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The Impact of Venture Capital Monitoring: Evidence from a Natural Experiment

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JEL Classification: D81, G24, L26, M13, O31, O32

Keywords: Venture Capital, Monitoring, Innovation, Agglomeration

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1 Introduction

It is often argued that venture capital (VC) plays an important role in promoting innovation and growth. Consistent with this belief, governments around the world have pursued a number of policies aimed at fostering local venture capital activity. The goal of these policies has been to replicate the success of regions like Silicon Valley in the United States. However, there remains scarce evidence that the activities of venture capitalists actually play a causal role in stimulating the creation of innovative and successful companies. Indeed, venture capitalists may simply select companies that are poised to innovate and succeed, even absent their involvement. In this case, efforts by policy-makers to foster local venture capital activity would be misguided. In this paper, we examine whether the activities of venture capitalists do indeed affect portfolio company outcomes.

Identifying the effect of venture capital is difficult for several reasons. First, in many cases, data are only available for VC-backed companies; thus there is no control group available to estimate a counterfactual. Second, even when data on seemingly comparable non-VC-backed companies are available, it is likely that these companies differ along unobservable dimensions that may drive differences in outcomes. This is especially true given that only coarse information can generally be observed about these privately held companies. Finally, expectations about future events may drive investment, leading to reverse causality concerns (Rin et al., 2011). For example, VC-backed companies may grow faster than their matched peers subsequent to investment; however, this may simply reflect the fact that VCs seek investment opportunities with the potential for near-term rapid growth. While the ideal experiment to identify the effect of venture capital would likely involve the random allocation of VC funding, finding a natural experiment that approximates this ideal has been difficult.

We attempt to make progress on this important question by taking a somewhat different approach. Rather than seeking exogenous variation in venture capital investment, we instead exploit a natural experiment that leads to exogenous variation in monitoring costs within existing VC-company relationships. If differences in outcomes for venture-backed companies are driven only by selection, reductions in monitoring costs subsequent to investment should have no effect. On the other hand, if VC activities do matter, reductions in the cost of monitoring should translate into better portfolio company performance by allowing VCs to engage in more of these activities. For example VCs may be able to spend more time advising and shaping senior management, providing access to key resources, and aiding in company professionalization in myriad other ways that have been documented in the literature.

The shock to monitoring costs that we utilize is the introduction of new airline routes that reduce the travel time between venture capital firms and their portfolio companies. Previous work suggests that such travel time reductions lower monitoring costs for firms with headquarters that are geographically separated from their production facilities (Giroud, 2013). In the context of venture capital, there is ample anecdotal evidence that venture capitalists are sensitive to distance and travel time. For example, in response to a new United Airlines flight between Raleigh-Durham and San Francisco in 2012, the president of the Durham Chamber of Commerce stated that the new route would be valuable to "venture capitalists who like to be a direct flight away from any company they're going to invest in" (News & Observer, August 12, 2012). Similarly, the lack of direct flights to Indianapolis is seen as an impediment to venture capital in the area: "Layovers and complicated connections are aggravating [...] That's an important consideration because most venture capitalists want to keep close tabs on the companies they invest in, which requires frequent in-person visits"

(Indianapolis Star, October 8, 2000).¹

Consistent with the anecdotal evidence, the academic literature shows that VC activity is sensitive to distance and travel time. For example, Lerner (1995) finds that VCs are more likely to sit on boards of geographically proximate companies. Chen et al. (2010) find that VCs are more likely to invest in a distant region if they already visit one portfolio company in the same region, arguing that the time associated with monitoring a distant investment affects the decision to invest. Bengtsson and Ravid (2009) find that VC contracts are more high-powered as geographic distance increases, indicating that monitoring costs increase with distance. The inclination to invest locally is not surprising given that, according to survey evidence, venture capitalists spend most of their time managing portfolio companies, and frequently visit company sites (Gorman and Sahlman, 1989; Sahlman, 1990).

We begin by documenting that there is indeed significant venture capital activity outside of the three main metropolitan areas of San Francisco, Boston and New York. Indeed, approximately 50% of both venture-backed companies and venture capital investment firms are located outside of these three regions. This is consistent with the findings of Chen et al. (2010). Moreover, we show that it is not uncommon for VCs to invest in distant portfolio companies. Given these patterns, we then explore how the introduction of airline routes affects aggregate venture capital flows between MSAs (Metropolitan Statistical Areas) in the United States. Using a difference-in-differences estimation framework, we find that the

¹Relatedly, the president of England & Company, an investment bank with major activities in venture capital, argues that limited air service to Madison tends to discourage relationships between Madison and the venture capital industries on the East and West coasts: "Many potential venture capital investors on the East and West coasts aren't willing to travel anywhere that isn't serviced by a direct flight, and early-stage investors often like to play an active role in a company's development, which is difficult to do from afar" (The Wisconsin State Journal, November 18, 2004). In an interview, Jim Nichols, director at the North Carolina Department of Commerce was asked: "So something seemingly as marginal as a direct flight to the money and technology mecca of Silicon Valley is absolutely crucial for [North Carolina]'s growth?" He answered: "You wouldn't think it would be that important, but it really is a factor for these companies" (Tribune Business News, November 27, 2000).

introduction of a new direct airline route leads to a 5.3% increase in total venture capital investment, and a 3% increase in likelihood of VC activity. This regional analysis also allows us to explore whether the overall increase in investment is driven by increases on the extensive margin, intensive margin, or both. We find that both first time investments as well as follow-up investments increase with reductions in travel time. In the case of new investments, this could be driven by reduced screening costs in addition to the aforementioned monitoring costs.

A natural concern is that local shocks, either in the source or target MSA could be driving the results. For example, a booming local economy may lead to the introduction of airline routes and also increased VC investment. In this case, we may estimate a spurious positive effect of travel time reductions on investment. However, since our treatment is defined at the MSA-pair level, we can control for such local shocks. Specifically, we include MSA by year fixed effects for both source and target regions in all the regressions.

New investments that occur after the treatment may tend to have different outcomes, not because the reduction in travel time affects the level of involvement of the VC, but because it changes the selection process. For example, VCs may have a lower hurdle rate for investments in a distant region subsequent to the introduction of a direct flight to that region. Therefore, in order to isolate the effect of venture capital involvement, the remainder of the analysis focuses on VC-company relationships that existed before the treatment. This also means that we move from doing analysis at the MSA-pair level (henceforth, "regional analysis") to analysis at the VC-company pair level (henceforth, "relationship analysis"). For the relationship analysis we again use a difference-in-differences estimation framework, controlling for local shocks in both the VC and company regions.

The primary outcomes we examine are the quantity and quality of innovation (as mea-

sured by the patent count and citations per patent, respectively), as well as ultimate success (as measured by exit via IPO or acquisition). We find that the introduction of a new airline route that reduces the travel time from a lead VC to a portfolio company leads to a 3.74% increase of in the number of patents the portfolio company produces and a 3.54% increase in the number of citations per patent it receives. Further, the treatment increases the probability of ultimately going public by 1.23%, and of having a successful exit (via IPO or acquisition) by 2.79%.

Next, we investigate the channel through which these effects operate. Our main hypothesis is that a reduction in monitoring costs should increase VC involvement, which may in turn improve portfolio company performance. Unfortunately, we cannot directly observe whether VC involvement actually increases when monitoring costs decline. However, we take advantage of the fact that involvement for certain VCs should be more sensitive to changes in monitoring costs than for others. Specifically, VCs often syndicate their investments, and when this occurs, one VC typically takes the role of the lead investor. The lead investor is generally more actively involved in the monitoring of the portfolio company, while others act more as passive providers of capital. Indeed, Gorman and Sahlman (1989) find that venture capitalists acting as lead investors spend significantly more time on their portfolio companies than they would otherwise. Given that lead VCs play a greater role in monitoring, their monitoring effort should be more sensitive to reductions in monitoring costs as should portfolio company performance. Consistent with this argument, we find that our results are driven primarily by reductions in travel time for lead VCs rather than other members of the investment syndicate.

We further verify the robustness of our results in several ways. First, it is possible that if a portfolio company is performing very well, a new airline route may be introduced in response. While we do not believe this to be likely, it would bias our estimates. To ensure that such pre-existing trends are not driving our results, we examine the dynamics of how company outcomes change in the years surrounding the treatment. We find the bulk of the effect coming 1 to 2 years after the treatment, with no "effect" prior to the treatment. Second, reductions in monitoring costs should be greater the greater the reduction in travel time. Consistent with this argument, we find larger effects associated with larger travel time reductions. Third, we show that the results are robust to considering only new airline routes that are the outcome of a merger between two airlines or the opening of a new hub. Such cases are likely to be even more exogenous to any given VC-company pair. Finally, we show that the results are robust to a host of alternative constructions of the outcome variables.

This paper contributes to several lines of research. First, it adds to a growing literature that explores the effects of venture capital on industry-, region-, and company-level outcomes.² For example, Kortum and Lerner (2000) structurally estimate industry-level patent production functions with corporate R&D and venture capital as inputs in order to compare their relative potency. Samila and Sorenson (2010) investigate the effect of venture capital on city-level employment using endowment returns as an instrumental variable. Sorensen (2007) models the two-sided matching process of venture capitalists and entrepreneurs to structurally estimate the relative importance of VC influence and sorting as explanations for why companies backed by more experienced VCs outperform. Puri and Zarutskie (2012) compare the life-cycle dynamics of a matched sample of VC-backed and non-VC-backed companies. Relative to the existing literature, this paper differs in that it provides evidence that VCs affect company-level performance and does not require any structural assump-

²Various dimensions explored in the literature include: post-IPO performance (Brav and Gompers, 1997), operational growth (Hellman and Puri, 2000), potential for scale (Puri and Zarutskie, 2012), research innovation and patenting activity (Kortum and Lerner, 2000), and firm productivity (Chemmanur et al., 2011).

tions for identification. Moreover, since our estimates are based off of exogenous changes in VC involvement with existing portfolio companies, our setting overcomes concerns about unobservable differences between venture-backed and non-venture-backed companies.

This paper also contributes to an extensive literature documenting the importance of geographic clusters (Porter, 1995; Ellison and Glaeser, 1997). Specifically, Chen et al. (2010) illustrate that VC firms and VC-backed companies are geographically concentrated in three cities—San Francisco, Boston, and New York. Such clustering may arise due to agglomeration economies (input sharing, labor market pooling and knowledge spillovers), which are likely to be important for both venture capital and the types of companies in which venture capital firms invest. Alternatively, clustering may arise due to variation in demography and industry concentration, as illustrated by Glaeser (2007). Yet another possibility is that it may result from robust financial infrastructure (Hochberg and Rauh, 2013), favorable local tax policies or regulatory systems. This paper identifies the role of travel time in explaining such clustering, as declines in travel time lowers monitoring costs and thus increases investment in new portfolio companies and improves the performance of existing portfolio companies.

The results in this paper have important policy implications. Governments around the world employ a wide range of initiatives to promote venture capital activity (Lerner, 2009). Some initiatives attempt to ensure that a region meets its entrepreneurial potential through various policies such as tax benefits, easing barriers to technology transfer, maintaining intellectual property protection and well-developed stock markets. Other initiatives involve more direct mechanisms in which governments co-invest with venture capitalists through matching funds or provide quasi-loans.³ This paper highlights the positive externalities

³For example, see the Israeli Yozma initiative or the SBIC program in the United States.

of transportation infrastructure: better airline connections foster venture capital activity.

Hence, policies aimed at improving access to venture capital hubs are likely an effective means of promoting entrepreneurship.

The remainder of this paper is organized as follows. Section 2 discusses the data and construction of key variables. Section 3 discusses our empirical strategy. Section 4 presents the results. Section 5 concludes.

2 Data

2.1 Sources and Sample Selection

We obtain data on venture-backed companies from the Thomson Reuters VentureXpert database (formerly called Venture Economics). VentureXpert, along with Dow Jones' VentureSource (formerly VentureOne) are the two primary venture capital data sources available. Both have been validated by previous researchers against known financing rounds (Kaplan et al., 2002). We choose to use VentureXpert, because VentureSource does not cover years prior to 1992, when many new airline routes were introduced. VentureXpert began compiling data in 1977 and has been back-filled through the early 1960s. It has detailed information about the dates of venture financing rounds, the investors and portfolio companies involved, the estimated amounts invested by each party, and the ultimate portfolio company outcome. The database also contains detailed information on the location of each VC firm and portfolio company. It should be noted that one shortcoming of these data for our purposes is that VentureXpert only associates a VC firm with a single location (its main office). However, some of the larger VC firms operate out of multiple offices. While ideally we would observe all of these offices, this should not present a systematic source of bias. We limit the sample

to US based portfolio companies coded as being in a venture stage (Seed, Early, Expansion, or Later Stage) in their first observed financing round. For our baseline analysis, we further limit the sample to only VC-company pairs involving the lead investor, which will be defined in Section 2.2.3.

To measure the innovative output of portfolio companies, we combine VentureXpert with data from the NBER Patent Data Project (Hall et al., 2001). The NBER data cover more than 3 million utility patents granted by the U.S. Patent and Trademark Office (USPTO) from 1976 to 2006.⁴ Among other things, the data provide information on the date a patent was applied for and ultimately granted as well as its detailed technology class. If a patent was assigned to one or more companies ("assignees"), the data also provide information on assignee name(s)/location(s). We match the NBER data with VentureXpert using standardized company and location names along with the company's founding date and the date of the assignee's first patent application. The details of the matching procedure are provided in Appendix A. Finally, we also supplement the NBER data with citation data from Google patents in some cases so that we can observe citations in a three-year window following the grant date for all patents, including those at the end of the NBER sample in 2006.

Data on airline routes are obtained from the T-100 Domestic Segment Database (for the period 1990 to 2006) and ER-586 Service Segment Data (for the period 1977 to 1989), which are compiled from Form 41 of the U.S. Department of Transportation (DOT). All airlines operating flights in the United States are required by law to file Form 41 with the DOT and are subject to fines for misreporting. Strictly speaking, the T-100 and ER-586 are not samples: They include all flights that have taken place between any two airports in

⁴In addition to utility patents, there are three other minor patent categories: Design, Reissue, and Plant patents. Following the literature we focus only on utility patents, which represent approximately 99% of all awards Jaffe and Trajtenberg (2002).

the United States. The T-100 and ER-586 contain monthly data for each airline and route (segment). The data include, for example, the origin and destination airports, flight duration (ramp-to-ramp time), scheduled departures, performed departures, enplaned passengers, and aircraft type.

After combining these three data sources we are left with a sample of venture backed companies that were active between 1977 (the beginning of the airline data) and 2006 (the end of the patent data). In total, we observe 22,986 companies, receiving funding from 3,158 lead venture firms. Table 1 shows the composition of the sample. Panel A shows the company region distribution broken down by whether the company was ever treated or not. Similarly, Panel C shows the VC region distribution broken down by whether the venture firm was ever treated or not. Perhaps the most striking finding from these tables is that, contrary to common perception, a significant amount of venture capital activity takes place outside of Northern California, New England, and New York. Indeed, approximately 50% of venture-backed companies and venture capital firms are located outside of these three regions. This is consistent with Chen et al. (2010). Overall, treated and untreated companies are distributed similarly across regions; however, as one might expect treated companies are less likely to be located in Northern California. Similarly, Panel C shows that treated VCs are also less likely to be located in Northern California. Finally, Panel B shows that treated and untreated companies are also distributed similarly across industries, although treated companies are somewhat less likely to be in the Internet sector.

While Table 1 shows that both portfolio companies and VC firms are fairly dispersed geographically, it does not directly show whether it is common for VCs to invest in distant portfolio companies. Figure 1 provides some perspective on this by showing all VC-company pairs in the data graphically, connected with solid lines. Following the decomposition from

Table 1, Panel A shows eventually treated pairs, while Panel B shows pairs that were never treated. In both cases, one can see that it is fairly common for portfolio companies to be funded by distant VCs, which lends power to our identification strategy. More detailed summary statistics on distance and travel time between VCs and portfolio companies will be discussed in Section 3.

2.2 Definitions of Variables

2.2.1 Treatment

To estimate the effect of reductions in travel time on portfolio company outcomes, we define a treatment indicator variable equal to one if a new airline route is introduced that reduces the travel time between the VC firm and the portfolio company. Travel time is estimated as the time it would take to travel from the VC's ZIP code to the company's ZIP code using the optimal itinerary and means of transportation (car or airplane). The details of the algorithm used to compute optimal itineraries and travel time are described in Appendix B. During our sample period (1977-2006), there are 1,131 treated VC-company pairs. The average travel time reduction is 126 minutes round-trip.⁵

2.2.2 Innovation

We use patent-based measures of the scale and quality of a company's innovation (Jaffe and Trajtenberg, 2002; Lanjouw et al., 1998). These measures have been widely adopted over the past two decades.⁶ Our primary measure of the scale of a company's innovation during

⁵In addition to the time savings, better flight connections likely reduce the disutility of traveling along other dimensions. In particular, not having a layover reduces the likelihood of missing a connection and/or being stuck overnight at a connecting airport.

⁶A few recent examples include Acharya and Subramanian (2009); Aghion et al. (2009); Atanassov et al. (2007); Belenzon et al. (2009); Bhattacharya and Guriev (2006); Chemmanur and Tian (2013); Fulghieri and

a year is the number of (eventually granted) patents it applied for. Our primary measure of the quality of a company's innovation during a year is the number of citations received per patent. Patent citations are important in patent filings since they serve as "property markers" delineating the scope of the granted claims. Hall et al. (2005) illustrate that citations are a good measure of innovation quality and economic importance. Specifically, they find that an extra citation per patent boosts a firm's market value by 3%. Moreover, Kogan et al. (2012) show that stock market reaction to patent approvals is a strong predictor of number of future citations a patent receives.

One challenge in measuring patent citations is that patents that are granted at the end of the sample period have less time to garner citations than those granted at the beginning. To address this issue, we only consider citations that occur during a three-year window following the date a patent is granted. In addition, we check that our results are robust to correcting for truncation using the estimated shape of the citation-lag distribution as in Hall et al. (2001). An additional consideration is that citation rates vary over time and across technologies. To ensure that this does not affect our results, we also explore scaling each patent's citation count by the average citation count for patents granted in the same year and technology class. Finally, we take logs and add one to both the patent count and citation variables.

2.2.3 Other Measures

In addition to innovation, we also measure success and investment annually. We define company success in two ways. The first is an indicator variable equal to one if the company went public during a given year. The second is an indicator variable equal to one if the company Sevilir (2009); Fang et al. (2013); He and Tian (2013); Lerner et al. (2011); Seru (2010); Tian and Wang (2011).

went public or was acquired. The issue with the second definition is that it likely captures some acquisitions that were not positive outcomes. Specifically, an acquisition may be a sell-off that was not very profitable for the company's investors or founders. Unfortunately, it is difficult to distinguish these cases in the data because the amount paid by the acquirer is frequently undisclosed. Nonetheless, given the increasing importance of acquisitions as a means of exit for successful venture-backed companies, this broader measure may better capture company success. To be conservative we focus primarily on the IPO indicator in our analysis, however, we show that considering acquisitions as well yields qualitatively similar results.

We define investment as the total amount of funding provided by VC firms to a portfolio company during a given year. For the regional analysis, we aggregate investment at the VC-company level into investment flows at the MSA-pair level. In this case, we also make a distinction between first time investments (investments in new companies) and follow-on investments (investments in existing companies).

Finally, as previously mentioned, in our baseline analysis, we limit the sample to only VC-company pairs involving the lead investor. We focus on the lead investor because it is likely to be the one most involved in monitoring. Following Gompers (1996), we define the lead investor as the one that has invested in the company the longest. This is also consistent with Gorman and Sahlman's (1989) finding that the venture firm originating the investment is usually the firm that acquires a board seat first and has the most input into the decisions of the company, even though it might not end up ultimately owning the largest equity stake. Our results are also robust to other commonly used definitions of the lead investor, such as

⁷We break ties by selecting the firm that invested the most. If there are still ties, we classify all of the tied VC firms as lead investors.

the investor that invested the most in a given round.

3 Empirical Strategy

3.1 Relationship Analysis

The introduction of new airline routes that reduce the travel time between VC firms and their portfolio companies makes it easier for VCs to spend time at their portfolio companies. If VC activities do matter, such reduction in travel time should translate into better portfolio company performance by allowing VCs to engage in more of these activities. To estimate the effect of the introduction of new airline routes ("treatments") on company outcomes, we use a difference-in-differences methodology. We estimate the following regression:

$$y_{ijt} = \beta \times treatment_{ijt} + \gamma' \mathbf{X_{ijt}} + \alpha_{ij} + \alpha_{MSA(i)} \times \alpha_t + \alpha_{MSA(j)} \times \alpha_t + \epsilon_{ijt}, \tag{1}$$

where i indexes portfolio companies, j indexes VC firms, t indexes years, MSA(i) indexes the Metropolitan Statistical Area (MSA) in which portfolio company i is located, and MSA(j) indexes the MSA in which VC j is located; y is the dependent variable of interest (e.g., number of patents, citations per patent, IPO), treatment is an indicator variable ("treatment indicator") that equals one if a new airline route that reduces the travel time between company i's ZIP code and VC j's ZIP code has been introduced by year t; \mathbf{X} is the vector of control variables which includes company age and a set of indicator variables for the stage of VC financing; α_t and α_{ij} are year and VC-company pair fixed effects, respectively; $\alpha_{MSA(i)} \times \alpha_t$ and $\alpha_{MSA(j)} \times \alpha_t$ are MSA by year fixed effects with respect to company i's MSA and VC j's MSA, respectively; ϵ is the error term. This methodology fully controls

for fixed differences between treated and non-treated VC-company pairs via the inclusion of pair fixed effects. The inclusion of MSA by year fixed effects further accounts for local shocks that may correlate with the introduction of new airline routes. To allow for serial dependence of the error terms, we cluster standard errors at the portfolio company level. The coefficient of interest is β which measures the effect of the introduction of new airline routes on y.

Our identification strategy can be illustrated with a simple example. From 1986 to 1994, Anesta Corporation, a biopharmaceutical company located in Salt Lake City, UT, was receiving VC funding from Flagship Ventures, a VC firm in Cambridge, MA. Until 1988, the fastest way to travel between Boston Logan Airport (BOS) and Salt Lake City International Airport (SLC) was an indirect flight operated by Delta Airlines with one stopover at Chicago O'Hare (ORD). In 1988, Delta introduced a direct flight between BOS and SLC, which substantially reduced the travel time between the two locations. To measure how this "treatment" affects, e.g., the number of patents filed by Anesta, one could compute the difference in the number of patents before and after 1988. However, other events may have happened around 1988 that also affect patenting. To account for this possibility, we use a control group that consists of all VC-company pairs that have not been treated by 1988. We then compare the difference in the number of patents at Anesta before and after 1988 with the difference in the number of patents at the control companies before and after 1988. The difference between these two differences is the estimated effect of the treatment on patenting at Anesta.

3.1.1 Local Shocks

Including a control group accounts for the possibility of economy-wide shocks that are contemporaneous with the introduction of the new airline routes. However, since a treatment is defined at the VC-company level, we can tighten the identification by also controlling for local shocks in the portfolio company's MSA, thereby separating out the effect of the new airline routes from the effect of contemporaneous local shocks. For example, Systemed Inc. is another biopharmaceutical company located in Salt Lake City. Around 1988, Systemed was receiving VC funding from Summit Capital Associates, a New York-based VC. (Direct flights between New York's John F. Kennedy Airport and SLC were offered in each year during our sample.) If patenting at Systemed also increases around 1988, then an increase in patenting at Anesta might not be due to the new airline route between BOS and SLC but rather due to a contemporaneous local shock that affects patenting in the Salt Lake City MSA. In Equation (1), we control for such local shocks by including the full set of MSA fixed effects (pertaining to the portfolio company's location) interacted with year fixed effects ($\alpha_{MSA(i)} \times \alpha_t$).

Since a treatment is defined at the VC-company level, we can make the identification even tighter by also controlling for shocks at the location of the VC firm. In the above example, suppose there is a local shock that affects patenting in Boston in 1988. This local shock may affect Flagship Ventures, the Cambridge VC financing Anesta, and in turn Anesta's ability to innovate. In this case, however, patenting should also increase in the Boston area. In Equation (1), we control for such local shocks by including MSA fixed effects (pertaining to the VC's location) interacted with year fixed effects ($\alpha_{MSA(j)} \times \alpha_t$).⁸

⁸In practice, it is computationally difficult to estimate a regression that has so many layers of fixed effects. Fortunately, recent algorithms have been developed that can handle such high-dimensional fixed effect regressions. In our analysis, we use the iterative algorithm of Guimaraes and Portugal (2010). See

3.1.2 Pair-Specific Shocks

One potential concern that is not addressed by controlling for local shocks is the possibility that a pair-specific shock (i.e., a shock that is specific to a VC-company pair, but not to the MSA of the company or the MSA of the VC) is driving both company-level outcomes (e.g., patenting) and the introduction of the new airline route. For example, it could be that a portfolio company that is successful in patenting becomes more salient to its VC. In response, the VC may want to spend more time at that company and lobbies for better airline connections to the company's location. Nevertheless, such alternative stories are unlikely for several reasons. First, portfolio companies and VC firms are relatively small business entities. Hence, it seems unlikely that a VC-company pair is sufficiently powerful to successfully lobby for better airline connections (or that an airline would introduce a new flight route in response to a shock to that pair). To further rule out this concern, we have verified that our results also hold if we restrict our sample to portfolio companies and VC firms whose size is below the median in our sample, i.e., those companies and VCs that are even less able to successfully lobby for a new airline route. Second, we examine the dynamic effects of the treatment. Arguably, if the new airline routes are introduced in response to pair-specific shocks, one may already observe an "effect" of the new airline routes before they are even introduced. However, when we examine the dynamics of the treatment, we find no such evidence: most of the effects we observe occur between 12 and 24 months after the introduction of the new airline routes. Third, in robustness checks, we show that our results also hold if we consider new airline routes that are introduced as part of the opening of a new hub or a merger between two airlines. Arguably, it is unlikely that a shock that is specific to a VC-company pair is sufficiently large to lead to a hub opening or an airline merger.

Gormley and Matsa (2013) for details.

3.1.3 Differences between Treated and Non-Treated Pairs

In order to be treated, a VC-company pair needs to be sufficiently far apart so that air travel is the optimal means of transportation between the two. Thus, by construction, treated pairs are farther apart compared to the average VC-company pair in the U.S. This is confirmed by looking at the summary statistics in Table 2. On average, treated pairs are located approximately 500 miles farther away than non-treated pairs. The other characteristics provided in the table further indicate that, for treated pairs, portfolio companies receive less funding, are less innovative, less likely to undergo a successful IPO or merger, and tend to receive funding from VCs that are more experienced and more diversified. These differences are consistent with our hypothesis that closer proximity between VC firms and their portfolio companies leads to more innovation, more capital, and ultimately is more likely to lead to a successful IPO or merger. However, such correlations are merely suggestive as they do not warrant a causal interpretation.

While these differences may be intuitive, they do raise the concern of whether our control group is an appropriate one. Nevertheless, this concern is minimized, for several reasons. First, in all our regressions, we include VC-company pair fixed effects, which fully controls for any fixed differences between treated and non-treated VC-company pairs. Since the main difference—the distance between VC and portfolio company—is a fixed characteristic, it seems likely that most of the relevant differences between the two groups are absorbed away. Second, because of the staggered introduction of the new airline routes over time, the eventually treated pairs are both control and treatment pairs (i.e., they remain in the control group until they become treated). Third, we show that our results are robust if we restrict the control group to those control pairs whose average distance matches the average

distance in the treatment group (i.e., we exclude short-distance control pairs so that the average distance is the same in both groups). Fourth, we show that our results also hold if we allow pairs that differ on the basis of the characteristics in Table 2 to be on different time trends. More precisely, this test is conducted by including as additional controls the characteristics in Table 2 interacted with the full set of year fixed effects (see Bertrand and Mullainathan (2003) for a similar robustness check). ¹⁰

3.2 Regional Analysis

The difference-in-differences specification in Equation (1) can be extended to study whether proximity fosters VC activity at the regional level. To conduct this analysis, we aggregate our data from the VC-company level to the MSA-pair level. We then estimate the following regression:

$$y_{mnt} = \beta \times treatment_{mnt} + \alpha_t + \alpha_{mn} + \alpha_m \times \alpha_t + \alpha_n \times \alpha_t + \epsilon_{mnt}, \tag{2}$$

where m indexes MSAs from which VC funding is coming (i.e., MSAs of the VC firms), n indexes MSAs to which VC funding is going (i.e., MSAs of the portfolio companies), and t indexes years; y is the dependent variable of interest (e.g., the total amount of VC funding provided by VCs in MSA m to portfolio companies in MSA n); treatment is the treatment

⁹In conducting this test, we lose about half of the control sample. The fact that the other half qualifies as "distance-matched" control group confirms that long-distance VC-company relationships are fairly common, as discussed in Section 2 (see also Figure 1).

¹⁰Another helpful robustness check proposed by Bertrand and Mullainathan (2003) consists of estimating the difference-in-differences specification using only observations of the eventually treated pairs—essentially, due to the staggered introduction of the new airline routes, Equation (1) can be estimated using only this subsample (in this case, the control group consists exclusively of pairs that are subsequently treated). In our context, a caveat of this test is that the number of observation would drop to 9,293 pair-year observations, which makes it infeasible to control for MSA times year fixed effects. Nevertheless, we have verified that all our results are robust if we perform this test (dropping the MSA times year fixed effects from the regressions).

indicator at the MSA-pair level; α_t and α_{mn} are year and MSA-pair fixed effects, respectively; $\alpha_m \times \alpha_t$ and $\alpha_n \times \alpha_t$ are the two sets of MSA times year fixed effects; ϵ is the error term. Standard errors are clustered at the MSA-pair level. The identification strategy is analogous to that at the VC-company pair level. In particular, we are able to include MSA-pair fixed effects as well as the two sets of MSA times year fixed effects, thus controlling for local shocks that may be correlated with airlines' decision to introduce new flight routes.

There are two main differences compared to the relationship analysis. First, "treatments" are coded in a different way. At the relationship level, a treatment is the introduction of a new airline route that reduces the travel time between the VC's ZIP code and the company's ZIP code, taking into account the optimal itinerary and means of transportation (see Appendix B). Since an MSA covers several ZIP codes, there is no notion of "optimal itinerary" at the MSA-pair level. Instead, we code as a treatment the first time a direct flight is introduced between any two locations in the two MSAs. Second, there are a large number of MSA pairs between which no VC activity ever occurred during our sample period. For these pairs, any dependent variable would be set to zero in all years, and thus be absorbed by the inclusion of MSA-pair fixed effects. In the regressions, we drop these MSA-pairs from the sample. This follows common practice in the trade literature in which a similar issue arises when measuring trade flows between country pairs (e.g. Feyrer, 2009).

4 Results

4.1 Regional Analysis

We start by exploring whether proximity fosters VC activity between regions. The results are presented in Table 3. They are obtained by estimating variants of Equation (2). Observations

are at the MSA-pair by year level and all regressions include MSA-pair and year fixed effects. Column (1) of Panel A shows the effect of the introduction of new airline routes between pairs of MSAs on total VC investment (in logs). The coefficient on the treatment indicator is 0.114, and statistically highly significant. This implies that total investment increases by 11.4% following the treatment. In Column (2), we account for the possibility of local shocks by including the two sets of MSA by year fixed effects. As expected, local shocks are an important determinant of VC investments across MSAs and hence accounting for them leads to a smaller treatment effect: the coefficient is now 0.053, corresponding to a 5.3% increase in total VC investment. Importantly, even after controlling for local shocks, the treatment effect remains highly significant and economically important. This finding indicates that better airline connections foster flows of VC investments between MSAs.

In Columns (3)-(6) of Panel A, we explore separately the treatment effect on initial investments (extensive margin) versus follow-up investments (intensive margin). After controlling for local shocks, the treatment effect is 2.3% and 4.7%, respectively. Both coefficients are highly significant. Thus, better airline connections lead to higher VC investment at both the extensive and intensive margin. Interestingly, the increase in investment at the intensive margin suggests that proximity not only facilitates the screening of portfolio companies, but also their monitoring after the initial investment. We examine the latter in detail in the relationship analysis (Section 4.2).

In Panel B, we explore alternative dependent variables that capture the intensity of VC activity following the treatment. In Columns (1) and (2), the dependent variable is the number of deals (in logs), in columns (3) and (4) it is an indicator variable equal to one if any VC investment occurs between the two MSAs. After accounting for local shocks, we find that the number of deals increases by 3.7%, and the likelihood of any VC activity increases

by 2.9%.

In Table 4 we examine the dynamic effects of the introduction of new airline routes. Specifically, we replace the treatment indicator in Equation (2) with a set of four indicator variables representing the years around the treatment. For example, the indicator "Treatment (-1)" equals one if the MSA-pair observation is recorded in the year preceding the treatment. The other indicator variables are defined analogously with respect to the year of the treatment (0), the first year after the treatment (1), and two or more years after the treatment (2+). We observe a similar pattern for all dependent variables. In particular, we always find that the coefficient on Treatment (-1), which measures the "effect" of the new airline routes before their introduction, is small and insignificant, suggesting that there are no pre-existing trends in the data. In the year of the treatment, we find that the treatment effect is positive, but relatively small and only marginally significant. It is only in the first year after the treatment that the effect becomes large and highly significant. It remains somewhat stable thereafter. Overall, this pattern indicates that it takes about 1 to 2 years for the new airline routes to translate into higher flows of VC investments between MSAs.

4.2 Relationship Analysis

New investments that occur after the treatment may tend to have different outcomes, not because the reduction in travel time affects the level of involvement of the VC, but because it changes the selection process. For example, VCs may have a lower hurdle rate for investments in a distant region subsequent to the introduction of a direct flight to that region. Therefore, in order to isolate the effect of venture capital involvement we focus only on portfolio companies that existed before the treatment for the remainder of the analysis. This also means that we move from doing analysis at the MSA-pair level to analysis at the VC-company pair

level. If differences in outcomes for portfolio companies are driven only by selection, travel time reductions subsequent to investment should have no effect. On the other hand, if VCs' physical presence does matter, travel time reductions should affect company outcomes.

Specifically, we estimate variants of Equation (1) to examine whether the introduction of new airline routes that reduce the travel time between VC firms and their portfolio companies affect portfolio companies' innovation and eventual success. The results are presented in Table 5. In Columns (1)-(3), the dependent variable is the number of patents (in logs). The regression in Column (1) includes VC-company pair and year fixed effects. In Column (2), we also control for company age and a set of indicators for the stage of VC financing. In Column (3), we further control for local shocks by including the two sets of MSA by year fixed effects. The coefficient on the treatment indicator is very stable across all specifications. It lies between 0.031 and 0.037, which implies that the number of patents increases by 3.1% to 3.7% after the treatment. In Columns (4)-(6), we re-estimate these specifications using citations per patent (in logs) as the dependent variable. The coefficient on the treatment indicator varies between 0.058 and 0.074, corresponding to an increase in citations per patent of 5.8% to 7.4%. In Columns (7)-(9) the dependent variable is an indicator variable equal to one if the company goes public (IPO) during the year. We find that the introduction of new airline routes leads to an increase in the likelihood of going public by approximately 1.0%. Overall, our findings indicate that a reduction in VC monitoring costs leads to significant increases in innovation and the likelihood of a successful IPO.

In Table 6, we study the dynamic effects of the treatment. As in the regional analysis, we do so by replacing the treatment indicator with a set of four indicator variables representing the years around the treatment. The underlying specification is the conservative specification used in Columns (3), (6), and (9) of Table 5, i.e. the specification that includes control

variables, VC-company pair fixed effects, year fixed effects, as well as the two sets of MSA by year fixed effects (henceforth, the "baseline specification"). We observe a very similar pattern for all three dependent variables. The effect is small and insignificant in the year preceding the treatment (year –1), which suggests that there are no pre-existing trends in the data.¹¹ The effect is positive but small in the year of the treatment (year 0). It is only one year after the treatment (year 1) that the effect becomes large and highly significant. Finally, the effect is persistent in the longer run (years 2+). In sum, the dynamic pattern suggests that it takes about 12 to 24 months until the reduction in travel time materializes into greater innovation and a higher likelihood of going public.

4.3 Cross-Sectional Heterogeneity

4.3.1 The Role of Lead versus Non-Lead VCs

Next, we investigate the channel through which these effects operate. Again, our main hypothesis is that a reduction in monitoring costs should increase VC involvement, which may in turn improve portfolio company performance. Unfortunately, we cannot directly observe whether VC involvement actually increases when monitoring costs decline. However, we take advantage of the fact that involvement for lead VCs should be more sensitive to changes in monitoring costs than involvement for non-lead VCs. This is because non-lead VCs generally act more as passive providers of capital (Gorman and Sahlman, 1989).

To investigate this hypothesis, we re-estimate our baseline specification in the sample of VC-company pairs involving a non-lead VC located in a different MSA than the lead investor. We now set the treatment indicator to one if a new airline route is introduced that

 $^{^{11}}$ We cannot identify the coefficient of Treatment (-1) in the regression whose dependent variable is the IPO indicator. Since companies exit the sample upon going public, companies that go public before the treatment cannot be in the treatment group by construction.

reduces the travel time between a portfolio company and a non-lead investor. The results are shown in Table 7. We find that, for all dependent variables, the estimated treatment effect is statistically insignificant. Moreover, the sample size in this analysis is comparable to that from the baseline analysis and the point estimates are close to zero, suggesting these are well-estimated zero effects. These results are consistent with the monitoring hypothesis; travel time reductions appear to matter primarily for active investors.¹²

4.3.2 Small versus Large Reductions in Travel Time

If travel time indeed matters, we expect to find a stronger treatment effect for larger reductions in travel time. In our baseline analysis, any new airline route that reduced the travel time between a VC firm and its portfolio company was coded as a treatment, regardless of the magnitude of the travel time reduction. We now interact the treatment indicator with two dummy variables indicating whether the reduction in travel time is "large" or "small". We consider a travel time reduction to be large if it is more than 1 hour round-trip. The results are reported in Table 8. For travel time reductions of less than 1 hour, the treatment effect is small and insignificant (except for the number of patents where the coefficient is marginally significant). In contrast, the treatment effect is strongest and highly significant for travel time reductions of more than 1 hour.

¹²These findings further reinforce our identification as they provide a placebo test in which the new airline routes connect passive (as opposed to active) investors.

4.4 Robustness

4.4.1 Hub Openings and Airline Mergers

As explained in Section 3, one potential concern that is not addressed by controlling for local shocks is the possibility that a VC-company pair-specific shock is driving both company outcomes and the introduction of a new airline route (e.g., through lobbying). Given the relatively small size of portfolio companies and venture capital firms, such alternative story seems unlikely. Moreover, we have verified that our results are robust if we restrict our sample to portfolio companies and VC firms whose size is below the median in our sample, that is, companies and VCs that are even less able to successfully lobby for a new airline route. In addition, if a new airline route is introduced in response to a pair-specific shock, one may already observe an "effect" of the new airline route before it is even introduced. However, when we looked at the dynamics of the treatment effect, we found no evidence for such pre-existing trends.

Another way to rule out this concern is by considering new airline routes that are introduced as part of a hub opening or a merger between airlines. Arguably, it is unlikely that a pair-specific shock could induce the opening of a new hub or the merger of two airlines. Thus, new airline routes of this kind are more likely to be exogenous. The data on hub openings and airline mergers are obtained from Giroud (2013). Hub and merger treatments account for about 15% of the treatments in our sample. In Panel A of Table 9, we replace the treatment indicator in our baseline specification with two dummy variables indicating hub/merger treatments ("Hub or Merger") and other treatments ("Other"), respectively. As can be seen, our results are robust when considering hub and merger treatments, which

alleviates concerns that our results may be driven by unobservable pair-specific shocks. 13

4.4.2 Distance-Matched Control Group

As discussed in Section 3.1.3, in order to be treated, a VC-company pair needs to be sufficiently far apart so that air travel is the optimal means of transportation between the two. Thus, by construction, treated pairs are farther away than control pairs. This difference raises the concern of whether our control group is an appropriate one. While the inclusion of VC-company pair fixed effects accounts for any time-invariant differences between pairs (such as differences in distance), a remaining concern is that long-distance VC-company pairs may be on a different trend. To mitigate this concern, we re-estimate our baseline specification after restricting the control group to those control pairs whose average distance matches the average distance in the treatment group. More precisely, we exclude short-distance control pairs (in increasing distance) until the average distance is the same in both groups. The results are presented in Panel B of Table 9. As is shown, our results are robust to using this "distance-matched" control group.

4.4.3 Heterogeneous Time Trends

Another way to address the possibility that control and treated pairs may be on different trends is to explicitly control for such heterogenous time trends. This can be done by interacting the cross-sectional characteristic of interest (e.g., distance) with the full set of year fixed effects, see Bertrand and Mullainathan (2003). Specifically, we interact all characteristics from Table 2 with year fixed effects and re-estimate our baseline specification with these

¹³The treatment effect is larger for hub and merger treatments compared to other treatments. This likely reflects the fact that new airline routes that are introduced as part of a hub opening or airline merger are mostly long-distance routes, which tend to be associated with larger travel time reductions.

additional controls.¹⁴ The results are reported in Panel C of Table 9. As can be seen, the estimated treatment effects are very similar to before.

4.4.4 Alternative Dependent Variables

Finally, in Panel D of Table 9 we explore whether our results are robust to alternative definitions of our main dependent variables. As discussed in Section 2.2.2, we only consider citations during a three-year window following a patent grant, so that all patents in our sample have the same amount of time to garner citations. Hall et al. (2001) propose an alternative adjustment method that uses the estimated shape of the citation-lag distribution. In Column (1), we re-estimate our baseline specification, adjusting for truncation in this manner. The coefficient on the treatment indicator is similar to that in our baseline specification in Table 5. Another common practice in the literature is the use of citationweighted patent counts (Trajtenberg, 1990). Columns (2) shows that using this weighting leads to qualitatively similar results. Citation intensity also varies considerably across time and industries. In Column (3) we normalize each patent's (three-year) citation count by the mean citation count for patents granted in the same year and in the same technology class. This again yields similar results. Finally, as discussed in Section 2.2.3, our IPO indicator variable may be too narrow a measure of ultimate success. Therefore, we define a broader success indicator variable equal to one in the case of an IPO or acquisition. Column (4) shows that the treatment effect is again similar, albeit larger in magnitude.

 $^{^{14}}$ Time-varying characteristics are measured in the first year of the pair (baseline year), see Bertrand and Mullainathan (2003).

5 Conclusion

Do venture capitalists contribute to the innovation and success of their portfolio companies, or do they merely select companies that are likely to innovate and succeed? To answer this question, we exploit exogenous variation in monitoring costs stemming from the introduction of new airline routes between venture capital firms and their existing companies. Focusing on existing relationships allows us to isolate the effect of the monitoring channel: if differences in outcomes for portfolio companies are driven only by selection, reductions in monitoring costs subsequent to investment should have no effect. On the other hand, if VC activities do matter, reductions in the cost of monitoring should translate into better portfolio company performance by allowing VCs to engage in more of these activities.

Within an existing relationship, we find that reductions in travel time are associated with an increase in the number of patents and number of citations per patent of the portfolio company, as well as an increase in the likelihood of an eventual IPO or acquisition. These results are robust when controlling for local shocks that could potentially drive the introduction of the new airline routes. We further document that the effect is concentrated in routes that connect lead VCs (as opposed to other investors) with portfolio companies. In addition, we find that the effect is stronger for larger reductions in travel time. Overall, these results are consistent with the monitoring channel and hence indicate that venture capitalists' physical presence at their portfolio companies is an important determinant of innovation and success.

Finally, our findings have relevant policy implications, as they point toward an important positive externality of transportation infrastructure: better airline connections foster venture capital activity. Accordingly, policies aimed at improving airline connections are likely to be an effective means of promoting entrepreneurship.

Figure 1 VC-Company Pairs

This figure shows VC-company pairs connected by solid lines. Panel A shows pairs that were "Ever Treated" and Panel B shows pairs that were "Never Treated." Both are defined in Table 1.

Panel A: Ever Treated Pairs



Panel B: Never Treated Pairs



 $\begin{array}{c} {\bf Table\ 1} \\ {\bf Sample\ Composition} \end{array}$

This table shows the composition of portfolio companies and VC firms in the sample. Portfolio companies are categorized as "Never Treated" if they never experienced a reduction in travel time to their lead VC investor, and "Ever Treated" otherwise. Similarly, venture firms are categorized as "Never Treated" if they never experienced a reduction in travel time to any of the companies in their portfolio (for which they were a lead investor), and "Ever Treated" otherwise. Panel A shows the company region distribution. Panel B shows the company industry distribution. Panel C shows the VC region distribution.

Panel A: Company Region

	Never	Never Treated		Ever Treated		All	
	Freq	Percent	Freq	Percent	Freq	Percent	
Alaska/Hawaii	22	0.10	1	0.09	23	0.10	
Great Lakes	1054	4.81	51	4.66	1105	4.81	
Great Plains	738	3.37	44	4.02	782	3.40	
Mid-Atlantic	1178	5.38	59	5.39	1237	5.38	
N. California	5464	24.96	146	13.35	5610	24.41	
New England	2529	11.55	115	10.51	2644	11.50	
New York Tri - State	2355	10.76	90	8.23	2445	10.64	
Northwest	854	3.90	48	4.39	902	3.92	
Ohio Valley	1169	5.34	59	5.39	1228	5.34	
Rocky Mountains	875	4.00	44	4.02	919	4.00	
S. California	1980	9.04	120	10.97	2100	9.14	
South	432	1.97	67	6.12	499	2.17	
Southeast	1475	6.74	121	11.06	1596	6.94	
Southwest	1740	7.95	129	11.79	1869	8.13	
US Territories	27	0.12	0	0	27	0.12	
Total	21892	100.00	1094	100.00	22986	100.00	

Panel B: Company Industry

	Never Treated		Ever Treated		All	
	Freq	Percent	Freq	Percent	Freq	Percent
Biotechnology	1221	5.58	70	6.40	1291	5.62
Communications and Media	2243	10.25	109	9.96	2352	10.23
Computer Hardware	1307	5.97	75	6.86	1382	6.01
Computer Software and Services	4526	20.67	192	17.55	4718	20.53
Consumer Related	1428	6.52	91	8.32	1519	6.61
Industrial/Energy	1222	5.58	77	7.04	1299	5.65
Internet Specific	4137	18.90	135	12.34	4272	18.59
Medical/Health	2329	10.64	144	13.16	2473	10.76
Other Products	1955	8.93	124	11.33	2079	9.04
$Semiconductors/Other\ Elect.$	1524	6.96	77	7.04	1601	6.97
Total	21892	100.00	1094	100.00	22986	100.00

Table 1 (Continued)

Panel C: VC Region

	Never Treated		Ever	Ever Treated		All	
	Freq	Percent	Freq	Percent	Freq	Percent	
Alaska/Hawaii	4	0.15	0	0	4	0.13	
Great Lakes	174	6.65	38	7.04	212	6.71	
Great Plains	90	3.44	29	5.37	119	3.77	
Mid-Atlantic	126	4.81	34	6.30	160	5.07	
N. California	502	19.17	60	11.11	562	17.80	
New England	210	8.02	84	15.56	294	9.31	
New York Tri - State	615	23.49	129	23.89	744	23.56	
Northwest	67	2.56	9	1.67	76	2.41	
Ohio Valley	143	5.46	34	6.30	177	5.60	
Rocky Mountains	82	3.13	13	2.41	95	3.01	
S. California	204	7.79	27	5.00	231	7.31	
South	58	2.22	20	3.70	78	2.47	
Southeast	145	5.54	26	4.81	171	5.41	
Southwest	196	7.49	37	6.85	233	7.38	
US Territories	2	0.08	0	0	2	0.06	
Total	2618	100.00	540	100.00	3158	100.00	

Table 2 Summary Statistics

This table shows summary statistics for our main variables. Observations are shown at the level at which variables vary and are broken down by those that are "Never Treated" and those that are "Ever Treated," as defined in Table 1. Great circle distance is the distance (in miles) between the VC's ZIP code and the company's ZIP code. Travel time is the amount of time (in minutes) it takes to travel from the VC's ZIP code to the company's ZIP code (round trip) based on the optimal itinerary and means of transportation (see Appendix B). Change in travel time is the reduction in travel time that occurs due to the treatment. Patents is the raw patent count, citations per patent is the number of citations garnered per patent in the three years after being granted, investment is the funding the portfolio company received from all VCs in a given year. IPO is an indicator variable equal to one if the company has an initial public offering that year. Success is an indicator variable equal to one if the company has an initial public offering or is acquired. VC firm experience is measured as the number of years since firm founding, the number of companies invested in to date, and the number of investments that have gone public to date.

	Never Treated			Ever Treated		
	Obs	Mean	Std Dev	Obs	Mean	Std Dev
Company-VC Pair Level:						
Great Circle Distance (Miles)	30373	735.89	931.84	1131	1236.13	845.38
Travel Time (Minutes)	30373	470.22	551.17	1131	719.82	252.37
Change in Travel Time (Minutes)				1131	126.18	87.57
Company-Year Level:						
Patents	111959	0.44	6.37	9293	0.28	1.28
Citations Per Patent	111959	1.43	7.89	9293	1.03	6.09
Investment (Millions)	111959	3.28	10.86	9293	1.70	7.14
IPO	111959	0.02	0.13	9293	0.01	0.10
Success	111959	0.06	0.23	9293	0.04	0.19
VC-Year Level:						
Experience (Years)	17404	11.00	13.43	8554	14.98	12.16
Experience (Companies)	17404	16.18	27.28	8554	53.85	74.36
Experience (IPOs)	17404	1.94	5.21	8554	8.26	15.21

Table 3
Regional Analysis: Main Regressions

This table shows the main results of our regional analysis. Observations are at the MSA-pair by year level. Only MSA pairs that ever have venture capital flows between them are included in the sample. Treatment is an indicator variable equal to one if a direct flight has been introduced between the two MSAs. Total investment is the log of (one plus) the total amount invested by VCs in the source MSA to companies in the target MSA. Initial investment represents investment in new companies. Follow-up investment represents investment in existing companies. Number of deals represents the number of rounds of funding closed between VCs in the source MSA and companies in the target MSA. VC activity is an indicator variable equal to one if any VCs from the source MSA invested in a company in the target MSA that year. Standard errors, clustered by MSA-pair, are shown in parentheses. * , **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Investment

	Total Investment		Initial In	Initial Investment		Follow-up Investment	
	(1)	(2)	(3)	(4)	(5)	(6)	
Treatment	0.114*** (0.0215)	0.0455*** (0.0171)	0.0486*** (0.0116)	0.0215** (0.0103)	0.0981*** (0.0208)	0.0398** (0.0167)	
Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	
$MSA(VC) \times Year FE$	No	Yes	No	Yes	No	Yes	
$MSA(Company) \times Year FE$	No	Yes	No	Yes	No	Yes	
R ² Observations	0.499 182970	0.618 182970	0.378 182970	0.468 182970	0.477 182970	0.602 182970	

Panel B: Deals

	Number of Deals		VC A	ctivity
	(1)	(2)	(3)	(4)
Treatment	0.0827*** (0.0134)	0.0318*** (0.0122)	0.0618*** (0.00728)	0.0248*** (0.00742)
Pair FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
$MSA(VC) \times Year FE$	No	Yes	No	Yes
$MSA(Company) \times Year FE$	No	Yes	No	Yes
\mathbb{R}^2	0.612	0.693	0.363	0.463
Observations	182970	182970	182970	182970

Table 4
Regional Analysis: Dynamics

This table shows the dynamics of the treatment effects in the regional analysis. All variables are defined as in Table 3. The variable Treatment(-1) is an indicator variable equal to one if the MSA-pair observation is recorded in the year preceding the treatment. Treatment(0), Treatment(1), and Treatment(2+) are defined analogously with respect to the year of the treatment, the first year after the treatment, and two or more years after the treatment, respectively. Standard errors, clustered by MSA-pair, are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
	Total Inv	Initial Inv	Follow-up Inv	Num Deals	VC Activity
Treatment(-1)	0.00461	0.00535	0.00898	0.00641	-0.00376
	(0.0180)	(0.0115)	(0.0171)	(0.0139)	(0.0106)
Treatment(0)	0.0218	0.0132	0.0246	0.0226	0.0162
	(0.0197)	(0.0125)	(0.0185)	(0.0148)	(0.0116)
Treatment(1)	0.0524***	0.0234*	0.0477^{**}	0.0414^{***}	0.0196*
	(0.0196)	(0.0137)	(0.0187)	(0.0149)	(0.0117)
$\operatorname{Treatment}(2+)$	0.0484^{**}	0.0232^*	0.0423^{**}	0.0328**	0.0258***
	(0.0200)	(0.0121)	(0.0195)	(0.0142)	(0.00863)
Pair FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
$MSA(VC) \times Year FE$	Yes	Yes	Yes	Yes	Yes
$MSA(Company) \times Year FE$	Yes	Yes	Yes	Yes	Yes
R^2	0.618	0.468	0.602	0.693	0.463
Observations	182970	182970	182970	182970	182970

Table 5

Relationship Analysis: Main Regressions

This table shows the main results of our relationship analysis. Observations are at the company-VC pair by year level. Only pairs involving a lead investor are included in the sample. Treatment is an indicator variable equal to one if a new airline route that reduces the travel time between the VC and the portfolio company has been introduced. Patents is equal to the log of (one plus) the number of patents the portfolio company applied for during the year. Citations/patent is equal to the log of (one plus) the number of citations those patents received (in the three years following their grant date) divided by the number of patents. IPO is an indicator variable equal to one if the company went public that year. Standard errors, clustered by portfolio company, are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

		Patents		Ci	Citations/Paten	ent		IPO	
	(1)	(2)	(3)	(4)		(9)	(7)	(8)	(6)
Treatment	0.0371^{***} (0.00975)	0.0352^{***} (0.00971)	0.0310^{***} (0.0113)	$0.0744^{***} $ (0.0178)	0.0698^{***} (0.0178)	0.0575^{***} (0.0203)	0.0103^{***} (0.00378)	0.00994^{***} (0.00373)	0.0104^{**} (0.00429)
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$MSA(VC) \times Year FE$	$N_{ m o}$	$_{\rm o}^{ m N}$	Yes	$N_{\rm o}$	$_{ m O}$	Yes	$ m N_{o}$	$_{ m O}$	Yes
$MSA(Company) \times Year FE$	$N_{\rm o}$	N_{0}	Yes	No	$_{ m O}$	Yes	No	$N_{\rm o}$	Yes
$ m R^2$	0.638	0.640	899.0	0.546	0.547	0.576	0.435	0.440	0.494
Observations	130169	130169	130169	130169	130169	130169	130169	130169	130169

Table 6
Relationship Analysis: Dynamics

This table shows the dynamics of the treatment effects in the relationship analysis. All variables are defined as in Table 5. The variable Treatment(-1) is an indicator variable equal to one if the observation is recorded in the year preceding the treatment. Treatment(0), Treatment(1), and Treatment(2+) are defined analogously with respect to the year of the treatment, the first year after the treatment, and two or more years after the treatment, respectively. Standard errors, clustered by portfolio company, are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
	Patents	Citations/Patent	IPO
Treatment(-1)	0.00639	0.0170	
	(0.0147)	(0.0285)	
Treatment(0)	0.0165	0.0244	0.00682
	(0.0155)	(0.0283)	(0.00502)
Treatment(1)	0.0391**	0.0690**	0.00805
	(0.0182)	(0.0333)	(0.00644)
$\operatorname{Treatment}(2+)$	0.0494***	0.106***	0.0158**
	(0.0182)	(0.0326)	(0.00655)
Controls	Yes	Yes	Yes
Pair FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
$MSA(VC) \times Year FE$	Yes	Yes	Yes
$MSA(Company) \times Year FE$	Yes	Yes	Yes
\mathbb{R}^2	0.668	0.576	0.494
Observations	130169	130169	130169

This table repeats the analysis of Table 5, but limiting the sample to company-VC pairs that do not involve a lead investor. Non-lead VCs located in the same MSA as the lead VC are also excluded from the sample. Standard errors, clustered by portfolio company, are shown in parentheses. * , **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) Patents	(2) Citations/Patent	(3) IPO
Treatment	-0.0128 (0.0203)	-0.0205 (0.0368)	0.00761 (0.00691)
Controls	Yes	Yes	Yes
Pair FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
$MSA(VC) \times Year FE$	Yes	Yes	Yes
$MSA(Company) \times Year FE$	Yes	Yes	Yes
R^2	0.758	0.688	0.673
Observations	90609	90609	90609

 ${\bf Table~8} \\ {\bf Relationship~Analysis:~Intensity~of~the~Treatment}$

This table repeats the analysis of Table 5, but separating the treatment indicator into two variables. Treatment \times Large is an indicator variable equal to one if the treatment is associated with a travel time reduction of at least 60 minutes. Treatment \times Small is an indicator variable equal to one if the treatment is associated with a travel time reduction of less than 60 minutes. Standard errors, clustered by portfolio company, are shown in parentheses. * , **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) Patents	(2) Citations/Patent	(3) IPO
	0.0336**	0.0684***	0.0115**
Treatment × Large	(0.0143)	(0.0248)	(0.00524)
Treatment \times Small	0.0259	0.0359	0.00822
	(0.0173)	(0.0333)	(0.00683)
Controls	Yes	Yes	Yes
Pair FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
$MSA(VC) \times Year FE$	Yes	Yes	Yes
$MSA(Company) \times Year FE$	Yes	Yes	Yes
\mathbb{R}^2	0.668	0.576	0.494
Observations	130169	130169	130169

Table 9
Relationship Analysis: Robustness

Panel A of this table repeats the analysis of Table 5, but separating the treatment indicator into two variables. Treatment (Hub or Merger) is an indicator variable equal to one if the treatment is due to the opening of a new airline hub, or the merger of two airlines. Treatment (Other) is an indicator variable equal to one if the treatment is not due to a hub opening or merger. Panel B restricts the control group to those control pairs whose average distance matches the average distance in the treatment group. That is, we exclude short-distance control pairs so that the average distance is the same in both groups. Panel C controls for heterogenous time trends by interacting baseline characteristics (funding, patents, experience, and distance) with year fixed effects. Panel D uses alternative versions of our dependent variables. HJT CPP adjusts for truncation in citations per patent by using the estimated shape of the citation-lag distribution following Hall et al. (2001). HJT WPC represents citation weighted patent counts (Trajtenberg, 1990), again using the HJT method to adjust for citation truncation. Relative CPP normalizes 3-year citations per patent by the mean citations per patent for other patents granted in the same year and technology class. Success is an indicator variable equal to one if the company has an IPO or is acquired that year. Standard errors, clustered by portfolio company, are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Hub Openings and Airline Mergers

atent (3) IPO
atent IPO
0.0237^*
(0.0142)
* 0.00842*
(0.00433)
Yes
0.494
130169

Panel B: Distance Matched Control Sample

	(1) Patents	$\begin{array}{c} (2) \\ \text{Citations/Patent} \end{array}$	(3) IPO
Treatment	0.0382*** (0.0126)	0.0660*** (0.0226)	0.00923** (0.00455)
Controls	Yes	Yes	Yes
Pair FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
$MSA(VC) \times Year FE$	Yes	Yes	Yes
$MSA(Company) \times Year FE$	Yes	Yes	Yes
\mathbb{R}^2	0.687	0.595	0.542
Observations	77129	77129	77129

Table 9 (Continued)

Panel C: Heterogenous Time Trends

	(1) Patents	$\begin{array}{c} \text{(2)} \\ \text{Citations/Patent} \end{array}$	(3) IPO
Treatment	0.0322*** (0.0117)	0.0593*** (0.0209)	0.0102** (0.00437)
Baseline Characteristics \times Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Pair FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
$MSA(VC) \times Year FE$	Yes	Yes	Yes
$MSA(Company) \times Year FE$	Yes	Yes	Yes
R^2	0.668	0.577	0.497
Observations	130169	130169	130169

Panel D: Alternative Dependent Variables

	(1) HJT CPP	(2) HJT WPC	(3) Relative CPP	(4) Success
Treatment	0.0860*** (0.0268)	0.107*** (0.0325)	0.0295*** (0.00922)	0.0252*** (0.00840)
Controls	Yes	Yes	Yes	Yes
Pair FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
$MSA(VC) \times Year FE$	Yes	Yes	Yes	Yes
$MSA(Company) \times Year FE$	Yes	Yes	Yes	Yes
R^2	0.589	0.640	0.567	0.424
Observations	130169	130169	130169	130169

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Appendix

A Matching VentureXpert with NBER Patent Data

A.1 Name Standardization

In order to match VentureXpert with data from the NBER Patent Project, we begin by standardizing the company names in both using the name standardization routines developed by the NBER Patent Data Project to create a bridge file to COMPUSTAT.¹⁵ These routines standardize common company prefixes and suffixes building on a list created by Derwent World Patent Index (Thomson-Reuters); they also identify a company's stem name excluding these prefixes and suffixes. Similarly, we standardize the location names from both datasets. This is done to correct for spelling errors as well as other types of errors that commonly occur, particularly in the patent data. For example, in some cases a neighborhood name is used rather than the name of a city. In other cases country codes are listed as state codes, e.g. a patent assignee from Germany (DE) may be coded as being from Delaware (DE). The city name standardization is done by running all location names through the Google Maps API, which automatically corrects close but inaccurate text representations of location names and returns a standardized name broken down into its component parts (city, state, country) along with latitude and longitude information.

A.2 The Matching Procedure

With these standardized company and city names we then use the following matching procedure:

 $^{^{15}} https://sites.google.com/site/patent data project/$

- 1. Each standardized name associated with a company in VentureXpert is matched with standardized names from the NBER data.¹⁶ If an exact match is found, this is taken to be the same company and hence it is removed from the set of names that need to be matched.
- 2. For the remaining companies in VentureXpert, each stem name associated with a company is matched with stem names from the NBER data. If an exact match is found and enough other identifying information matches as well, this is taken to be the same company and it is removed from the set of names that need to be matched. If an exact match is found, but not enough other identifying information matches as well, the match is added to a list of borderline matches to be checked manually.
 - (a) For a stem match to be considered definite, the standardized city/state combination also has to match. Or the state has to match along with the time period (first patent application was after the company founding year).
- 3. For the remaining companies in VentureXpert, each stem name associated with a company is matched with up to 10 close stem names from the NBER data using a padded bi-gram comparator. Fuzzy matches with match quality between 1.5 and 2 that also had a city/state match were kept for review as were fuzzy matches with quality above 2 with only a state match.
- 4. The borderline matches identified using the above procedure were reviewed by hand, now also using other qualitative information from both data sources including full patent abstracts, and paragraph-long company descriptions.

¹⁶Many companies have multiple names listed in VentureXpert, reflecting the fact that young companies often change their name as they mature.

B Measuring Travel Time

The procedure to compute travel times between VC firms and portfolio companies is the same as in Giroud (2013). The core of the algorithm is done using Visual Basic in the MS Mappoint software. Importantly, the results are not sensitive to the various assumptions listed below. The algorithm goes as follows:

- 1. Using MS Mappoint, we first compute the travel time by car (in minutes) between the two ZIP codes. This travel time is used as a benchmark and is compared to the travel time by air based on the fastest airline route. Whenever traveling by car is faster, air transportation is ruled out by optimality, and the relevant travel time is the driving time by car.
- 2. To determine the fastest airline route between any two ZIP codes, we use the itinerary information from the T-100 and ER-586 data. The fastest airline route minimizes the total travel time between the VC and the company. The total travel time consists of three components: (1) the travel time by car between the VC and the origin airport, (2) the duration of the flight, including the time spent at airports and, for indirect flights, the layover time, and (3) the travel time by car between the destination airport and the company. The travel time by car to and from airports is obtained from MS Mappoint. Flight duration per segment is obtained from the T-100 and ER-586 data, which include the average ramp-to-ramp time of all flights performed between any two airports in the United States. The only unobservable quantities are the time spent at airports and the layover time. We assume that one hour is spent at the origin and destination airports combined and that each layover takes one hour.
- 3. Additional assumptions we made are as follows:

- (a) If the distance between the two ZIP codes is less than 100 miles, driving is always optimal.
- (b) A new route dominates a previous one if the time saving is more than 15 minutes one-way (i.e., 30 minutes round-trip).
- (c) In the data, we also "smoothed" the optimal itinerary by keeping the previously optimal route if a new route is introduced but does not dominate the current route (e.g., a new flight from LGA instead of JFK with a saving of merely 5 minutes).