exits via IPO or Mergers & Acquisitions (M&A); it is equal to 0 otherwise. *IPO* is a dummy variable equal to 1 if a startup exits via IPO only; it is equal to 0 otherwise. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup, which is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup, which is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	Past Collaboration	IPO or M&A	Past Collaboration	IPO
	(1)	(2)	(3)	(4)
Dist_Less_50	0.1042***		0.1042***	
	(0.0083)		(0.0083)	
Past Collaboration		0.1680**		0.0658**
		(0.0740)		(0.0293)
Startup_Age	-0.0039***	-0.0009	-0.0039***	-0.0002
	(0.0005)	(0.0008)	(0.0005)	(0.0004)
Emp	0.0000	0.0000	0.0000	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
VC_Age	0.0044***	-0.0000	0.0044***	0.0001
	(0.0001)	(0.0006)	(0.0001)	(0.0002)
First_Round_Inv	0.0005**	0.0011**	0.0005**	0.0010**
	(0.0002)	(0.0004)	(0.0002)	(0.0004)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.0926	–	0.0926	–
Number of Obs.	8,196	8,196	8,196	8,196
Kleibergen-Paap rk Wald F stat	159.16		159.16	

Table 8: IV Analysis: Past VC Collaboration and Startup Employment Growth

This table reports the results of IV regression of startups' employment growth on their VC investors' past collaboration. We instrument the *Past Collaboration* with *Dist_Less_50*, which is constructed, for each startup, as the number of pairs between lead VC and any other syndicate members from the first round that has a distance less than 50 miles between the MSAs of their headquarters. $\Delta\%$*Emp_3y* is the 3-year employment growth (in decimal term) of a startup starting from the year when it receives its first VC investment. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup, which is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup, which is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	Past Collaboration	$\Delta\%$Emp_3y
	(1)	(2)
Dist_Less_50	0.1076***	
	(0.0138)	
Past Collaboration		0.5763***
		(0.1158)
Startup_Age	-0.0031***	-0.0166***
	(0.0010)	(0.0058)
Emp	-0.0000	-0.0004**
	(0.0000)	(0.0002)
VC_Age	0.0043***	0.0027
	(0.0002)	(0.0031)
First_Round_Inv	0.0010*	0.0070
	(0.0005)	(0.0044)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.0854	–
Number of Obs.	4,111	4,111
Kleibergen-Paap rk Wald F stat	61.13	

Table 9: IV Analysis: Past VC Collaboration and Startup Sales Growth

This table reports the results of IV regression of startups' sales growth on their VC investors' past collaboration. We instrument the *Past Collaboration* with *Dist_Less_50*, which is constructed, for each startup, as the number of pairs between lead VC and any other syndicate members from the first round that has a distance less than 50 miles between the MSAs of their headquarters. $\Delta\%$*Sales_3y* is the 3-year sales growth (in decimal term) of a startup starting from the year when it receives its first VC investment. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup, which is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup, which is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	Past Collaboration	$\Delta\%$Sales_3y
	(1)	(2)
Dist_Less_50	0.1075***	
	(0.0138)	
Past Collaboration		1.0365***
		(0.3251)
Startup_Age	-0.0031***	-0.0148*
	(0.0010)	(0.0087)
Emp	-0.0000	-0.0005***
	(0.0000)	(0.0002)
VC_Age	0.0043***	0.0039
	(0.0002)	(0.0040)
First_Round_Inv	0.0010*	0.0113*
	(0.0005)	(0.0061)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.0852	–
Number of Obs.	4,110	4,110
Kleibergen-Paap rk Wald F stat	61.52	

Table 10: IV Analysis: Past VC Collaboration and Probability of Startup Successful Innovation

This table reports the results of IV regression of startups' filing of new patents on their VC investors' past collaboration. We instrument the *Past Collaboration* with *Dist_Less_50*, which is constructed, for each startup, as the number of pairs between lead VC and any other syndicate members from the first round that has a distance less than 50 miles between the MSAs of their headquarters. *New_Pat_1_3* is an indicator variable equal to 1 if a startup files any new patents (that are eventually granted) from the year when it receives its first VC investment to 3 years after; it is equal to 0 otherwise. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup, which is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup, which is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	Past Collaboration	New_Pat_1_3
	(1)	(2)
Dist_Less_50	0.1042***	
	(0.0083)	
Past Collaboration		0.1770***
		(0.0361)
Startup_Age	-0.0039***	-0.0039***
	(0.0005)	(0.0005)
Emp	0.0000	0.0000
	(0.0000)	(0.0000)
VC_Age	0.0044***	0.0003
	(0.0001)	(0.0004)
First_Round_Inv	0.0005**	0.0005**
	(0.0002)	(0.0002)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.0926	–
Number of Obs.	8,196	8,196
Kleibergen-Paap rk Wald F stat	159.16	

Table 11: IV Analysis: Past VC Collaboration and Startup Innovation Quality

This table reports the results of IV regression of startups' innovation quality on their VC investors' past collaboration. We instrument the *Past Collaboration* with *Dist_Less_50*, which is constructed, for each startup, as the number of pairs between lead VC and any other syndicate members from the first round that has a distance less than 50 miles between the MSAs of their headquarters. *CPP_1_3* is the average number of citations per patent of a startup from the year when it receives its first VC investment to 3 years after. It is constructed as the truncation-adjusted number of citations received by all the patents filed within this 3-year period divided by the truncation-adjusted number of patents filed during the same period. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup, which is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup, which is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	Past Collaboration	CPP_1_3
	(1)	(2)
Dist_Less_50	0.1042***	
	(0.0083)	
Past Collaboration		0.1409***
		(0.0157)
Startup_Age	-0.0039***	-0.0039***
	(0.0005)	(0.0006)
Emp	0.0000	-0.0000
	(0.0000)	(0.0000)
VC_Age	0.0044***	0.0001
	(0.0001)	(0.0003)
First_Round_Inv	0.0005**	0.0004**
	(0.0002)	(0.0002)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.0926	–
Number of Obs.	8,196	8,196
Kleibergen-Paap rk Wald F stat	159.16	

Table 12: VCs' Past Collaboration and Composition of VC Syndicates

This table reports the results of OLS regression of VC composition on VC investors' past collaboration. *VC_Comp* is constructed as $(\sum_{i=1}^{N}\sum_{r=1}^{R} VC_{i,r})/(Num\_VC \times Num\_Rounds)$, where $VC_{i,r}$ in the numerator denotes VC i investing in round r. We count the number of rounds in which each VC investor participates, and we then aggregate this across all the VC investors in different rounds. Num_VC in the denominator denotes the number of VC investors across all financing rounds. Num_Rounds in the denominator denotes the number of financing rounds a startup receives. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are excluded in column (1) and are included in other specifications. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	VC_Comp		
	(1)	(2)	(3)
Past Collaboration	0.0099**	0.0125***	0.0205***
	(0.0038)	(0.0039)	(0.0041)
Startup_Age			0.0025***
			(0.0002)
Emp			0.0000
			(0.0000)
VC_Age			-0.0002
			(0.0002)
First_Round_Inv			-0.0002**
			(0.0001)
Industry FE	No	Yes	Yes
Year FE	No	Yes	Yes
Adjusted R^2	0.0004	0.0521	0.0741
Number of Obs.	11,631	11,628	6,306

Table 13: Past VC Collaboration, VCs' Past Syndicate Success, and Successful Startup Exit

This table reports the results of OLS regression of startups' exits on their VC investors' past success, conditional on the subsample of startups where the VC investors from the first round have co-invested in the past. *IPO or M&A* is a dummy variable equal to 1 if a startup exits via IPO or Mergers & Acquisitions (M&A); it is equal to 0 otherwise. *IPO* is a dummy variable equal to 1 if a startup exits via IPO only; it is equal to 0 otherwise. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Past Success* is an indicator variable equal to 1 if at least one pair between the lead VC investor and any other syndicate members from the first round has previously brought a startup into IPO; it is equal to 0 otherwise. *Startup_Age* is the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	IPO or M&A	IPO
	(1)	(2)
	(Past Collaboration = 1)	
Past Success	0.0628***	0.0595***
	(0.0098)	(0.0180)
Startup_Age	-0.0039**	-0.0019***
	(0.0015)	(0.0006)
Emp	0.0000	0.0001***
	(0.0000)	(0.0000)
VC_Age	0.0007	0.0003
	(0.0006)	(0.0003)
First_Round_Inv	0.0007**	0.0006*
	(0.0003)	(0.0003)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.1764	0.1475
Number of Obs.	2,344	2,344

Table 14: Past VC Collaboration, VCs' Past Syndicate Success, and Startup Employment and Sales Growth

This table reports the results of OLS regression of startups' employment and sales growth on their VC investors' past success, conditional on the subsample of startups where the VC investors from the first round have co-invested in the past. $\Delta\%$*Emp_3y* is the 3-year employment growth (in decimal term) of a startup starting from the year when it receives its first VC investment. $\Delta\%$*Sales_3y* is the 3-year sales growth (in decimal term) of a startup starting from the year when it receives its first VC investment. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Past Success* is an indicator variable equal to 1 if at least one pair between the lead VC investor and any other syndicate members from the first round has previously brought a startup into IPO; it is equal to 0 otherwise. *Startup_Age* is the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	$\Delta\%$Emp_3y	$\Delta\%$Sales_3y
	(1)	(2)
	(Past Collaboration = 1)	
Past Success	0.2447***	0.2714**
	(0.0873)	(0.1288)
Startup_Age	-0.0566***	-0.0694***
	(0.0094)	(0.0147)
Emp	-0.0006***	-0.0007***
	(0.0001)	(0.0002)
VC_Age	-0.0022	-0.0013
	(0.0081)	(0.0085)
First_Round_Inv	0.0080***	0.0128**
	(0.0026)	(0.0050)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.0220	0.0261
Number of Obs.	1,172	1,171

Table 15: Past VC Collaboration, VCs' Past Syndicate Success, and Startup Innovation

This table reports the results of OLS regression of startups' innovation capacity on their VC investors' past success, conditional on the subsample of startups where the VC investors from the first round have co-invested in the past. *New_Pat_1_3* is an indicator variable equal to 1 if a startup files any new patents (that are eventually granted) from the year when it receives its first VC investment to 3 years after; it is equal to 0 otherwise. *CPP_1_3* is the truncation-adjusted number of citations received by all the patents of a startup filed within 3-year period after the first investment divided by the truncation-adjusted number of patents filed during the same period. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Past Success* is an indicator variable equal to 1 if at least one pair between the lead VC investor and any other syndicate members from the first round has previously brought a startup into IPO; it is equal to 0 otherwise. *Startup_Age* is the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	New_Pat_1_3	CPP_1_3
	(1)	(2)
	(Past Collaboration = 1)	
Past Success	0.0686***	0.0746***
	(0.0162)	(0.0205)
Startup_Age	-0.0047**	-0.0062***
	(0.0019)	(0.0016)
Emp	0.0001***	0.0000***
	(0.0000)	(0.0000)
VC_Age	0.0009*	0.0005
	(0.0005)	(0.0006)
First_Round_Inv	0.0008***	0.0007***
	(0.0001)	(0.0001)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.1449	0.1160
Number of Obs.	2,344	2,344

Appendices

Table A.1: Past VC Collaboration and Successful Startup Exit: Continuous Measure of Past Collaboration

This table reports the robustness checks of baseline OLS regression of startups' exits on their VC investors' past collaboration using a continuous measure of VCs' past collaboration (instead of a dummy variable). *IPO or M&A* is a dummy variable equal to 1 if a startup exits via IPO or Mergers & Acquisitions (M&A); it is equal to 0 otherwise. *IPO* is a dummy variable equal to 1 if a startup exits via IPO only; it is equal to 0 otherwise. *Num of Collaboration* is the natural logarithm of 1 plus the average number of past collaborations (i.e., number of prior co-investments) between the lead VC investor of a startup and any other syndicate members from the first round. *Startup_Age* is the age of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	IPO or M&A (1)	IPO (2)
Num of Collaboration	0.0501***	0.0384***
	(0.0124)	(0.0092)
Startup_Age	-0.0016**	-0.0004
	(0.0007)	(0.0003)
Emp	0.0000	0.0000***
	(0.0000)	(0.0000)
VC_Age	0.0005	0.0002
	(0.0003)	(0.0002)
First_Round_Inv	0.0012***	0.0010**
	(0.0004)	(0.0004)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.1888	0.1330
Number of Obs.	8,196	8,196

Table A.2: Past VC Collaboration and Startup Employment and Sales Growth: Continuous Measure of Past Collaboration

This table reports the robustness checks of baseline OLS regression of startups' employment and sales growth on their VC investors' past collaboration using a continuous measure of VCs' past collaboration (instead of a dummy variable). $\Delta\%$*Emp_3y* is the 3-year employment growth (in decimal term) of a startup starting from the year when it receives its first VC investment. $\Delta\%$*Sales_3y* is the 3-year sales growth (in decimal term) of a startup starting from the year when it receives its first VC investment. *Num of Collaboration* is the natural logarithm of 1 plus the average number of past collaborations (i.e., number of prior co-investments) between the lead VC investor of a startup and any other syndicate members from the first round. *Startup_Age* is the age of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	$\Delta\%$Emp_3y	$\Delta\%$Sales_3y
	(1)	(2)
Num of Collaboration	0.1211	0.2164**
	(0.0729)	(0.0983)
Startup_Age	-0.0187***	-0.0185**
	(0.0049)	(0.0078)
Emp	-0.0004**	-0.0005***
	(0.0002)	(0.0002)
VC_Age	0.0048*	0.0077**
	(0.0026)	(0.0031)
First_Round_Inv	0.0075*	0.0122**
	(0.0043)	(0.0059)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.0268	0.0244
Number of Obs.	4,111	4,110

Table A.3: Past VC Collaboration and Startup Innovation: Continuous Measure of Past Collaboration

This table reports the robustness checks of baseline OLS regression of startups' innovation capacity on their VC investors' past collaboration using a continuous measure of VCs' past collaboration (instead of a dummy variable). *New_Pat_1_3* is an indicator variable equal to 1 if a startup files any new patents (that are eventually granted) from the year when it receives its first VC investment to 3 years after; it is equal to 0 otherwise. *CPP_1_3* is the truncation-adjusted number of citations received by all the patents filed by a startup within 3-year period after the first investment divided by the truncation-adjusted number of patents filed during the same period. *Num of Collaboration* is the natural logarithm of 1 plus the number of past collaborations (i.e., number of prior co-investments) between the lead VC investor of a startup and any other syndicate members from the first round. *Startup_Age* is the age of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	New_Pat_1_3	CPP_1_3
	(1)	(2)
Num of Collaboration	0.0510***	0.0456***
	(0.0141)	(0.0152)
Startup_Age	-0.0046***	-0.0045***
	(0.0005)	(0.0006)
Emp	0.0000	0.0000
	(0.0000)	(0.0000)
VC_Age	0.0009***	0.0006**
	(0.0003)	(0.0002)
First_Round_Inv	0.0005**	0.0005**
	(0.0002)	(0.0002)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.1463	0.1109
Number of Obs.	8,196	8,196

Table A.4: Past VC Collaboration and Successful Startup Exit

This table reports the robustness checks of baseline OLS regression of startups' exits on their VC investors' past collaboration, conditional on the subsample of startups where we exclude startups in San Francisco/New York/Boston areas. *IPO or M&A* is a dummy variable equal to 1 if a startup exits via IPO or Mergers & Acquisitions (M&A); it is equal to 0 otherwise. *IPO* is a dummy variable equal to 1 if a startup exits via IPO only; it is equal to 0 otherwise. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	IPO or M&A	IPO
	(1)	(2)
Past Collaboration	0.0435***	0.0290***
	(0.0106)	(0.0070)
Startup_Age	-0.0014*	-0.0004
	(0.0007)	(0.0004)
Emp	0.0000	0.0000**
	(0.0000)	(0.0000)
VC_Age	0.0005	0.0003
	(0.0003)	(0.0002)
First_Round_Inv	0.0011**	0.0010**
	(0.0005)	(0.0004)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.1825	0.1349
Number of Obs.	6,453	6,453

Table A.5: Past VC Collaboration and Startup Employment and Sales Growth

This table reports the robustness checks of baseline OLS regression of startups' employment and sales growth on their VC investors' past collaboration, conditional on the subsample of startups where we exclude startups in San Francisco/New York/Boston areas. $\Delta\%$*Emp_3y* is the 3-year employment growth (in decimal term) of a startup starting from the year when it receives its first VC investment. $\Delta\%$*Sales_3y* is the 3-year sales growth (in decimal term) of a startup starting from the year when it receives its first VC investment. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	$\Delta\%$Emp_3y	$\Delta\%$Sales_3y
	(1)	(2)
Past Collaboration	0.0789*	0.1678
	(0.0423)	(0.1163)
Startup_Age	-0.0145***	-0.0123
	(0.0049)	(0.0086)
Emp	-0.0004***	-0.0006***
	(0.0001)	(0.0001)
VC_Age	0.0075***	0.0130***
	(0.0022)	(0.0027)
First_Round_Inv	0.0069	0.0113*
	(0.0041)	(0.0057)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.0270	0.0250
Number of Obs.	3,216	3,215

Table A.6: Past VC Collaboration and Startup Innovation

This table reports the robustness checks of baseline OLS regression of startups' innovation capacity on their VC investors' past collaboration, conditional on the subsample of startups where we exclude startups in San Francisco/New York/Boston areas. *New_Pat_1_3* is an indicator variable equal to 1 if a startup files any new patents (that are eventually granted) from the year when it receives its first VC investment to 3 years after; it is equal to 0 otherwise. *CPP_1_3* is the truncation-adjusted number of citations received by all the patents filed by a startup within 3-year period after the first investment divided by the truncation-adjusted number of patents filed during the same period. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round; it is equal to 0 otherwise. *Startup_Age* is the age of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when a startup is founded. *Emp* is the number of employees of a startup when it receives its first VC investment. *VC_Age* is the age of the lead VC investor of a startup. It is constructed as the difference between the year when a startup receives its first VC investment and the year when the lead VC is founded. *First_Round_Inv* is the dollar investment amount (in million) received by a startup in the first round. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	New_Pat_1_3	CPP_1_3
	(1)	(2)
Past Collaboration	0.0423***	0.0470***
	(0.0093)	(0.0120)
Startup_Age	-0.0051***	-0.0048***
	(0.0007)	(0.0006)
Emp	0.0000	0.0000
	(0.0000)	(0.0000)
VC_Age	0.0010**	0.0006
	(0.0004)	(0.0004)
First_Round_Inv	0.0003*	0.0003*
	(0.0002)	(0.0002)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.1495	0.1062
Number of Obs.	6,453	6,453

Table A.7: Past VC Collaboration and Successful Startup Exit: IV Analysis Using Different Distance Cutoff Points

This table reports the robustness checks of IV regression of startups' exits on their VC investors' past collaboration. We instrument the *Past Collaboration* with variables using different distance cutoff points. For example, *Dist_Less_25* is the number of pairs between the lead VC of a startup and any other syndicate members from the first round that has a distance less than 25 miles between the MSAs of their headquarters. *IPO or M&A* is a dummy variable equal to 1 if a startup exits via IPO or Mergers & Acquisitions (M&A). *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round. All other control variables are defined similarly as in previous tables. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

Panel A: First-stage regressions				
	Past Collaboration			
	(1)	(2)	(3)	(4)
Dist_Less_25	0.1037***			
	(0.0101)			
Dist_Less_100		0.1027***		
		(0.0076)		
Dist_Less_150			0.0998***	
			(0.0077)	
Dist_Less_200				0.0988***
				(0.0083)
Firm-Level Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.0772	0.0926	0.0907	0.0906
Number of Obs.	8,196	8,196	8,196	8,196
Kleibergen-Paap rk Wald F stat	107.23	186.41	172.02	144.64
Panel B: Second-stage regressions				
	IPO or M&A			
	(1)	(2)	(3)	(4)
Past Collaboration (Dist_Less_25)	0.1329*			
	(0.0759)			
Past Collaboration (Dist_Less_100)		0.1745**		
		(0.0716)		
Past Collaboration (Dist_Less_150)			0.1511**	
			(0.0722)	
Past Collaboration (Dist_Less_200)				0.1564**
				(0.0680)
Firm-Level Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	–	–	–	–
Number of Obs.	8,196	8,196	8,196	8,196

Table A.8: Past VC Collaboration and Startup Employment Growth: IV Analysis Using Different Distance Cutoff Points

This table reports the robustness checks of IV regression of startups' employment growth on their VC investors' past collaboration. We instrument the *Past Collaboration* with variables using different distance cutoff points. For example, *Dist_Less_25* is the number of pairs between the lead VC of a startup and any other syndicate members from the first round that has a distance less than 25 miles between the MSAs of their headquarters. $\Delta\%$*Emp_3y* is the 3-year employment growth (in decimal term) of a startup starting from the year when it receives its first VC investment. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round. All other control variables are defined similarly as in previous tables. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

Panel A: First-stage regressions				
	Past Collaboration			
	(1)	(2)	(3)	(4)
Dist_Less_25	0.1167***			
	(0.0170)			
Dist_Less_100		0.1070***		
		(0.0123)		
Dist_Less_150			0.1037***	
			(0.0116)	
Dist_Less_200				0.1023***
				(0.0123)
Firm-Level Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.0747	0.0859	0.0840	0.0840
Number of Obs.	4,111	4,111	4,111	4,111
Kleibergen-Paap rk Wald F stat	47.67	76.47	80.78	69.73
Panel B: Second-stage regressions				
	$\Delta\%$Emp_3y			
	(1)	(2)	(3)	(4)
Past Collaboration (Dist_Less_25)	0.8038			
	(–)			
Past Collaboration (Dist_Less_100)		0.5386		
		(–)		
Past Collaboration (Dist_Less_150)			0.4718	
			(–)	
Past Collaboration (Dist_Less_200)				0.4298
				(–)
Firm-Level Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	–	–	–	–
Number of Obs.	4,111	4,111	4,111	4,111

Table A.9: Past VC Collaboration and Startup Sales Growth: IV Analysis Using Different Distance Cutoff Points

This table reports the robustness checks of IV regression of startups' sales growth on their VC investors' past collaboration. We instrument the *Past Collaboration* with variables using different distance cutoff points. For example, *Dist_Less_25* is the number of pairs between the lead VC of a startup and any other syndicate members from the first round that has a distance less than 25 miles between the MSAs of their headquarters. $\Delta\%$*Sales_3y* is the 3-year sales growth (in decimal term) of a startup starting from the year when it receives its first VC investment. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round. All other control variables are defined similarly as in previous tables. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

Panel A: First-stage regressions				
	Past Collaboration			
	(1)	(2)	(3)	(4)
Dist_Less_25	0.1165***			
	(0.0169)			
Dist_Less_100		0.1070***		
		(0.0123)		
Dist_Less_150			0.1036***	
			(0.0116)	
Dist_Less_200				0.1022***
				(0.0123)
Firm-Level Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.0745	0.0858	0.0839	0.0839
Number of Obs.	4,110	4,110	4,110	4,110
Kleibergen-Paap rk Wald F stat	47.94	76.99	81.31	70.12
Panel B: Second-stage regressions				
	$\Delta\%$Sales_3y			
	(1)	(2)	(3)	(4)
Past Collaboration (Dist_Less_25)	1.5206***			
	(0.3225)			
Past Collaboration (Dist_Less_100)		0.9842***		
		(0.3356)		
Past Collaboration (Dist_Less_150)			0.8735*	
			(0.4262)	
Past Collaboration (Dist_Less_200)				0.9132**
				(0.3546)
Firm-Level Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	–	–	–	–
Number of Obs.	4,110	4,110	4,110	4,110

Table A.10: Past VC Collaboration and Probability of Startup Successful Innovation: IV Analysis Using Different Distance Cutoff Points

This table reports the robustness checks of IV regression of startups' filing of new patents on their VC investors' past collaboration. We instrument the *Past Collaboration* with variables using different distance cutoff points. For example, *Dist_Less_25* is the number of pairs between the lead VC of a startup and any other syndicate members from the first round that has a distance less than 25 miles between the MSAs of their headquarters. *New_Pat_1_3* is an indicator variable equal to 1 if a startup files any new patents (that are eventually granted) from the year when it receives its first VC investment to 3 years after. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round. All other control variables are defined similarly as in previous tables. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

Panel A: First-stage regressions				
	Past Collaboration			
	(1)	(2)	(3)	(4)
Dist_Less_25	0.1037***			
	(0.0101)			
Dist_Less_100		0.1027***		
		(0.0076)		
Dist_Less_150			0.0998***	
			(0.0077)	
Dist_Less_200				0.0988***
				(0.0083)
Firm-Level Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.0772	0.0926	0.0907	0.0906
Number of Obs.	8,196	8,196	8,196	8,196
Kleibergen-Paap rk Wald F stat	107.23	186.41	172.02	144.64
Panel B: Second-stage regressions				
	New_Pat_1_3			
	(1)	(2)	(3)	(4)
Past Collaboration (Dist_25)	0.0871			
	(0.0648)			
Past Collaboration (Dist_100)		0.1511***		
		(0.0375)		
Past Collaboration (Dist_150)			0.1442***	
			(0.0405)	
Past Collaboration (Dist_200)				0.1298***
				(0.0462)
Firm-Level Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	–	–	–	–
Number of Obs.	8,196	8,196	8,196	8,196

Table A.11: Past VC Collaboration and Startup Innovation Quality: IV Analysis Using Different Distance Cutoff Points

This table reports the robustness checks of IV regression of startups' innovation quality on their VC investors' past collaboration. We instrument the *Past Collaboration* with variables using different distance cutoff points. For example, *Dist_Less_25* is the number of pairs between the lead VC of a startup and any other syndicate members from the first round that has a distance less than 25 miles between MSAs of their headquarters. *CPP_1_3* is truncation-adjusted number of citations received by all patents filed by a startup within 3-year period after first investment divided by the truncation-adjusted number of patents filed during the same period. *Past Collaboration* is a dummy variable equal to 1 if the lead VC investor of a startup has co-invested in the past with any other syndicate members from the first round. All other control variables are defined similarly as in previous tables. 2-digit SIC industry and year fixed effects are included. Robust standard errors are double clustered by industry and year. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

Panel A: First-stage regressions				
	Past Collaboration			
	(1)	(2)	(3)	(4)
Dist_Less_25	0.1037***			
	(0.0101)			
Dist_Less_100		0.1027***		
		(0.0076)		
Dist_Less_150			0.0998***	
			(0.0077)	
Dist_Less_200				0.0988***
				(0.0083)
Firm-Level Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.0772	0.0926	0.0907	0.0906
Number of Obs.	8,196	8,196	8,196	8,196
Kleibergen-Paap rk Wald F stat	107.23	186.41	172.02	144.64
Panel B: Second-stage regressions				
	CPP_1_3			
	(1)	(2)	(3)	(4)
Past Collaboration (Dist_Less_25)	0.0992**			
	(0.0428)			
Past Collaboration (Dist_Less_100)		0.1312***		
		(0.0200)		
Past Collaboration (Dist_Less_150)			0.1270***	
			(0.0230)	
Past Collaboration (Dist_Less_200)				0.1086***
				(0.0283)
Firm-Level Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	–	–	–	–
Number of Obs.	8,196	8,196	8,196	8,196