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Local bias in venture capital investments

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ABSTRACT

This paper examines local bias in the context of venture capital (VC) investments. Based on a sample of U.S. VC investments between 1980 and June 2009, we find more reputable VCs (older, larger, more experienced, and with stronger IPO track record) and VCs with broader networks exhibit less local bias. Staging and specialization in technology industries increase VCs' local bias. We also find that the VC exhibits stronger local bias when it acts as the lead VC and when it is investing alone. Finally, we show that distance matters for the eventual performance of VC investments.

1. Introduction

In practice, venture capital (VC) is not about the people you know but rather where you are: "FIBER networks cross the world. Data bits move at light speed. The globe has been flattened, and national boundaries obliterated. Yet…physical distance is very much on the minds of the investors who provide venture capital."[1] Some VCs even make their investment decisions based on the "20-minute rule", which is that if a start-up company seeking venture capital is not within a 20-minute drive of the VCs' offices, it will not be funded.[2] Generally speaking, both theoretical work (e.g., Kanniainen and Keuschnigg, 2003, 2004; Schwienbacher, 2007) and empirical evidence (e.g., Sapienza, 1992; Sapienza et al., 1996, 2005; Lerner, 1995; Maginart et al., 2000, 2001, 2002, 2006; Davila et al., 2003; Engel and Keilbach, 2006; Jääskeläinen et al., 2006; Bruton et al., 2006; Mäkelä and Maula, 2007; Meuleman and Wright, 2006; Tian, 2007) are consistent with these observations in the recent popular press. However, prior evidence on local bias in venture capital markets has not fully investigated how local bias depends on VCs' characteristics. Further, whether and how local bias differs for VC markets versus other forms of financial intermediation has not been fully considered. As well, there is no or little empirical evidence on the performance implications of local bias, which should be important for the diversification/specialization issue in VC fund management (Knill, 2009). This paper aims to fill this gap.

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[1] Stross, Randall, "It's not the people you know. It's where you are." The New York Times, 10/22/2006.
[2] ibid.

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The strong bias in favor of domestic securities is a well-documented characteristic of investment in public equities. French and Poterba (1991) document that U.S. equity traders allocate nearly 94% of their funds to domestic securities, even though the U.S. equity market comprises less than 48% of the global equity market. This "home-country bias" exists in other countries as well. We note that home-country bias is different than the type of bias we study in this paper, as country bias may reflect patriotism and regulatory issues, unlike the case of U.S.-state-level analyses considered in our paper. The local bias we examine here is close to the definition in Coval and Moskowitz (1999, 2001). They find that among all domestic stocks, U.S. mutual fund managers prefer to own stocks of companies located nearby.

The extension of the analysis of local bias to VC and entrepreneurial markets is nontrivial and interesting for at least three reasons. First, there is a two-sided matching in VC finance whereby the VCs must select the entrepreneurs and likewise the entrepreneurs must also select the VCs (Wright and Lockett, 2003; Hsu, 2004; Engel and Keilbach, 2006; Dushnitsky and Lenox, 2006; Franke et al., 2006; Mäkelä and Maula, 2007). By contrast, mutual fund investments in publicly listed securities do not involve a two-sided matching.

Second, information asymmetry between new ventures and VCs is expected to be worse than investments in public firms (Gompers and Lerner, 1999). There are no SEC required documentations, no popular financial websites, and no recommendations by financial analysts to rely on for investment in private firms. Generally, VCs know about the available investment opportunities from businesses plans submitted by entrepreneurs, venture capital and entrepreneur conferences, and personal and organizational networks. Geographic distance between VCs and new ventures reduces the effectiveness of these channels, and thus affects the ability of VCs to access to high quality investment opportunities.

Third, VCs often require frequent in-person contact with entrepreneurs both before and after making the funding decision. Starting from submitting the business plan to successfully getting the funding from the venture capital fund, on average, the entrepreneur needs to have three to eight face-to-face meetings with the venture capital fund. Furthermore, physical distance restricts the ability of VCs to closely monitor entrepreneurs, for example, attending the board meeting, which is critical for reduction of the moral hazard problem (Lerner, 1995).

In view of these differences in entrepreneurship and markets for entrepreneurial finance, we theorize a number of hypotheses in this paper pertaining local bias in venture capital investments. We expect local bias to depend on characteristics of the VC in terms of reputation, staging activities, and syndication networks. We also expect local bias to be related to clusters of both entrepreneurial firms and VCs in a geographic region. Our predictions are outlined in Section 2 of this paper.

We use a sample of new ventures and VCs in the U.S. from 1980 to June 2009 provided by VenturExpert. We estimate the geographic distance between the VCs and each of its portfolio companies and compare the equally weighted-average distance of each VC's actual portfolio with that of a hypothetical industry and stage specific benchmark portfolio that a VC could have invested in a specific year.[3] The percentage difference is used as a proxy for the local bias in VC investments.

We find that VCs consistently exhibit significant local bias over the sample period. Various factors seem to contribute to the local bias in VC investments, including VC reputation, VC network, staging, industry specialization, syndication activities, and being the lead VC. Specifically, we find that more reputable VCs, in general, exhibit less local bias. We also show that VCs with broader networks and more geographically diversified networks exhibit less local bias. On the other hand, staging and specialization in technology industries increase the VCs' local bias. For VCs with similar reputation, network, staging activities, and industry specialization, we further show that being a lead VC and investing alone significantly increase the VC's local bias. Overall, these empirical findings suggest that distance is an important factor that impacts the VCs' investment decision as it increases information asymmetry and the cost of monitoring.

Furthermore, we find that some characteristics of the states where the VCs are located also impact the VCs' local bias. For instance, we find that the cluster of new ventures in the local area increases the VCs' preference to invest in local new ventures, while the competition among VCs in the local area decreases their local bias.

We further link the geographic distance to the performance of the VC's investments. We find that local ventures are more likely to have successful ultimate exits (IPOs or M&As) controlling for venture quality and VC reputation.

The remainder of the study is organized as follows. Section 2 describes relevant theory and develops empirically testable predictions. Section 3 describes the sample and data employed in this study. Section 4 develops measures of local bias in VC investments and examines whether there is local bias in VC investments. Section 5 analyzes the factors that contribute to local bias. Section 6 links the geographic distance to VC investment performance. Section 7 summarizes the main findings of this study.

2. Hypotheses

Scholars have offered two different rationales for the investors' preference for geographic proximity. First, Coval and Moskowitz (1999) suggest that investors have better access to information about companies located near them. "Local investors can talk to employees, managers, and suppliers of the firm; they may obtain important information from the local media; and they may have close personal ties with local executive—all of which may provide them with an information advantage in local stocks." (p. 2046) Coval and Moskowitz (2001) link local bias to mutual fund performance and find that fund managers earn substantial abnormal returns in their geographically proximate investments. The average fund manager generates an additional return of 1.84% per year from her local investments above passive portfolios and earns 1.18% per year more than her distant holdings after

[3] As a robustness check, we also use a hypothetical market portfolio which consists of all new ventures that a VC investor could have invested as a benchmark to estimate local bias. The detailed description on the methodology is available in Section 4.2.

adjusting for risk. Coval and Moskowitz (2001) attribute this ability to select local stocks to fund managers' information advantage for local firms, which may be the result of improved monitoring capabilities or access to private information. Parwada (2008) provides further supporting evidence to the information asymmetry rationale. He examines the local bias among entrepreneurial money managers and finds that new money managers are less capable of overcoming information asymmetry problem and thus show a stronger local bias in their equity holdings. Second, Huberman (2002) and Franke et al. (2006) explain the local bias from the perspective of human psychology, i.e., preference to invest in the familiar.[4] They argue that people simply feel more comfortable investing their money in a business that is visible to them.

While VCs may similarly feel comfortable with investing in proximate firms as mutual fund managers, the information asymmetry problem in VC investments is much more severe than for investments in public firms. First of all, the information about investment opportunities is not public. VCs' personal network or professional network is one of the key information sources about investment opportunities. Research in sociology establishes that the likelihood of forming a social relationship declines as a function of distance in social space and physical space.[5] A plausible notion would be that VCs are more informed about investment opportunities in the local area. Furthermore, VCs need to closely monitor the management in order to alleviate the moral hazard problem after the funding decision. Lerner (1995) finds that the VCs' board representation is a decreasing function of the physical distance between the VCs and the entrepreneurial firms. Therefore, we expect that VCs exhibit stronger local bias than mutual fund managers.

Information asymmetry due to geographic distance could be potentially alleviated by the reputation of the VCs (Hsu, 2004; Atanasov et al., 2006). For example, more reputable VCs may be more capable of overcoming information asymmetry problem given that they have more experience and broader network. Therefore, consistent with the information asymmetry rationale, we expect that VCs with better reputation exhibit less local bias. Nevertheless, unlike public companies, which can have a large number of investors and almost have no control on who become their investors, private ventures have more power in the selection process. According to Hsu (2004), entrepreneurs select offers among competing VCs not only based on the financial terms, but more often considering the VCs' reputation. This two-sided matching process suggests that the VCs' reputation would be potentially an entry barrier to young VCs, particularly when proximity warrants better performance (Engel and Keilbach, 2006; for a similar insight in the underwriting literature, see Fernando et al., 2005). Therefore, we have two opposite predictions for the effect of VC's reputation on the local bias based on the two aforementioned theories, as stated in Hypothesis 1a and 1b.

Hypothesis 1a. *Reputation reduces VCs' local bias (based on information asymmetry argument).*

Hypothesis 1b. *Reputation increases VCs' local bias (based on two-sided matching argument).*

VCs often syndicate with each other when they invest in a new venture. Prior work has shown that syndication facilitates portfolio diversification in terms of portfolio size (Kanniainen and Keuschnigg, 2003, 2004; Keuschnigg, 2004; Cumming, 2006; Jääskeläinen et al., 2006). It is also well-documented that syndicates among VCs alleviate the information asymmetry (Bergemann and Hege, 1998; Lockett and Wright, 1999, 2001; Manigart et al., 2006; Wright and Lockett, 2003). Syndication networks facilitate information flow and monitoring, as well as the ability to form effective boards of directors and provide value-added advice to entrepreneurial firms through strategic, marketing, administrative and financial leadership for a firm. Therefore, we expect that syndication networks are most likely related to distance in the following way indicated in Hypothesis 2.

Hypothesis 2. *Syndication networks reduce VCs' local bias.*

VCs stage their investments to mitigate information asymmetries and agency costs (Gompers, 1995). Staging is costly insofar as there are contracting and negotiation costs with each financing round. We may expect that VCs will anticipate the number of financing rounds at the time of first investment (Cumming and Johan, 2008), and as such, the number of financing rounds is expected to be correlated with the distance between the VC and the entrepreneurial firm. Where VCs anticipate a greater need for monitoring (and hence expect a need for more frequent staging), all else being equal they will pick entrepreneurial firms that are more geographically proximate to facilitate such monitoring. To this end, we would anticipate staging to be positively associated with local bias.[6]

Hypothesis 3. *Staging is positively associated with VCs' local bias.*

Market structures and competition are likely to impact the extent of local bias. First, excessive competition among VCs in the same geographic area increases deal prices and lowers returns. This supply side pressure of too much capital chasing too few local deals gives rise to incentives whereby local investments are relatively more expensive. Prior theory and evidence is consistent with this prediction, insofar as evidence from the U.S. and Canada has shown excessive capital in the venture capital market gives rise to overvaluations (Gompers and Lerner, 2000) and lower returns (Cumming and MacIntosh, 2006). As such, we expect greater competition among VCs in a geographic region diminishes incentives to invest locally. That is, while investing locally has benefits of mitigating information asymmetry, excessive competition among the VCs to invest locally increases deal prices of local

[4] See also Zacharakis and Shepherd (2001), Zacharakis et al. (2003), and Parhankangas and Landstrom (2006).
[5] Lazarsfeld and Merton (1954), Blau (1977), Blau and Schwartz (1984).
[6] An alternative prediction is that geographic proximity generates more "soft" information about the entrepreneurial firm and therefore there is less need for staging (Tian, 2007).

Table 1
Summary Statistics. The sample consists of 1908 venture capital firms headquartered in the U.S. that made investments in 20,875 new ventures headquartered in the U.S. between 1980 and June 2009. The data are based on VenturExpert database.

Overview		
N of VCs		1908
N of New Ventures		20,875
Average rounds of financing each firm		2.8
Median rounds of financing each firm		2.0
Average number of investors in each round of financing		3.5
Median number of investors in each round of financing		3.0
Average amount of capital raised in each round of financing ($M)		7.5
Median amount of capital raised in each round of financing ($M)		3.1
New ventures industry distribution		
Information technology	13,417	64.3%
Medical/health/life science	3737	17.9%
Others	3721	17.8%
Status by June 2009		
N of firms public	2274	10.9%
N of firms acquired	5339	25.6%
N of firms defunct	2637	12.6%
N of firms that are private & independent	10,593	50.7%
Status unknown	32	0.2%

investments and lowers the expected returns of local investments, thereby making non-local investments relatively more attractive in terms of price despite the higher information asymmetry (Babcock-Lumish, 2009).

Second, in contrast to the effect of concentration of VCs in a geographic area, we expect entrepreneurial clusters and agglomeration to positively impact the incentive of a VC to invest locally. Agglomeration and entrepreneurial clusters have significant benefits for entrepreneurial firms in terms of resource acquisition (Agarwal et al., 2007; Audretsch and Dohse, 2007; Audretsch and Keilbach, 2007; Fujita and Thisse, 2002; Venkataraman, 2004). Entrepreneurs based in an agglomeration have an advantage of knowledge acquisition, communication and information spillovers. Further, there is greater specialization in abilities and stronger access to other entrepreneurs as mentors and governance provided through superior board representation. As such, we may expect that agglomeration advantages increase the benefit to VCs that invest in entrepreneurial firms based in a cluster. Hypotheses 4 and 5 summarize the different effects of concentration of the VCs and entrepreneurs, respectively, in a geographic region.

Hypothesis 4. *The greater the competition among the VCs in a local area, the smaller the degree of local bias.*

Hypothesis 5. *The greater the cluster of new ventures in a local region, the greater the degree of local bias in VC investment.*

While our first five hypotheses considered the determinants of distance, our last hypothesis relates distance to performance. In the extant literature on mutual funds, it is worth recognizing that several papers examining local bias in public equity investments find that investors earn higher returns on stocks of local firms (see e.g., Coval and Moskowitz, 2001; Ivkovic and Weisbenner, 2005). As such, it is natural to posit if there is a relationship between distance and performance in entrepreneurial finance.

Further, in VC investments, the two key determinants of the VCs' performance are their ability to select high quality new ventures and to nurture new ventures (Barry et al., 1990; Megginson and Weiss, 1991). The geographic distance between the VC investor and the new venture likely affects both factors. If geographic proximity reduces information asymmetry between the VCs and firms and facilitates VCs' close monitoring in firms, VCs would have better performance or higher successful exit rates (IPOs and M&As) from investments in local firms.

Hypothesis 6. *Local ventures perform better than distant ventures.*

In summary, by analyzing how the information asymmetry associated with geographic distance affects the VCs' investment decision, and whether the information advantage of local new ventures improves their successful exit rates, we are able to shed some light on the economic reasons of local bias which seems to be prevalent in equity investments.

3. Data and summary statistics

Our primary data source is VenturExpert. We start with all VC investments in the U.S. from 1980 to June 2009. To be included in our sample, we request the observation to have zip codes of both the portfolio company and the VC fund available.[7] This leaves us 122,248 VC-Company-Round observations, representing 20,875 new ventures that receive financing from 1908 VCs (Table 1).

[7] We restrict our analysis to investments by independent VCs in this paper.

Table 2
Distribution of VCs and new ventures across states. This table presents the top 10 states ranked by the number of new ventures, and the number of VCs over the period from 1980 to June 2009.

(A) Top 10 states by the number of new ventures		
State	*N*	Percentage
CA	7750	37.1%
MA	2236	10.7%
TX	1211	5.8%
NY	1185	5.7%
PA	712	3.4%
WA	702	3.4%
CO	615	2.9%
NJ	597	2.9%
GA	531	2.5%
VA	517	2.5%
Total	16,056	76.9%
(B) Top 10 states by the number of VCs		
VC headquarter state	*N*	Percentage
CA	585	30.7%
NY	251	13.2%
MA	190	10.0%
TX	109	5.7%
IL	70	3.7%
CT	65	3.4%
PA	65	3.4%
CO	48	2.5%
WA	45	2.4%
MN	39	2.0%
Total	1467	76.9%

New ventures on average raise about three rounds of financing. The average number of VCs in each round of financing is 3.5, with a median of 3. The average dollar amount of capital raised in each round of financing is $7.5 million, with a median of $3.1 million.

VenturExpert groups new ventures into three industry classes, which are information technology, medical/health care/life science, and non-high technology. About 64.3% of the new ventures are in the information technology industry group. About 17.9% of the new ventures are in the medical/health care/life science group. And the remaining 17.8% of the new ventures are in the non-high technology group.

By June of 2009, among the 20,875 new ventures in our sample, 10.9% of the firms are public; about 25.6% were acquired; about 12.6% were defunct; and the remainder appears to be still private and independent.

We present the top 10 states ranked by the number of new ventures and the number of VCs in Table 2A and B. About 59.3% of the new ventures are located in CA, MA, NY, and TX. About 59.6% of the VCs are located in the same top four states. We define these four states as “hot” states.

4. Testing local bias

In this section we present evidence of the extent of local bias among U.S. VC investments. Subsection 4.1 provides the estimates of geographic distance and subsection 4.2 discusses our measure of local bias.

4.1. Geographic distance between the VCs and new ventures

To gauge more precisely how VCs make decisions with regard to the geographical location of their investments, we calculate geographic distance between the VCs and their portfolio companies. We obtain the latitude and longitude data for the center of each zip code from the *U.S. Census Bureau's Gazetteer* and estimate the distance between centers of two zip codes using the following equation:

$$d_{ij} = 3963 \times \text{ar}\, cos[sin(\text{lat}_i)sin(\text{lat}_j) + cos(\text{lat}_i)cos(\text{lat}_j)cos(|\text{long}_i - \text{long}_j|)]$$

where latitude (lat) and longitude (long) are measured in radians and 3963 is a constant representing the Earth's radius in statute miles.[8]

[8] Sorenson and Stuart (2001) use “3437” as the constant representing the radius of the Earth in nautical miles; Coval and Moskowitz (1999, 2001)) use “6379” as the constant representing the radius of the Earth in kilometers. Adopting these different units (such as nautical or kilometer) does not change our measure of local bias.

Table 3
Geographic distance between VCs and their portfolio firms. In Panel A, we categorize the sample according to the industry and the stage of the new venture. If the new venture is at seed/startup or early stage, we define it as early stage ventures. Following the definition of VenturExpert, ventures that surpass their early stage and enter fast growth period are defined as expansion stage ventures. Other ventures are grouped as later stage ventures. In Panel B, we categorize the sample into five sub-periods based on the cyclicity of the VC industry. We report the *p*-value of *F*-test on differences in distance across various categories. A distance of zero indicates that the VC and the venture indicates that they are located in the same zip code. ***, **, and * denote significant at 1%, 5%, and 10% confidence level respectively.

	Mean	Median	Min	Max	Std
Panel A: Distance by industry and stage					
Full sample	783	233	0	5419	972
Information technology	756	179	0	5419	975
Medical/health/life science	870	383	0	5235	987
Others	773	334	0	3627	916
F-test across groups *p*-value	0.000***	0.000***			
Early stage	721	169	0	5419	952
Expansion stage	800	259	0	5419	979
Later stage	828	320	0	5419	982
F-test across groups *p*-value	0.000***	0.000***			
Panel B: Distance by year					
1980–1989	891	356	0	3361	356
1990–1997	800	306	0	2844	306
1998–2000	781	215	0	5217	215
2001–2006	733	183	0	5419	183
2007–June 2009	707	180	0	5419	180
F-test across periods *p*-value	0.000***	0.000***			

In Table 3, we report the geographic distance between the headquarters of the VCs and the headquarters of the new ventures. The mean distance is 783 miles, with a median of 233 miles. Typically, technology ventures at their early stages have greater information asymmetry. Thus, VCs could be more sensitive to geographic distance when investing in these firms. In Table 3, we further compare the distance across industries and stages. We show that the distance between the VCs and the information technology ventures and early stage ventures are significantly shorter than those of the ventures in other industries and at later stages.

In Table 3B, we compare the geographic distance between the VCs and the new ventures in different time periods. We divide our 30-year sample period into five sub-periods, 1980–1989, 1990–1997, 1998–2000 (bubble period), 2001–2006, and 2007–2009 (financial crisis).We observe that in general the distance has become shorter over time. The differences in local bias across these sub-periods are statistically significant.

4.2. Measures of local bias

Following the formula developed in Coval and Moskowitz (1999), we measure the local bias as the percentage difference between the weighted-average distance of the actual investment portfolio for each VC and the weighted-average distance of a hypothetical benchmark portfolio. We estimate equally weighted-average distance for both the actual investment portfolio and the benchmark portfolio.[9]

Most of the VCs have their preference for industry sectors and financing stages when they choose investment targets. In other words, for a specific VC, the investment opportunity set might be smaller than the market portfolio. Therefore, our benchmark portfolio is industry and stage restricted, which consists of all new ventures available in a certain year with the same industry and stage as the one that a VC actually invested in that year. Specifically, our methodology follows two steps. First, we categorize all the new ventures into three industry sectors, information technology, medical/health/life science, and others, and three stages, including early stage, expansion stage, and later stage, which represents a 3×3 matrix or nine industry and stage specific portfolios. For a specific VC in a specific year, its investment must fall in one or more of these nine portfolios. We assume that without distance consideration, the VC could have invested in any other ventures available in the same industry and stage specific portfolio with its actual investment. If all the investments of a VC are in the same industry and stage specific portfolio, then the percentage difference between the average distance of the industry and stage specific benchmark portfolio and the distance of its actual investments represents its local bias. If the VC had invested in multiple industries and stages, we estimate its actual weight in each industry and stage specific portfolio and then apply this weight to its benchmark portfolio which consists of multiple industry and stage specific portfolios.

Suppose there are VCs (M) that have invested in new (N) ventures in a specific industry and at a specific stage in year t. Assuming that VCs are equally likely to invest in a new venture within their industry and stage specialization if there is no location

[9] The data about the amount of capital invested by each VC investor in each round of financing are missing for most of the observations. Therefore, we are not able to estimate value-weighted indexes.

preference, its investment weight in each available new venture thus is $\frac{1}{N}$. Let $d_{i,j}$ denote the geographic distance between VC i and new venture j. The distance of VC i's benchmark portfolio, or the equally weighted-average distance between VC i and all available new ventures in the same industry and at the same stage that it could have invested in year t is equal to

$$d_{iM} = \frac{1}{N}\sum_{j=1}^{N} d_{ij}$$

The local bias exhibited by a VC can be calculated as the following:

$$\mathrm{LB}_i = \frac{d_{iM} - d_i}{d_{iM}} = 1 - \frac{d_i}{d_{iM}}$$

where d_i is the actual portfolio distance for VC i, and d_{iM} is the benchmark portfolio distance for VC i. LB_i measures how much closer VC i is to her actual portfolio than to the benchmark portfolio.

If the actual portfolio of the VC consists of more than one industry and/or more than one stage, we estimate d_{iM}^{p} for each industry and stage specific portfolio following the above method, where p represents one of the nine industry and stage specific portfolios. Let W_p represents the VC's actual investment weight in portfolio p, the average distance of this VC's benchmark portfolio is the following:

$$d_{iM} = \sum_{p=1}^{P} W_p d_{iM}^{p}$$

To illustrate how this works, we assume a simple case where there are two VCs (A and B) that have invested in three ventures (a, b, and c) that are in the information technology sector and at the early stage in year t. Ventures a and b are invested by VC A and venture c is invested by VC B. The actual portfolios of A and B are {Aa, Ab}, and {Bc}, respectively. Assuming VCs are equally likely to invest in a new venture as long as one of them has invested in the new venture, the benchmark portfolios of A and B should be {Aa, Ab, Ac}, and {Ba, Bb, Bc}, respectively. Let's assume the distance between each VC and each venture is the following:

$$\begin{pmatrix} \mathrm{Aa} = 10 \\ \mathrm{Ab} = 20 \\ \mathrm{Ac} = 150 \end{pmatrix} \begin{pmatrix} \mathrm{Ba} = 150 \\ \mathrm{Bb} = 150 \\ \mathrm{Bc} = 30 \end{pmatrix}$$

Thus, the average distance of A's actual portfolio is 15 miles ((10 + 20)/2), while the average distance of A's benchmark portfolio is 60 miles ((10 + 20 + 150)/3). The local bias of A is 75% ((60 − 15)/60). Similarly, the average distance of B's actual portfolio is 30 miles, while the average distance of B's benchmark portfolio is 110 miles ((150 + 150 + 30)/3). The local bias of B is 73% ((110 − 30)/110).

The results, as shown in Table 4, suggest that VCs consistently show significant local bias in their investments over time. The average (median) distance of the actual portfolios is about 48.5% (60.4%) closer than the average distance of the benchmark

Table 4

Test for local bias. In (A), we report the local bias across industries and across stages. In (B), we report the local bias across different time periods. We examine whether the local bias is significantly different from zero. ***, **, and * denote significant at 1%, 5%, and 10% confidence level respectively. We further report the p-values of F-test on differences in means and medians across different categories.

(A) Local bias by industry and stage preferences

	Early stage	Expansion	Later stage	F-test on diff. p-value
Information technology	54.2%***	48.7%***	46.5%***	0.000
	(75.7%)***	(67.8%)***	(65.3%)***	0.000
Medical/health/life science	46.5%***	37.4%***	36.4%***	0.000
	(68.7%)***	(57.1%)***	(56.0%)***	0.000
Other	47.4%***	42.5%***	37.9%***	0.000
	(77.5%)***	(71.8%)***	(63.6%)***	0.000
F-test on diff. in means (p-value)	0.000	0.000	0.000	
F-test on diff. in medians (p-value)	0.000	0.000	0.000	

(B) Local bias across years

	Mean	Median
1980–1990	43.3%***	50.8%***
1991–1997	44.5%***	54.2%***
1998–2000	45.8%***	56.7%***
2001–2006	52.2%***	66.8%***
2007–June 2009	51.7%***	66.0%***
F-test on diff. p-value	0.000	0.000

Table 5
Characteristics of states and VCs. This table compares characteristics of hot states and other states, as well as characteristics of VCs located in hot states and those located in other states. All state characteristics are based on per thousand residents. *T*-statistics are 2-tailed. ***, **, and * denote that the differences in means and medians are significant at 1%, 5%, and 10% confidence level respectively.

	Full sample	Hot states	Other states
(A) Characteristics of VCs			
Local Bias	48.5%	48.9%	47.8%
	(60.4%)	(61.4%)***	(58.8%)***
VC Age	9.4	9.8***	8.7***
	(7.0)	(7.0)***	(7.0)***
VC Size ($M)	708.9	806.7***	556.7***
	(148.0)	(180.0)***	(100.0)***
General Experience	86.9	100.0***	66.0***
	(24.0)	(26.0)***	(20.0)***
Industry specific experience			
Information technology	56.5	69.2***	36.5***
	(11.0)	(14.0)***	(8.0)***
Medical/health/life science	15.8	16.3	14.9
	(0.0)	(0.0)***	(0.0)***
Non-high technology	7.3	0.7	0.8
	(0.0)	(0.0)***	(0.0)***
N of IPOs	2.6	3.1***	1.9***
	(0.0)	(0.0)***	(0.0)***
Degree	2.8	3.2***	2.1***
	(1.2)	(1.4)***	(1.0)***
Network Distance (miles)	954.6	986.9***	900.9***
	(945.4)	(980.2)***	(894.4)***
Staging	2.3	2.2	2.3
	(2.2)	(2.1)	(2.2)
N	13,590	8325	5265
(B) Characteristics of states			
N of Ventures	17.2	23.5***	7.2***
	(12.2)	(22.3)***	(5.4)***
N of Local VCs	4.9	6.3***	2.6***
	(3.9)	(6.9)***	(1.9)***
N of Outside VCs	11.6	13.2***	9.0***
	(9.4)	(12.4)***	(7.2)***
N of Patents	355.8	405.0***	277.9***
	(312.5)	(359.2)***	(247.9)***
N of Universities	15.4	14.5***	(16.8)***
	(15.2)	(12.5)***	(16.1)***
N	13,590	8325	5265

portfolio.[10] Furthermore, VCs exhibit significant local bias, no matter their industry and stage preferences. Within each industry sector, VCs exhibit significantly greater local bias when the new ventures are at their early stage than at their later stage. Across industry sectors, VCs specializing in information technology show significantly greater local bias. As investments in technology ventures and early stage ones typically involve greater uncertainty, the results are expected.

In sum, we find significant local bias in VC markets in the U.S. Relative to mutual funds, for example, local bias is about 37.3–58.2% more pronounced in the venture capital market.[11]

5. Factors contributing to the local bias in VC investments

In this section, we analyze how the VCs' characteristics affect their preference for proximate investments and empirically assess our Hypotheses 1–5 (Section 2).

5.1. Summary statistics of characteristics of states and VCs

In Table 5A, we examine various characteristics of VCs, including VCs' reputation, broadness of their network, general experience and industry specific experience, and their staging activities. In Table 5B, we further present characteristics of the

[10] Sorenson and Stuart (2001) find similar evidence based on the U.S. VC data and artificially constructed variables. Cumming and Johan (2006) use the Canadian VC data to study the likelihood of interprovincial investment and also show similar results; however, the geography of Canada and dearth of details in the data do not enable many generalizable inferences for other contexts.

[11] Coval and Moskowitz (1999) report a local bias of 8.95%–11.20% in the mutual fund industry using different benchmark portfolios.

Table 6
Correlation matrix. Correlations significant at the 5% level are highlighted in underline font.

	Local bias	*VC Age*	*VC Size*	*Degree*	*Network Distance*	*N of IPOs*	*General Exp.*	*IT Exp.*	*Medical Exp.*	*Non-tech Exp.*	*Staging*	*N of Ventures*	*N of Local VCs*	*N of Outside VCs*	*N of Patents*
VC Age	−0.068														
VC Size	−0.115	0.169													
Degree	−0.124	0.155	0.208												
Network Distance	−0.475	0.027	0.099	0.165											
N of IPOs	−0.112	0.520	0.302	0.294	0.104										
General Exp.	−0.083	0.508	0.291	0.348	0.089	0.915									
IT Exp.	−0.062	0.477	0.281	0.346	0.076	0.857	0.955								
Medical Exp.	−0.105	0.302	0.186	0.261	0.094	0.678	0.719	0.534							
Non-tech Exp.	−0.067	0.344	0.281	0.290	0.058	0.600	0.670	0.584	0.462						
Staging	0.018	0.183	0.086	0.383	0.044	0.310	0.417	0.373	0.356	0.280					
N of Ventures	0.089	0.024	0.042	−0.048	−0.001	0.111	0.109	0.135	0.051	−0.010	0.017				
N of Local VCs	0.037	0.060	0.108	−0.096	0.003	0.118	0.114	0.135	0.052	−0.004	−0.030	0.838			
N of Outside VCs	0.058	0.035	0.081	−0.087	−0.000	0.094	0.094	0.108	0.049	0.006	0.025	0.812	0.849		
N of Patents	0.046	0.079	0.026	−0.179	−0.023	0.143	0.157	0.157	0.094	−0.011	−0.004	0.474	0.688	0.551	
N of Universities	−0.026	0.010	0.084	−0.167	−0.04	−0.042	−0.047	−0.050	−0.047	0.011	−0.006	−0.538	−0.055	0.262	−0.167

states, such as the intensity of entrepreneurial activities, the competition of the local VC industry, the R&D activities, and the number of local universities and colleges.[12]

We use the following measures as proxies for the VC's reputation, including VC age, VC size, the number of firms that the VC has previously taken public, and the VC's investment experience. VC age is estimated by taking the difference between the deal year and the year that the VC was founded. VC size is measured as the amount of capital under management in millions of dollars. For the VC's investment experience, following Sorenson and Stuart (2001), we examine both the general experience (the number of rounds that the VC had invested in all industries before the deal year) and industry specific experience (the number of rounds that the VC had invested in a specific industry before the deal year).

We use two measures to capture two different attributes of VCs' network to test Hypothesis 2.[13] The first measure is referred to as *degree*, which captures the broadness of the network that a VC firm is able to participate. Hochberg et al. (2007) develop five measures of how well networked a VC is, including *degree*, *indegree*, *outdegree*, *betweenness*, and *eigenvector.*[14] The most relevant measure for the purpose of this paper is *degree*, which we calculate for each VCs every year. We code two VCs co-investing in the same portfolio company in the same round of financing as having a tie. We count the number of ties each VC firm has each year. *Degree* is measured as the percentage of ties that each VC firm has relative to the maximum number of ties the VC firm could have had each year assuming it can syndicate with any other VCs who are active that year.

Degree measures how many other VCs that each VC is able to access to, but it does not capture how geographically diversified the network is. For example, a VC with five partners who are all located within the same state, has higher degree but is worse geographically diversified than a VC with only three partners who are located in different states. Therefore, we develop the second measure, *Network Distance*, which is the mean distance between the VC and all its network partners. It captures how geographically diversified the network is.

Staging is another commonly used control mechanism in venture capital investments to deal with the information asymmetry and moral hazard problem. We use the average number of rounds that the VC invests in portfolio companies as a proxy.

As we mentioned earlier, VCs often specialize in certain industry sectors. To examine whether the VC's industry specialization has an impact on local bias, we include a *Tech* dummy which is equal to 1 if more than 50% of the VC's investments are in the information technology and medical/health care/life science sectors.

Anecdotal evidence suggests that entrepreneurial activities are highly clustered. We use the total number of new ventures located in a state each year normalized by the state population as a proxy for the density of the entrepreneurial activities.

We develop two measures to estimate how competitive the local VC industry is in a state. The first measure is the number of VCs located in that state normalized by the state population. The second measure is the number of VCs not located in that state but invested in new ventures in that state normalized by the state population.

We also include two measures representing the R&D and innovation activities in the state. The first measure is the number of patents of the state per year normalized by the population. The second measure is the number of universities and colleges in the state normalized by the population.

In Table 5A, we compare the VC characteristics between the four “hot” states (CA, MA, NY, and TX) and other states. We find that “hot” states VCs exhibit stronger local bias than VCs located in other states, however, only the difference in medians is statistically significant. VCs in hot states are significantly more senior and larger, have more investment experience (particularly in information technology), and have stronger IPO track record. Hot states VCs are also significantly better networked and their networks are more geographically diversified.

As shown in Table 5B, the four hot states exhibit very different distributions of ventures and VCs from the other states. For instance, the number of ventures per thousand residents in the four hot states is 23.5 with a median of 22.3, while that is 7.2 with a median of 5.4 in other states. The average number of local VCs and outside VCs available for investments in the four hot states is 6.3 and 13.2, respectively. In contrast, the average number of local VCs in other states is 2.6 and the average number of outside VCs is 9.0. Furthermore, we show that the number of patents per thousand residents in the four hot states is significantly greater than those of the other states, while the number of universities and colleges per thousand residents of the former is significantly smaller than the latter.

In Table 6, we report the correlation coefficients among the aforementioned variables. Some of the variables are highly correlated, for instance, the four measures of VC reputations, the R&D activities of the states and the number of ventures/VCs. In the regression analysis that follows, we use state fixed effect regressions to control for the potential collinearity.

5.2. Regression analysis of local bias

In this section, we analyze factors contributing to the local bias in VC investments using multivariate regressions.

Table 7A displays regressions of local bias using the full sample. The dependent variable is the percentage local bias. The independent variables can be categorized into two groups. The first group of variables represents characteristics of VCs, including

[12] Please see the detailed definitions of these variables in the Appendix.

[13] The two measures mentioned here represent the VC's ability to syndicate with other VCs. In the section that follows, we further consider how the fact of syndicate impacts local bias, which provides more direct evidence to Hypothesis 2.

[14] These measures are commonly used in network analysis. *Degree* measures the number of relationships a VC investor in the network has. *Indegree* is a measure of the frequency with which a VC investor is invited to co-invest in other VCs' deals. *Outdegree* counts the number of other VCs a VC investor invites into its own syndicates. *Eigenvector* measures the extent to which a VC investor is connected to other well-connected VCs. *Betweeness* proxies for the extent to which a VC investor may act as an intermediary by bringing together VCs with complementary skills or investment opportunities who lack a direct relationship between them.

Table 7

Regression analysis of local bias. This table displayed the results of the multivariate regressions of local bias on various factors. In (A), we examine the local bias of all VCs focusing on the impact of VC reputation and state characteristics on local bias. Local bias is measured based on the whole portfolio of a VC in a specific year. In (B), we conduct state fixed effect regressions to control for the potential collinearity of the variables we use to describe characteristics of the states. In (C), we repeat state fixed effect regressions (as shown in (B)) for the following five sub-periods, 1980–1990, 1991–1997, 1998–2000, 2001–2006, and 2007–June 2009, respectively. Only the coefficients of measures for VC reputation are reported for briefness. In (D), we examine the impact of being a lead VC (Models 1–5) and syndicate (Models 6–10) on local bias. In Models 1–5, we divide each VC's portfolio into the lead VC portfolio and non-lead-VC portfolio, where the lead VC is defined as the VC that had invested the largest amount of capital in the company, and then we estimate local bias separately. In Models 6–10, we divide each VC's portfolio into solo-VC portfolio and Syndicate portfolio, where Syndicate is defined as that there are at least two VCs investing in the same round, and then we estimate local bias separately. All specifications in (C) include the state fixed effect. *P*-value is 2 tailed. ***, **, and * denote significant at 1%, 5% and 10% confidence level respectively.

(A) The impact of VC and state characteristics on local bias

	1	2	3	4	5	6	7	8	9	10
Intercept	105.329***	117.942***	92.789***	99.359***	96.096***	94.180***	100.318***	79.707***	86.591***	86.259***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
VC characteristics										
Ln(VC Age)	−1.342***					−2.343***				
	(0.006)					(0.000)				
Ln(VC Size)		−3.124***					−3.671***			
		(0.000)					(0.000)			
Ln(N of IPOs)			−5.843***					−7.005***		
			(0.000)					(0.000)		
Ln(General Experience)				−1.393***					−1.680***	
				(0.000)					(0.000)	
Ln(IT Experience)					0.746**					1.038***
					(0.013)					(0.001)
Ln(Medical Experience)					−2.089***					−2.612***
					(0.000)					(0.000)
Ln(Non-tech Experience)					0.464					−0.025
					(0.218)					(0.949)
Degree	−1.192***	−0.715***	−0.718***	−1.029***	−1.134***	−1.055***	−0.490***	−0.482***	−0.854***	−0.925***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Network Distance)	−11.164***	−11.252***	−10.995***	−11.120***	−11.119***	−11.472***	−11.496***	−11.265***	−11.417***	−11.390***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Staging	5.859***	5.867***	7.131***	6.606***	6.042***	7.515***	7.211***	8.835***	8.224***	7.638***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tech	4.115**	3.400**	4.756***	4.701***	5.315***	5.681***	4.749***	6.115***	6.085***	5.810***
	(0.013)	(0.050)	(0.003)	(0.000)	(0.004)	(0.001)	(0.008)	(0.000)	(0.000)	(0.002)
State characteristics										
Ln(N of Ventures)	34.938***	31.376***	33.424***	34.549***	33.961***					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
Ln(N of Local VCs)	−27.749***	−23.847***	−25.569***	−27.126***	−27.285***					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
Ln(N of Outside VCs)	−11.727***	−10.430***	−11.352***	−11.592***	−11.429***					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
Ln(N of Patents)	−9.421***	−8.934***	−8.734***	−9.418***	−9.132***					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
Ln(N of Universities)	11.810***	9.193***	10.980***	11.812***	12.281***					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
Hot states dummy						4.477***	4.935***	5.443***	4.724***	3.547***
						(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
State characteristics										
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	13,590	13,590	13,590	13,590	13,590	13,590	13,590	13,590	13,590	13,590
Adjusted *R*-square (%)	18.62	19.69	19.51	18.64	18.99	13.24	14.98	14.60	13.32	13.91

(B) State fixed effect regressions

	1	2	3	4	5
Intercept	97.053***	102.852***	83.641***	89.980***	88.846***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(*VC Age*)	−2.294***				
	(0.000)				
Ln(*VC Size*)		−3.479***			
		(0.000)			
Ln(*N of IPOs*)			−6.733***		
			(0.000)		
Ln(*General Experience*)				−1.535***	
				(0.000)	
Ln(*IT Experience*)					1.19***
					(0.000)
Ln(*Medical Experience*)					−2.667***
					(0.000)
Ln(*Non-tech Experience*)					−0.158
					(0.682)
Degree	−0.969***	−0.418***	−0.396***	−0.780***	−0.856***
	(0.000)	(0.001)	(0.003)	(0.000)	(0.000)
Ln(*Network Distance*)	−11.510***	−11.559***	−11.326***	−11.475***	−11.420***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Staging	7.286***	6.843***	8.487***	7.871***	7.437***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tech	6.247***	5.473***	6.752***	6.623***	5.858***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
Year fixed effect	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes
N	13,590	13,590	13,590	13,590	13,590
Adjusted R-square (%)	13.29	15.00	14.54	13.35	14.05

(C) Robustness check by sub-periods

	1980–1990	1991–1997	1998–2000	2001–2006	2007–2009
Ln(*VC Age*)	−1.356***	3.204**	−1.472	−2.604***	−4.751***
	(0.000)	(0.010)	(0.161)	(0.004)	(0.000)
Ln(*VC Size*)	−1.972***	−3.764***	−3.482***	−2.870***	−5.440***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(*N of IPOs*)	−3.001**	−5.101***	−5.985***	−5.774***	−9.014***
	(0.019)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(*General Experience*)	0.213	−0.210	−1.071	−1.421**	−3.460***
	(0.784)	(0.805)	(0.272)	(0.031)	(0.001)
Ln(*IT Experience*)	2.162***	0.477	−0.162	0.880*	−0.004
	(0.007)	(0.525)	(0.864)	(0.092)	(0.996)
Ln(*Medical Experience*)	−3.338***	−1.386*	−1.345*	−2.151***	−2.205***
	(0.000)	(0.069)	(0.099)	(0.000)	(0.004)
Ln(*Non-tech Experience*)	0.946	1.484*	2.557**	0.075	−0.294
	(0.293)	(0.069)	(0.013)	(0.913)	(0.762)

(continued on next page)

Table 7 *(continued)*

(D) The impact of being the lead VC and Syndicate on the local bias

	Lead VCs vs. non-lead VCs					Solo-VC vs. Syndicate				
	1	2	3	4	5	6	7	8	9	10
Intercept	102.247***	102.852***	86.294***	89.980***	91.603***	103.416***	110.062***	88.845***	95.379***	94.105***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lead VC	6.543***	6.493***	6.692***	6.661***	6.440***					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
Syndicate						−5.367***	−5.547***	−6.021***	−5.772***	−5.414***
						(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
VC characteristics										
Ln(VC Age)	−2.462***					−2.710***				
	(0.000)					(0.000)				
Ln(VC Size)		−3.726***					−3.709***			
		(0.000)					(0.000)			
Ln(N of IPOs)			−6.910***					−7.342***		
			(0.000)					(0.000)		
Ln(General Experience)				−2.210***					−2.089***	
				(0.000)					(0.000)	
Ln(IT Experience)					0.947***					0.930***
					(0.000)					(0.000)
Ln(Medical Experience)					−2.673***					−2.597***
					(0.000)					(0.000)
Ln(Non-tech Experience)					−0.664**					−0.563*
					(0.035)					(0.093)
Degree	−1.026***	−0.492***	−0.472***	−0.790***	−0.851***	−1.035***	−0.502***	−0.454***	−0.821***	−0.877***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Network Distance)	−11.376***	−11.523***	−11.101***	−11.231***	−11.221***	−10.984***	−10.981***	−10.731***	−10.886***	−10.883***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Staging	6.157***	6.276***	8.484***	7.298***	6.790***	6.397***	6.111***	7.729***	7.314***	6.817***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tech	7.428***	7.009***	8.063***	7.998***	6.680***	7.241***	7.221***	7.769***	7.707***	6.592***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	20,186	20,186	20,186	20,186	20,186	18,300	18,300	18,300	18,300	18,300
Adjusted *R*-square (%)	10.17	11.69	11.36	10.30	10.82	10.28	11.55	11.65	10.37	10.86

various measures of VC reputation, such as *Ln*(*VC Age*), *Ln*(*VC Size*), *Ln*(*N of IPOs*), *Ln*(*General Experience*), *Ln*(*IT Experience*), *Ln*(*Medical Experience*), and *Ln*(*Non-Tech Experience*), two measures of VCs' network, *Degree* and *Ln*(*Network Distance*), VCs' industry specialization, a *Tech* dummy, and finally, *Staging*. The second group includes the state-level variables, such as *Ln*(*N of Ventures*), *Ln*(*N of Local VCs*), *Ln*(*N of Outside VCs*), *Ln*(*N of Patents*), and *Ln*(*N of Universities*). All these state-level variables are adjusted by the state population. There could be additional state-level characteristics that impact local bias. [15] In Models 6–10, we include the *hot states dummy*, which is equal to 1 if the VC firm is located in one of the following four states, CA, MA, NY, and TX. We included year fixed effect in all models.

A problem with the specifications in Table 7A is that the state-level variables and the hot state dummy, as shown in Table 6, are highly correlated with some characteristics of VCs. To control for this collinearity problem, we run state fixed effect regressions in Table 7B.

To examine whether the relation between VC reputation and local bias changes over time, in Table 7C, we repeat the state fixed effect regressions (as shown in Table 7B) for each of the following five sub-periods that reflect the cycles of the VC industry, 1980–1990, 1991–1997, 1998–2000, 2001–2006, and 2007–June 2009. For briefness, we only report the coefficients of measures for VC reputation.[16]

VCs often syndicate with each other when investing in a company. Some VCs are the lead investors and distance could be more of their concerns since typically lead VCs do most of the due diligence and monitoring. If more or less, syndicate members facilitate information flows and monitoring (see, e.g., Bergemann and Hege, 1998; Lockett and Wright, 1999, 2001; Manigart et al., 2006; Wright and Lockett, 2003), then we should observe that VCs exhibit larger local bias when they are investing by themselves alone. In Table 7D, we further examine whether being a lead VC (Models 1–5) and investing alone (Models 6–10) leads to stronger local bias controlling for VC reputation and other characteristics.

We find a significantly negative relation between local bias and VC reputation, no matter which measure we use, when the full sample is utilized. The result is robust when we apply the state fixed effect regressions. This suggests that more reputable VCs, in general, are more capable of reducing information asymmetry and distance is less a barrier for their investment decisions, supporting Hypothesis 1a.

When we repeat the regressions for sub-periods in Table 7C, we find mixed results depending on which measure of VC reputation is used. For instance, we show that *Ln*(*VC Size*) and *Ln*(*N of IPOs*) are significantly and negatively associated with local bias in all five sub-periods, consistent with Table 7A and B. On the contrary, *Ln*(*VC Age*) is significantly and positively associated with local bias in the period of 1991–1997, but the correlation is negative in all the other four periods. Furthermore, we find that the VCs' experience in information technology is positively associated with local bias during the period of 1980–1990 and 2001–2006, but not significantly correlated with local bias in other periods. VCs' experience in non-tech industry is significantly and positively associated with local bias in periods of 1991–1997 and 1998–2000, but not in other periods. VCs' experience in medical/health care industry, on the other hand, is significantly and negatively correlated with local bias in all five sub-periods. These mixed results, to some extent, reflect the imperfectness of measures of VC reputation. For instance, VC age and VC investment experience have more to do with the seniority of VC firms, but not necessarily reflect their performance.

Other VC characteristics also have important influence on local bias. For instance, VCs specializing in investing in technology ventures exhibit stronger local bias as the technology ventures are often associated with greater uncertainty. Degree and network distance are significantly and negatively associated with local bias, supporting Hypothesis 2. We further find that staging significantly increases local bias, consistent with the prediction of Hypothesis 3.[17]

VCs' local bias is also impacted by various state-level characteristics. For instance, we find a significantly positive relation between local bias and the number of local ventures, supporting Hypothesis 5. The competition level of the local VC industry, proxied by *Ln*(*N of Local VCs*) and *Ln*(*N of outside VCs*), significantly decrease local bias, supporting Hypothesis 4. The number of patents is negatively correlated with local bias, while the number of universities is positively correlated with local bias. It is well know that a large number of ventures are university spin-offs, who are often located near the universities. Thus states with higher university populations could exhibit stronger local bias. In general, VCs located in the four hot states exhibit stronger local bias than those in other states.

As shown in Table 7C, being the lead VC significantly increases local bias, indicating distance is more of a concern for lead VCs as they do most or all of the due diligence and post-investment monitoring. Concurrently, we also show that syndicate significantly reduces local bias (which provides further supporting evidence to Hypothesis 2) and VCs are more concerned with distance while they are investing alone, suggesting syndicate members more or less help with information collection and monitoring.

[15] For instance, Castilla (2003) finds that the VC firms in Silicon Valley tend to invest more locally than the VC firms in Route 128.

[16] There are a total of 25 regressions (five for each sub-period using different measures of VC reputation).

[17] We considered the possibility of endogeneity vis-à-vis local bias and staging, and noted the following. First, if we exclude staging from the regressions, none of the other results are impacted in any material way. Second, for various instruments, we did not find a material effect of considering two-step estimates. For instance, for a subset of the data where we had relevant information, we considered differences in state wide legal fees for writing contracts (which would arguably be correlated with staging but not distance), and did not find any material differences in the results. Finally, we note our results are slightly different than those reported by Tian (2007), but Tian's estimates are based on actual distance between the VC and portfolio company, while our estimates of local bias are based on the percentage difference between the actual average distance of the VC's portfolio and the industry and stage restricted benchmark portfolio. Our measures and methods are consistent with that of Coval and Moskowitz (1999, 2001).

Table 8
Are local ventures more successful? The sample consists of 41,250 venture financing rounds during the period from 1980 to June 2004. We analyze the relation between the likelihood of IPO or M&As and the distance between VCs and ventures. Our dependent variable is equal to one if the venture had successfully exited via IPO or M&A by June 2009, 0 otherwise. ***, **, and * denotes significant at 1%, 5%, and 10% confidence level respectively.

	1	2	3	4	5	6	7	8	9	10	11	12
Intercept	−1.958***	−1.846***	−1.645***	−1.815***	−1.890***	−1.786***	−1.582***	−1.749***	−1.928***	−1.845***	−1.636***	−1.793***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln (lead VC distance)	0.004	−0.001	−0.001	0.002								
	(0.185)	(0.621)	(0.793)	(0.470)								
Ln (syndicate distance)					−0.009***	−0.013***	−0.012***	−0.010***				
					(0.001)	(0.000)	(0.000)	(0.000)				
Local (<50 miles)									0.039***	0.054***	0.047***	0.042***
									(0.004)	(0.000)	(0.001)	(0.002)
Control Variables												
Early stage venture	−0.110***	−0.115***	−0.101***	−0.107***	−0.115***	−0.119***	−0.105***	−0.112***	−0.115***	−0.119***	−0.104***	−0.112***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tech venture	0.333***	0.307***	0.304***	0.304***	0.329***	0.302***	0.300***	0.300***	0.329***	0.302***	0.300***	0.300***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln (syndicate size)	0.143***	0.130***	0.131***	0.133***	0.136***	0.120***	0.123***	0.126***	0.138***	0.122***	0.125***	0.128***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln (lead VC age)	0.082***				0.084***				0.083***			
	(0.000)				(0.000)				(0.000)			
Ln (lead VC size)		0.058***				0.060***				0.060***		
		(0.000)				(0.000)				(0.000)		
Ln (lead VC IPOs)			0.110***				0.112***				0.111***	
			(0.000)				(0.000)				(0.000)	
Ln (lead VC general experience)				0.063***				0.065***				0.064***
				(0.000)				(0.000)				(0.000)
Ln(*N* of patents)	0.105***	0.038*	0.048**	0.068***	0.104***	0.037*	0.047**	0.067***	0.101***	0.034*	0.045**	0.065***
	(0.000)	(0.061)	(0.015)	(0.001)	(0.000)	(0.073)	(0.012)	(0.001)	(0.000)	(0.009)	(0.025)	(0.001)
Ln(*N* of universities)	0.041	0.043	0.087***	0.073**	0.044	0.045	0.089***	0.076***	0.041	0.042	0.086***	0.073**
	(0.154)	(0.142)	(0.003)	(0.011)	(0.128)	(0.121)	(0.002)	(0.008)	(0.157)	(0.147)	(0.003)	(0.011)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	41250	41250	41250	41250	41250	41250	41250	41250	41250	41250	41250	41250
Pseudo *R*-square (%)	3.24	3.34	3.69	3.39	3.26	3.38	3.72	3.41	3.25	3.38	3.71	3.41
Log likelihood	−24,072.92	−23,674.04	−24,461.27	−24,536.06	−24,072.80	−23,667.96	−24,456.49	−24,533.92	−24,082.92	−23,677.65	−24,467.56	−24,543.85
LR Chi^2	1613.66	1638.29	1873.29	1723.70	1620.55	1657.09	1889.41	1734.56	1619.75	1657.17	1886.61	1734.03
Prob>Chi^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

In summary, we find strong support for Hypotheses 1–5 that the VCs' local bias is affected by the information asymmetry level of the portfolio companies, VCs' capability of reducing information asymmetry through various means, and the role of VCs in the investments. In particular, the VCs' local bias decreases with the VCs' reputation and network broadness, the competition of the local VC industry, and the R&D activities, and increases with being the lead VC and/or the solo investor, staging, specialization in technology, the intensity of local entrepreneurial activities and the local University population.

6. Are local ventures more likely to be successful?

In this section we test Hypothesis 6 (Section 2) on the relation between distance and performance.

6.1. The impact of distance on the likelihood of ultimate success

In Table 8, we run probit regressions to analyze the marginal impact of geographic distance on the final performance of new ventures using a sample of VC investments between 1980 and June 2004.[18] We use successful exits as a proxy for the final performance. We define successful exits as that the new venture exited via an IPO or Mergers & Acquisitions (M&A) by June of 2009, which allows a minimum of 5 years for the investment to exit. The dependent variable is the probability of IPO or M&A. We use three proxies for the distance between ventures and VCs. In Models 1–4, we use the natural logarithm of the distance between the lead VC and the portfolio company; in Models 5–8, we use the natural logarithm of the syndicate distance, which is the shortest distance between the portfolio company and the syndicate members; finally, in Models 9–12, we design a dummy variable, *Local*, which is set to one if the venture is located within 50 miles from any syndicate member.[19] To control for the quality of ventures at the time of financing round, we consider the following firm characteristics. The first, *Early Stage Venture,* is an indicator variable which is set to equal to 1 if the venture is at the seed/start-up stage or early stage, 0 otherwise. The second characteristic we control for is the industry that the venture resides. *Tech* is an indicator variable which is set to equal to 1 if the venture in either in information technology or medical/health care/life science, 0 otherwise. We also control for the R&D activities in the state where the venture is located by including *Ln*(*N of Patents*) and *Ln*(*N of Universities*). Both are normalized by the state population. In addition to controlling for the quality of ventures at the time of financing round, we also control for reputation of the lead VC by considering the following measures, *Ln*(*Lead VC Age*), *Ln*(*Lead VC Size*), *Ln*(*Lead VC IPOs*), and *Ln*(*Lead VC General Experience*). *Lead VC Age* is the age of the lead VC. *Lead VC Size* is the amount of capital under management in millions of dollars by the lead VC. *Lead VC IPOs* is the number of portfolio companies that the lead VC had taken public before the transaction. *Lead VC general Experience* is the total number of rounds that the lead VC has invested before the transaction. In addition, to control for the potential impact of syndicate on performance, we include *Ln*(*Syndicate Size*), where syndicate size is the number of co-investors in a specific round of financing. Finally, we add year fixed effects in all specifications.

The R^2 of the specifications in Table 8 range from 3.24 to3.72%. We do not find that the distance between the lead VC and the portfolio company significantly impacts the performance. In contrast, we show that the syndicate distance significantly decreases the probability of successful exit, indicating that syndicate members are probably not just capital providers, instead, they also play a role in information collection and monitoring. This result is consistent with our earlier finding that syndicate helps reduce local bias. The *Local* dummy (based on syndicate distance) is significantly and positively associated with ventures' performance, consistent with the findings using continuous measures.

Firm characteristics and VC reputations, as expected, have significant impacts on ventures' final success. For example, later stage ventures, technology ventures, and ventures located in states with active R&D activities and high university population, are more likely to go public.[20] Ventures associated with more senior, larger, more experienced VCs, and VCs with a strong track record have significantly higher probability of IPO or M&A. Syndicate size also has a significantly positive impact on the ultimate success.

One potential problem with the above specifications is that given the limited data available regarding the true quality of the ventures, the omitted variables may introduce biases that lead to mistaken interpretations of the results. To address this issue, we run firm-fixed effect regressions. Our results are robust.[21]

Some may argue that the distance itself could be endogenous. If VCs are more careful when selecting distant ventures given the frictions associated with distance, distant ventures could be endogenously of higher quality. However, this endogeneity will not impact the interpretation of our findings as it leads to upward-bias of the impact of distance on performance while we find a negative association between distance and performance. We also conduct a Wald test on the exogeneity of our specifications. The statistics are not significant and thus do not reject the null that our specifications are not impacted by endogeneity.

[18] In unreported regressions, we applied logit models. Our results are robust. For briefness, these results are not reported. They are available upon request.

[19] We also tried 100 miles, 200 miles, and 500 miles as thresholds. The results are robust.

[20] To avoid collinearity with *Ln*(*N of Patents*) and *Ln*(*N of Universities*), we do not include the *hot state dummy*. In unreported regressions in which we include the *hot state dummy* and exclude *Ln*(*N of Patents*) and *Ln*(*N of Universities*), we show that the *hot state dummy* is significantly and positively correlated with the probability of successful exits.

[21] For briefness, we do not report the empirical results from firm-fixed effect regressions. They are available upon request.

Overall, the above analysis shows that after controlling for the venture quality at the time of investment and characteristics of VCs, the syndicate distance has a negative impact on the ultimate performance of ventures. Given everything else equal, local ventures are more likely to have successful exits. This result supports our Hypothesis 6 that local ventures outperform distant ones.

6.2. Other robustness check

In addition to the probability of successful exits, we also examine how fast the investment exits and how much the value of the venture has grown by the time of exit. We measure the speed of exit as the difference between exit date and the time of financing round. We calculate the value growth as the ratio of pre-money valuation on the exit date and pre-money valuation on the round date scaled by the time between the exit date and the round date. We regress the exit speed and value growth on geographic distance after controlling for various characteristics of ventures and VCs. We do not find that distance (either lead VC distance or syndicate distance) significantly impacts exit speed or value growth.

7. Conclusions, implications, and future research

We find that the VCs exhibit strong local bias in their investment decisions. VCs invest predominantly in the new ventures that are located in their home states. More precisely, about 50% of the new ventures are located within 233 miles from their VCs. Compared to a hypothetical benchmark portfolio, which is industry and stage restricted and consists of all new ventures in the same industry and at the same stage that a VC could have invested, 50% of the VCs are about 60% closer to their actual investment portfolio.

Various characteristics of the U.S. VCs affect their local bias. For example, more reputable U.S. VCs exhibit less local bias, suggesting that more reputable VCs are better capable of reducing information asymmetry associated with distance. This pattern is similar with what is found in the mutual fund industry (see, e.g., Coval and Moskowitz, 1999; Parwada, 2008). VCs with better networking ability (broader networks and more geographically diversified network) exhibit less local bias. VCs specializing in technology industries exhibit stronger local bias. Staging is positively associated with local bias. Furthermore, we show that for the same VC, it exhibits stronger local bias when it is the lead VC and when it is investing alone.

Some state-level characteristics also impact the VCs' local bias. For instance, we find entrepreneurial cluster attracts local VC investment; however, our findings are also consistent with the view that excessive local VC competition drives up deal prices and diminishes the returns to investment locally. Local R&D activities (patents) decrease VCs' local bias while the local university population increases local bias.

We further find that geographic distance, in particular, the syndicate distance, has important implication for the ultimate exits of entrepreneurial firms. Specifically, local ventures are more likely to exit successfully via IPO or M&A controlling for the quality of ventures and VC reputation, suggesting local ventures benefit from being proximate to the VCs potentially due to less information asymmetry and close monitoring. An additional insight from our findings is that even though the lead VC presumably conducts most of the due diligence and post-investment monitoring, and thus distance is more of a concern to the lead VC, syndicate members more or less help with information collection and monitoring. Having a partner close to the portfolio company actually increases the probability of its ultimate success.

The results of this study have implications for regional development policies (see Keuschnigg, 2003, 2004; Keuschnigg and Nielsen, 2001, 2003 for related theoretical work; see also Leleux and Surlemont, 2003 for related empirical work). For example, to encourage the development of the new ventures in the local area, given the pervasive existence of local bias in VC investments, it is helpful to have some local VCs. They can either directly invest in the local new ventures or form syndicates with VCs in other areas to help finance the local new ventures.

In this study, we limit our sample to independent VCs. Future work could investigate whether the organizational forms of VCs impact local bias and thus impact their performance. It would also be interesting to investigate the evolution of clustering activity by entrepreneurs and VCs in different geographic regions in the U.S. to better understand how these clusters are formed (in the spirit of the work of Audretsch and Dohse, 2007; Audretsch and Keilbach, 2007, and other related papers on the formation of entrepreneurial clusters and agglomeration). As well, further work could study distance internationally in terms of other countries' local markets (as in Cumming and Johan, 2006, for Canada) and in terms of international cross-border investment (as in Bruton et al., 2006).

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Appendix A. Definition of key variables

Variables [a]	Definition
Distance	The geographic distance in miles between the headquarters of the VC and the headquarters of the new venture. The geographic distance is calculated using following equation: $d_{ij} = 3963 \times \text{ar cos}\left[\sin(\text{lat}_i)\sin(\text{lat}_j) + \cos(\text{lat}_i)\cos(\text{lat}_j)\cos(\lvert\text{long}_i - \text{long}_j\rvert)\right]$ where latitude and longitude are measured in radians. Latitude and longitude data for the center of each five-digit zip code are obtained from the *U.S. Census Bureau's Gazetteer*.
Lead VC	A dummy variable that is equal to 1 if the VC invests the largest amount of capital in the portfolio company, and 0 otherwise.
Lead VC Distance	The geographic distance in miles between the headquarters of the new venture and the headquarters of the lead VC.
Syndicate	A dummy variable that is equal to 1 if there are more than two VCs invest in the same round of financing, and 0 otherwise.
Syndicate Distance	The geographic distance in miles between the headquarters of the new venture and the VC investor in a syndicate which is closest to the new venture.
Local bias	The percentage difference in miles between the weighted-average distance of the actual investment portfolio for each VC investor and the weighted-average distance of a hypothetical benchmark portfolio, which is industry and stage constrained. The industry and stage restricted portfolio consists of all new ventures available in a certain year with the same industry and stage as the one that a VC firm chose to invest.
N of New Ventures	Number of new ventures with headquarters in a specific state per thousand residents.
N of Local VCs	Number of VCs with headquarters in a specific state per thousand residents.
N of Outside VCs	Number of VCs whose headquarters are not in a specific state while investing in that state per thousand residents.
N of Patents	Number of patents in a specific state per thousand residents.
N of Universities	Number of universities in a specific state per thousand residents.
VC Age	The difference in years between the deal year and the year the VC firm is founded.
VC Size	The amount of total capital under management in millions of dollars by each VC firm.
N of IPOs	Number of portfolio companies that the VC firm had taken public before the deal year.
General Experience	Number of portfolio companies the VC has invested before the deal year.
IT Experience	Number of portfolio companies in information technology the VC has invested before the deal year.
Medical Experience	Number of portfolio companies in medical/health care/life science the VC has invested before the deal year.
Non-tech Experience	Number of portfolio companies in non-high technology industries the VC has invested before the deal year.
Degree	The percentage of ties that each VC investor has relative to the maximum number of ties the VC investor could have had each year assuming it can syndicate with any other VCs who are active that year.
Network Distance	The mean distance in miles between the VC investor and all its network partners.
Tech	A dummy variable, equal to if more than 50% of the VC's investments are in the information technology and medical/health care/life science sectors.
Tech Venture	A dummy variable, equal to 1 if the venture firm is in information technology or medical/health care/life science.
Staging	The average number of rounds that a VC invests in portfolio companies.
Hot states dummy	An indicator variable which is equal to 1 if the VC firm is located in one of the following four states, CA, MA, NY, and TX.
Local	A dummy variable which is set to equal to 1 if the venture is located with 50 miles from any of the syndicate member, 0 otherwise.
Early Stage Venture	An indicator variable, equal to 1 if the venture is at seed or start-up stage, 0 otherwise.
Syndicate Size	Number of VCs participating in the same financing round.
Lead VC General Experience	Number of investments the lead VC firm has made in all industries before a specific financing round.
Lead VC Age	Age of the lead VC.
Lead VC Size	Capital under management in millions of dollars by the lead VC.
Lead VC IPOs	Number of portfolio companies that the lead VC has taken public before the deal year.

[a] We transform many variables into natural logarithm format in regressions to satisfy the normal distribution requirement. These variables are denoted as *Ln*(*Variable Name*).

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