Social Connectedness and the Geography of Venture Capital*

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Abstract

This paper examines the role of social connectedness in shaping cross-county venture capital (VC) investments. I study yearly county-to-county VC investments, and find a very large effect: a 1% increase in social connectedness is associated with a $\sim 0.5\%$ increase in VC investment. When controlling for social connectedness, physical distance becomes irrelevant as a determinant of VC flows. This result is robust to the addition of several bilateral controls (travel time, trade, commuting, migration). I find that early stage funding is more strongly impacted, and that counties with higher levels of social access to VC host more and better startups.

JEL Codes: G24, G41, R11

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Introduction

The venture capital (VC) industry has grown strongly over recent decades. Between 2008 and 2022, the amount of yearly VC investment in the US increased from $37.1bn in 2008 to $240.9bn 2022 (NVCA, 2023).[1] What determines the allocation of this venture capital across the economy? How important are geographic and social frictions in determining the flow of risky investments from investors towards entrepreneurs? This paper argues that social ties are the key determinant of VC investments.

Young firms with high growth ambition are routinely capital constrained (Kerr and Nanda, 2011). At the same time, young firms contribute importantly to the development of novel ideas and production methods, as well as overall economic growth (Akcigit and Kerr, 2018). Furthermore, venture capitalists directly increase the productivity of companies in which they invest (Kortum and Lerner, 2000; Bernstein et al., 2016; Akcigit et al., 2022), and create knowledge spillovers through these investments (Schnitzer and Watzinger, 2022).[2] Increasing the amount of venture capital investment and understanding the ways in which VC investment impacts innovation and economic development therefore has been a priority of academics and policy makers (Lerner, 2009; Bai et al., 2021). For all of these reasons, understanding the determinants of venture capital investment can help us understand the potential barriers to the founding and growth of young firms with high growth potential.

To study the determinants of venture capital investments across the economy, I build a large investment-level database of VC investments within the US between 1960 and 2019, which I aggregate up to the county-pair-year level. I use gravity style analysis to study

[1] Janeway et al. (2021) discuss the implications of VC booms for startup financing.

[2] Relatedly, Puri and Zarutskie (2012) report that under 0.5% of companies receive venture capital, whereas Lerner and Nanda (2020) notes that 47% of non-financial companies that have an IPO were at some point VC backed.

the bilateral factors that shape these flows. In particular, I focus on the role that social connectedness plays in determining VC investments. A literature in entrepreneurial finance has used surveys (see Gompers et al. (2020) and literature cited therein) to study the factors that determine VC investments. However, little empirical evidence exists on the economy-wide determinants of realized investments. This paper presents, to the best of my knowledge, the first gravity-style analysis of VC flows within an economy.

In the first part of the paper, I study the determinants of VC investment flows across the US economy. Starting from a sample of all individual VC-related investments contained in the Thompson Reuters database, I aggregate a yearly measure of the amount of VC equity investment between each pair of US counties in all years between 1960 and 2019. I estimate a gravity model on these data.[3] I find that the only factor with conditional impact on venture capital flows is the degree of social connectedness across counties. A 1% increase in social connectedness between counties is associated with a $\sim 0.5\%$ increase in venture capital investment. Strikingly, I find that physical distance has no explanatory power after controlling for social connectedness. I.e. for two pairs of counties with the same degree of bilateral social connectedness, variation in physical distance has no explanatory power; for two pairs of counties at the same physical distance, variation in social connectedness has strong explanatory power. This result is robust to the inclusion of several sets of fixed effects, as well as control variables varying across county-pairs and over time. It strongly suggests that we should think of markets for venture capital investment as highly social in nature. The social connections of venture capitalists are a major determinant of their investments.

Endogeneity is unlikely to pose a significant concern for the main result for the following

[3] Gravity theories are widely used in models of bilateral financial and trade flows, and are motivated by the heuristic that two economies that are closer to each other, and bigger will have more bilateral interaction. See Head and Mayer (2014) for a review of empirical and theoretical aspects.

reasons. First, I incorporate an extensive set of fixed effects in all regressions. County-by-year-inbound and county-by-year-outbound fixed effects account for numerous critical factors potentially associated with both investment and social connections. Such factors encompass the proximity of large university campuses, the presence of venture capitalists, and weighted averages of social connectedness at the county-year level. Second, all regressions feature fixed effects that control for additional county-bilateral elements that could influence both investment and social networks, such as *same county* and *same state* fixed effects. Third, even after accounting for the aforementioned fixed effects, if the relationship between social connectedness and VC investment is influenced by simultaneity (i.e., an unobserved variable affecting both *bilateral social relations* and *bilateral investment*), I introduce a series of time-varying bilateral control variables. These include trade in physical goods, commuting, travel time, and migration. Notably, the estimation results are highly robust even after incorporating these control variables. Lastly, it appears implausible that a macro-level metric like the social connectedness index, derived from Facebook friendships spanning the entire economy, would be substantially influenced by an industry as niche as venture capital[4].

Social connectedness may exert a significant influence on venture capital (VC) investments through several mechanisms.[5] First, it can aid the initiation of contact between venture investors and potential entrepreneurs. For instance, a venture capitalist might utilize her social network to discover investment opportunities in a specific locale. In a similar vein, an entrepreneur might leverage his social network to identify potential investors and secure

[4]Refer to IBISWorld (2023), which indicates that the VC industry in the US employed between 70,000 and 80,000 individuals annually from 2013 to 2023.

[5]See Gompers et al. (2020) for a description of the VC investment process, and Burg et al. (2022) for an analysis of how social networks matter for entrepreneurs. Sorenson (2018) reviews the literature on the importance of social networks for entrepreneurs from a sociological point of view. Reviews of the literature on venture capital include Hall and Lerner (2010); Da Rin et al. (2013); Kerr and Nanda (2015); Tykvová (2018); Lerner and Nanda (2020); Ewens and Farre-Mensa (2022); Ewens (2022).

capital. Secondly, these networks can provide investors and investees with valuable insights regarding the prospects of a potential investment opportunity. Lastly, social connectedness can bolster the trust factor between disparate geographical locations (Guiso et al., 2009; Agarwal and Hauswald, 2010; Bottazzi et al., 2016; Cochardt et al., 2018). Therefore, an investor, upon identifying an investment opportunity, might be more inclined to trust entrepreneurs from certain locations, given the existing social connections and networks (cf. the literature on agency conflicts Da Rin et al. (2013)).

Delving deeper into these mechanisms, Burg et al. (2022) suggest that social networks can aid entrepreneurs via five mechanisms: accessing, acquiring, diversifying, embedding, and associating. Accessing denotes the action of identifying a resource or piece of information, while acquiring signifies the act of receiving the aforementioned resource or information. Crucially, the latter usually necessitates stronger network ties, facilitating the transfer of the resource or information. In the scope of this paper, a VC equity investment can be analogized to the acquisition of capital, a process inherently preceded by resource or contact access. This resource access and acquisition dynamic operates differently across startup phases. Burg et al. (2022) note that weak ties can be especially beneficial during the emergent phase of a startup, helping in the gathering of ideas. Conversely, during phases demanding expensive and scarce resources, such as VC funding rounds, the acquisition of resources through strong ties becomes critical. More generally, Garfinkel et al. (2021) suggest that social relationships can potentially compensate for otherwise unobserved information.

The decision-making process of venture capital (VC) firms and the significance of social connectedness within this process is central to understanding the relationship between social networks and VC investments (Bernstein et al., 2017; Gompers et al., 2020). Gompers et al. (2020) offer a comprehensive review of the VC decision-making journey. The study surveyed 885 venture capitalists and found that the most critical factor influencing investment decisions is the management team of the startup. Gompers et al. split the VC investment process into three stages - namely deal sourcing, investment selection, and valuation. While all stages of the investment process bear relevance, deal selection emerges as the most significant value-creating step, suggesting its pivotal role in generating returns. The study highlights the management team as the most critical factor in investment decisions, even outshining other business-related factors such as the product or technology. In early stages of investment, VCs place increased emphasis on the team factor, likely due to the high uncertainty levels associated with startups at this stage. Gompers et al. (2020) also report that social networks matter differently throughout the investment process. In the early stages, they are instrumental in facilitating deal flow, while at later stages, they play a key role in vetting and information gathering. This varying role of networks - from deal sourcing to investment selection - aligns with the extensive margin result of this paper, suggesting that social networks bear more relevance during the first two stages than the last. In my paper, I find that early stages are most sensitive to social connectedness, which points towards an especially large role for social networks during the deal flow phase.

In the second part of the paper I study the effect of social access to venture capital on entrepreneurial outcomes at the county level (Glaeser et al., 2010b,a; Chatterji et al., 2014; Glaeser et al., 2015). Do locations with higher degrees of social connectedness to locations that invest in VC benefit from this? To study this question, I build a *social access to venture capital* (SAVC) index. I find that this index has significant explanatory power for (i) the number of startups, and (ii) the average quality of startups. These results are conditional on controlling for the level of physical access to venture capital, and suggest that the results from the first part of the paper do not only affect financial flows, but also translate into entrepreneurial outcomes. Social relations of venture capitalists matter for entrepreneurial outcomes at the county level.

The results in this paper have several implications for policy. The results of the two parts of the paper taken together suggest that a location's social connections with venture capital investors are a key determinant of local entrepreneurship. If one assumes that more entrepreneurship is generally positive for a local economy, it then follows that policy makers should consider the social access to venture capital of their local economy. With the caveat that neither intervention is directly studied in this paper, two ways of improving a location's access to venture capital logically flow from this paper. First, this study provides supportive evidence for programs that encourage the local/dispersed settlement of venture capital funds. Policy makers who want to increase the supply of venture capital may want to consider supporting the establishment of VC funds in locations that are highly socially connected to their location. Importantly, this paper shows that social connectedness seems to be a more important driver of investment that physical distance. Being socially connected to sources of venture capital and other entrepreneurs may thus be a promising way towards higher rates of local entrepreneurship, above and beyond the local establishment of venture capitalists and hubs of entrepreneurship. More generally, a strong interpretation of the findings in this paper would argue for a more dispersed, and therefore more widely accessible VC industry. If social connections have a limit in terms of how wide and strong they could grow, dispersing venture capitalists more widely in the economy would be a logical way of promoting entrepreneurship. Second, policy makers may want to target social networks directly. It may be possible to foster the creation of social connections with locations with high VC activity. This could be achieved by organizing industry fairs or exchange programs associated with industrial bodies or universities. This recommendation is also in-line with Crisanti et al. (2021), who advocate higher connectedness among VC investing hubs. Again, these policy implications are to be interpreted with the caveat that these types of interventions are not directly observed in this study.[6] It is also important to keep in mind that entrepreneurial activity does not solely depend on the supply of funding, but rather depends on many aspects, including other inputs like qualified labor, legal advice, innovative ideas, etc. A third policy implication from this paper is that the identity of venture capitalists may matter. While I do not directly observe aspects like race and gender in this study, the results in this paper strongly suggest that social networks are important determinants of the VC investment process. This result could be interpreted through the lens of the strong homophily in VC investment in terms of race and gender described by in the literature (Ewens, 2022). If one takes social networks as given, a policy maker with the goal of increasing entrepreneurship among underrepresented groups may want to consider encouraging individuals from these groups themselves to be more active as venture capitalists. Note, however, that Howell and Nanda (2019) report that females experience no benefits from being exposed to female or male VCs.

This paper contributes to several strands of literature. A recent literature has focused on the role of social networks for financial markets (Kuchler et al., 2021; Rehbein and Rother, 2022).[7] This paper contributes to that literature by demonstrating the importance of social connectedness in the context of the allocation of risky capital to startups. Relative to Kuchler et al. (2021), I find that social connectedness is more important for young firms than for firms with access to public capital markets.

A literature focuses on frictions in venture capital and entrepreneurial finance. Ewens (2022) discusses the literature on race and gender related bias in entrepreneurial finance.

[6] See Lerner (2009) andBai et al. (2021) for discussions of policy efforts to increase VC investments in local economies.

[7] Bailey et al. (2018) discuss the measurement of social connectedness, its determinants, and impact more generally.

Samila and Sorenson (2017) argue that higher racial integration in a region is associated with higher benefits from venture capital. Fisman et al. (2017) study bank lending in India and the role of cultural differences between the bank clerk and the loan applicant. Both papers find evidence consistent with in-group lending. Fisman et al. (2017) interpret their evidence as cultural proximity mitigating information frictions in lending. The results in my paper are consistent with a mechanism where social networks are (at least partially) determined by race and culture. Whereas I do not directly observe information on culture, ethnicity, or race, my results strongly suggest that social networks are an important vector of VC investment. To the extent that social connectedness is determined by factors like race and culture, my results are in line with this literature.

The literature on venture capital studied the VC investment process with surveys and evidence on VC contracts (Sahlman, 1990; Kaplan and Strömberg, 2001; Kaplan and Stromberg, 2003; Kaplan and Strömberg, 2004; Kaplan et al., 2009; Gompers et al., 2020) and from a theoretical point of view (Kaplan and Strömberg, 2001; Hart, 2001; Ewens et al., 2022). This paper is, to my knowledge, the first using a broad sample of realized VC investments over a long period of time, that links these investments explicitly to the economy-wide measure of social networks.

This paper also relates to a literature within economic geography on the differences in access to finance across space and the influence of this on agglomeration (Chen et al., 2010; Chen and Ewens, 2021; Glaeser and Kerr, 2009; Glaeser et al., 2010b,a, 2015). Relative to this literature, this paper emphasizes and measures the role of social connections to financiers of young companies. I find that social access to venture capital is an important determinant of entrepreneurial outcomes. Poelhekke and Wache (2023) examine the broader question of how social access to venture capital affects local economic growth.

Finally, a literature has used a gravity-style approach to estimate the determinants of financial flows (Portes and Rey, 2005; Okawa and van Wincoop, 2012; Pellegrino et al., 2023; Head and Ries, 2008; Head and Mayer, 2014; Wache, 2023). Relative to this literature, this paper is the first application of the gravity framework to a within-country flow context.

The rest of the paper is as follows. Section 1 describes the data. Section 2 outlines the empirical strategy and results of the county-to-county flow analysis. Section 3 describes the analysis of the influence of social access to venture capital on local entrepreneurial outcomes. Section 4 concludes.

1 Data and Descriptive Statistics

The main variable of interest is the yearly aggregate *flow of venture capital equity investment between two US counties*, i and j, in year t. To construct this variable, I gathered data on all venture capital investments in the United States reported between 1960 and 2019 from the ThomsonOne database. This database is a widely used source for the study of venture capital (Da Rin et al., 2013)[8]. Using investment level information, I geocode the reported addresses of the investor (VC firm) and the receiving company. I then aggregate the amounts invested for each possible combination of county pair and year. See the Appendix for further details on the construction of the VC flow variable.

Data on *social connectedness* across US counties is taken from the Social Connectedness Index (SCI), published by Bailey et al. (2018) in collaboration with Facebook. The index measures social connections across US counties as of August 2020, based on the relative frequency of Facebook friendships. Specifically, the index is defined as the absolute number of Facebook friendships between two counties i and j, divided by the product of the Facebook

[8]See Garfinkel et al. (2021) for a discussion of other recent sources.

populations in the two counties:

$$SCI_{i,j} = \frac{\text{Facebook Connections}_{i,j}}{\text{Facebook Users}_i * \text{Facebook Users}_j} \tag{1}$$

An ideal measure of cross-county social connections would be time-varying and available at least at yearly frequency across the whole sample period. Data from the SCI is available only from a snapshot in August 2020. I therefore follow the approach of Kuchler et al. (2021) and Rehbein and Rother (2022), and use the SCI data published in August 2020 for all previous years. Similar to Kuchler et al. (2021), I document below that the influence of SCI (as measured in August 2020) on VC investment is very stable across time, and conclude that SCI is a slow-moving object. Using a measure from August 2020 for earlier years thus seems like a justifiable proxy.

Bailey et al. (2018) discuss the SCI, as well as its degree of representativeness for social networks in the United States of America more generally. They cite evidence showing that as of September 2014, more than 58% of the US adult population, and 71 % of the US online population used Facebook. Furthermore, Facebook usage is found to be relatively constant across income, education, and racial groups, whereas it declines with age (87% of 18-to-29 year olds versus 56% of above-65 year-olds). Furthermore, they report evidence that in the US Facebook is primarily used as a platform for real-world friends and acquaintances to interact online, and that connections are usually only added when people know each other in the real world. The authors therefore argue that Facebook data has the 'unique ability to provide a large-scale representation of US friendship networks'.

County to county travel times are constructed as follows. Using the TIGER/Line data by the US Census on primary and secondary roads I calculate the shortest travel path by car from each county to each county in the US mainland. As start and finish point for each county I use the center of population as reported in the 2020 US Census. Additionally, I use ER-586 and T-100 data on domestic segment flights to identify airports that are connected by direct flights in each year between 1970 and 2020. All two airports that have at least 100 direct scheduled passenger flights between them in a given year are coded as connected. I assume that it takes the reported ramp to ramp time from T-100/ER-586 plus 2.5 hours to travel between two counties that are connected by a direct flight in a given year. I combine the flight and car data by taking the minimum over the two county-to-county travel time matrices. I then use Dijkstra's algorithm to compute the shortest travel time between each pair of counties in each year between 1970 and 2020, taking roads as well as all direct flights into account.

Data on entrepreneurial outcomes at the county-year level are taken from Andrews et al. (2022). In particular, these variables include a county's startup formation rate (SFR), the entrepreneurial quality index (EQI), the regional entrepreneurship cohort potential index (RECPI), and regional entrepreneurship acceleration index (REAI). See Andrews et al. (2022) for details on the construction and measurement of these variables.

Further variables are generated as follows. Physical distances across counties are taken from the NBER County Distance Database. County to county migration data between 1992 and 2018 are taken from the SOI Tax Stats Migration Data of the IRS. The observations on migration are always counted for the earlier year (e.g. IRS data for migration between the tax reports in 2005 and 2006 are counted as migration data for the year 2005). County to county commuting data are taken from American Community Survey of the US Census. Trade data between US states are taken from the Commodity Flow Survey, as provided by Stephen Redding via the NBER. State to state trade flows are copied down to the county to county level. For migration, commuting, and trade, gaps in the time series are filled by linear interpolation.

Table 1 contains descriptive statistics on the VC flow dataset used in Section 2. Table 2 contains descriptive statistics on the social access to VC dataset used in Section 3.

Table 1: Descriptive Statistics - VC Investment Flows

	N	Coverage	Mean	Median	SD	% of 0's	Min	Max
Dependent Variables								
VC Equity Flow (mln $)	600,680,856	1960 - 2019	0.001	0	0.588	99.987	0	3188.063
VC Debt Flow (mln $)	600,680,856	1960 - 2019	0.000	0	0.091	99.9987	0	2000
Explanatory Variables								
Social Connectedness	600,680,856	1960 - 2019	46771.3	1996	2170850	00.00	1	1,000,000,000
asinh(Social Connectedness)	600,680,856	1960 - 2019	8.365	8.292	1.704	00.00	0.881	21.416
Physical Distance	600,680,856	1960 - 2019	909.663	784.916	608.781	00.03	0	6273.086
asinh(Physical Distance)	600,680,856	1960 - 2019	7.276	7.359	0.740	00.03	0	9.437
Migration	276,885,544	1992 - 2019	9.975	0	1876.5	99.01	0	3,768,511
asinh(Migration)	276,885,544	1992 - 2019	0.041	0	0.428	99.01	0	15.835
Commuting	440,617,322	1970 - 2013	11.115	0	1934.0	99.20	0	4,181,968
asinh(Commuting)	440,617,322	1970 - 2013	0.033	0	0.414	99.20	0	15.939
Trade	249,286,075	1993 - 2017	6237.9	1188	34202.7	01.33	0	1,432,562
asinh(Trade)	249,286,075	1993 - 2017	7.565	7.773	2.115	01.33	0	14.868
Travel Time (hours)	502,553,328	1970 - 2019	10.6	9.3	7.4	00.03	0	114.0
asinh(Travel Time)	502,553,328	1970 - 2019	2.899	2.928	.552	00.03	0	5.430

Description: This table shows descriptive statistics for the main sample used to estimate Equation (2) in Section 2.2.
The data come from a full sample of county-to-county-by-year observations of Venture Capital Flows between 1960 and 2019.

Table 2: Descriptive Statistics - Social Access to VC

	N	Coverage	Mean	Median	SD	% of 0's	Min	Max
Dependent Variables								
SFR	87,862	1988 - 2016	345.6	28.8	1839.0	0.02	0	78201.1
asinh(SFR)	87,862	1988 - 2016	4.2	4.1	2.1	0.02	0	12.0
Growth Events	87,862	1988 - 2016	0.2	0	1.5	0.94	0	90.8
asinh(Growth Events)	87,862	1988 - 2016	0.1	0	0.4	0.94	0	5.2
EQI	87,862	1988 - 2016	0.0004	0.0003	0.0005	0.00	0.0000	0.0546
log(EQI)	87,862	1988 - 2016	-8.2	-8.2	0.7	0.00	-11.7	-2.9
RECPI	86,138	1988 - 2016	0.2	0.008	1.8	0.02	0	120.9
log(RECPI)	86,138	1988 - 2016	-4.7	-4.8	2.3	0.00	-16.9	4.8
REAI	74,420	1988 - 2012	0.9	0	90.2	0.94	0	24400.4
asinh(REAI)	74,420	1988 - 2012	0.1	0	0.5	0.94	0	10.8
Explanatory Variables								
Social Access to VC (SAVC)	87,862	1988 - 2016	4.61e+07	2.46e+07	1.01e+08	0.00	725585.8	6.16e+09
log(SAVC)	87,862	1988 - 2016	16.9	17.0	1.2	0.00	13.5	22.5
Physical Access to VC (PAVC)	87,862	1988 - 2016	22.7	17.0	34.2	0.00	0.5	2689.6
log(PAVC)	87,862	1988 - 2016	2.7	2.8	1.0	0.00	-0.7	7.9

Description: This table shows descriptive statistics for the main sample used to estimate Equation (4) in Section 3.2.
The share of 0's is the share of 0's among non-missing observations.

2 Venture Capital Investment Flow Analysis

This section presents the main analysis of the paper. Using the county-to-county VC investment flow dataset described in Section 1, I investigate the frictions that determine the flow of VC across counties.

2.1 Empirical Strategy

This section describes the empirical strategy used in this section. The main approach is to use a gravity model to examine how county-to-county VC investment flows can be explained by bilateral frictions. The main regression equation is

$$\text{VC Equity}_{ijt} = exp(\beta\Phi_{ijt} + \eta_{it} + \nu_{jt} + \mu_{ii} + \sigma_{s(i)s(j)} + \varepsilon_{ijt}) \tag{2}$$

where VC Equity_{ijt} is the aggregate flow of VC equity investment between county i and county j in year t. Φ_{ijt} are variables that capture bilateral frictions varying on the county-to-county level, some of which also vary by year. These variables include social connectedness, physical distance, commuting, trade, migration, and travel time. η_{it} and ν_{jt} are investment-origin-year, and investment-destination-year fixed effects, respectively. In the trade literature these terms are referred to as multilateral resistance terms. They capture any variable that does not vary on the county-by-year level, like county GDP, demographics, wealth, entrepreneurial ecosystems, etc. Note that this includes a county's 'average friction with other counties'. Hence, the impact of any bilateral friction is estimated controlling for the average friction faced by a given county in a given year.[9] μ_{ii} are county-specific fixed effects for same-county investments, which account for potential 'home county bias' (Yotov,

[9]See e.g. Head and Mayer (2014) for details on the interpretation of gravity type estimates and multilateral resistance terms.

2012). Similarly, σ_{ij} are state-specific fixed effects for same-state investments. State-specific investment laws may make it harder for investors to invest across state borders. Unless mentioned otherwise, Equation (2) is estimated with a PPML estimator, an efficient log-level estimator, that deals well with heteroskedasticity and the occurrence of many 0's in the dependent variable (Santos Silva and Tenreyro, 2006; Head and Mayer, 2014). When estimating Equation (2), the independent variables will usually be log-transformed (or transformed with the inverse hyperbolic sine function for variables with many 0's (Card et al., 2020; Aihounton and Henningsen, 2021)); for continuous regressors, this gives the estimated β coefficients the interpretation of an elasticity.

Figure 1 gives a visual impression of the empirical strategy. This figure plots the inverse hyperbolic sines of SCI against physical distance.[10] Unsurprisingly, the figure shows a strong negative correlation between the two variables. However, the figure also shows substantial variation in physical distance at given levels of SCI and vice versa. Regression equation Equation (2) holds one variable fixed while estimating the conditional influence of the other variable on the dependent variable VC flows.

[10]For computational reasons I include only county-pair-year observations with a positive VC flow in this figure.

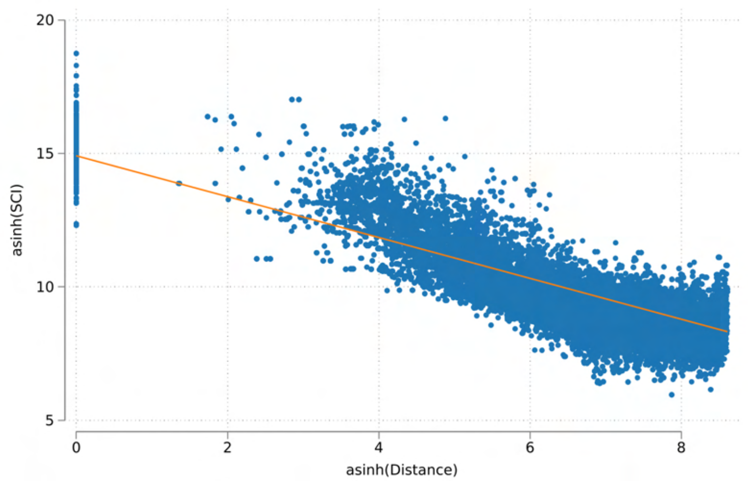

Figure 1: SCI and Distance Across County Pairs

Description: This figure plots asinh(SCI) and asinh(Distance) for all county-pair-year observations with a positive equity flow.

2.2 Baseline Results - SCI Strongly Associated with VC Flows

This section presents results on the impact of several bilateral frictions on county-to-county venture capital flows.

Table 3 shows results of a PPML gravity regression of yearly county to county VC equity flows between 1960 and 2019. Column 1 includes only physical distance as a control variable. The estimation results in column 1 show that VC investments decline with distance. The estimate indicates that a 10% increase in physical distance between two counties is associated with an approximately 2% decrease in VC flow. This result is intuitive and echoes results found in the literature. Compared to Chen et al. (2010), column 1 in Table 3 uses gravity-type estimation methodology (Head and Mayer, 2014; Yotov et al., 2016), which controls for multilateral resistance terms and therefore produces consistent estimates of the impact of bilateral frictions, in this case physical distance; the qualitative message is the same as in Chen et al. (2010), namely that venture capital investment decreases with physical distance.

Column 2 displays estimation results from a regression with only social connectedness as a control variable. The results indicate that venture capital investments strongly increase with social connectedness. A 10% increase in social connectedness between two counties is associated with a 4% increase in VC flow. This result is again intuitive and consistent with results from the literature on the effect of social connectedness on other types of domestic financial flows (Kuchler et al., 2021; Rehbein and Rother, 2022).

What happens when both physical distance and social connectedness are included in the same regression? Such a regression shows the influence of each friction while keeping the level of the other variable fixed. Column 3 shows the results of this regression. The estimates show that social connectedness continues to be a strong predictor (as in column 2). The estimates indicate that a 10% increase in social connectedness is associated with a roughly 5% increase in VC flows. For physical distance on the other hand, the estimates indicate a precisely estimated null effect - i.e. at the same level of social connectedness, variation in physical distance does not explain variation in the amount of venture capital flows.

Columns 4-8 furthermore include several bilateral control variables. I include bilateral county-to-county variables on migration (column 4), commuting (column 5), trade (measured at the state-to-state level, column 6), and travel time (column 7). Column 8 includes all control variables simultaneously. Migration and commuting capture other potential forms of social interaction at the regional level. Trade captures connections of industry across states. Travel time captures part of the variation in physical distance in an arguably more accurate way, while also proxying for the intensity of latent economic and social interaction across locations (to the extent that flight networks are shaped such that they minimize travel time on the most high value connections). In each regression, the coefficient on the social connectedness index is the main significant and important regressor.

This is the key insight of the paper: social connectedness is a strong conditional predictor of VC flows, and physical distance is estimated to have approximately no influence on VC flows after controlling for social connectedness. A strong interpretation of the results would be that physical distance matters for VC flows only to the extent that social connectedness varies with distance.

In light of the literature on gravity in trade, financial flows, and other flows (Head and Mayer, 2014), this is a striking result. Even after including many bilateral explanatory variables in a gravity-type regression on a flow variable, physical distance typically retains some explanatory power. The fact that it is estimated to have precisely no explanatory power after controlling for social connectedness therefore stands out. One can interpret this as implying that physical distance matters for venture capital investments only to the extent that social connections vary over space.

When comparing the effect sizes on social connectedness from Table 3 to the one found by Kuchler et al. (2021), social connectedness matters roughly 1.5 to 3 times more for the flow of startup funding as it does for equity holdings of institutional investors.

As argued in the introduction, endogeneity does not pose a significant threat to the main result. The model incorporates a comprehensive set of fixed effects and bilateral control variables, addressing many potential sources of endogeneity bias due to omitted variables or simultaneity. Furthermore, the possibility of reverse causality is limited given the size of the venture capital industry. For instance, IBISWorld (2023) indicates that the VC industry in the US employed between 70,000 and 80,000 persons annually from 2013 to 2023. Therefore, it is improbable that a macro-level variable like the social connectedness index, derived from

Facebook friendships spanning the entire economy, would be influenced by an industry of this scale.

Table C1 in the Appendix shows that the same results hold true for VC debt investments, with somewhat larger coefficients in absolute terms for comparable estimations.

As stated in Section 1, I use one measurement of the social connectedness index from August 2020 to proxy for social connectedness in all other years.[11] Doing so would lead to measurement error if social connectedness were changing significantly over time. To test for this possibility, Table B1 in the Appendix repeats the regression in column 3 from Table 3 for five year periods of the data (1970 - 1974, 1975 - 1979, ...).[12] The estimation results show that the influence of SCI on VC flows is very stable for the period 1990 - 2019. For the sample before 1990, the result is less clear, as the sample size is decreased significantly, and $\beta \approx 0.45$ is still contained in conventional confidence intervals. I interpret this as indicating that social networks change fairly slowly over time. Hence, I conclude that social connectedness as measured in 2020 is likely to be a good approximation of social connectedness in previous years in the data.

2.3 Extensive Margin

At what point in the investment process does social connectedness play a role? Gompers et al. (2020) distinguish three phases within the VC investment decision process: (i) deal flow, (ii) investment selection, (iii) valuation. In this section, I will examine the extensive margin of investment, in order to investigate when in the VC investment process social connectedness may matter.

[11] See Kuchler et al. (2021) and Rehbein and Rother (2022) for a similar approach.

[12] Due to very small sample sizes, five year buckets before 1970 do not converge and can hence not be included in this exercise. Note that any county-year observation with 0 inbound or outbound VC investment will be automatically absorbed by a fixed effects.

Table 3: PPML Regressions of VC Equity Investments in Companies

Dependent Variable →	VC Equity							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
asinh(Distance)	-0.213***		0.056	0.061	0.035	0.074	0.057	0.065
	(0.041)		(0.039)	(0.039)	(0.048)	(0.046)	(0.063)	(0.078)
asinh(SCI)		0.424***	0.486***	0.489***	0.438***	0.488***	0.486***	0.476***
		(0.037)	(0.052)	(0.055)	(0.077)	(0.056)	(0.056)	(0.082)
asinh(Migration)				0.001				-0.030
				(0.018)				(0.020)
asinh(Commuters)					0.007			0.008
					(0.012)			(0.013)
asinh(Trade)						0.034		0.021
						(0.059)		(0.064)
asinh(Travel Time)							-0.002	-0.021
							(0.092)	(0.091)
Observations	1,693,972	1,693,972	1,693,972	1,343,077	1,363,682	1,232,695	1,691,505	1,028,210
County×Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Same County FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Same State FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors clustered at the county inbound and county outbound level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. *VC Equity* is the total amount of VC equity invested in millions of dollars from county i to county j in year t. *Distance* is the physical distance between two counties; *SCI* is the social connectedness index between two counties (as of August 2020); *Migration* is the amount of migrants moving from county i to county j in year t;*Commuters* is the amount of commuters from county i to county j in year t;*Trade* is the amount of trade from county i's state to county j's state in year t ;*Travel Time* is the shortest travel time between county i and county j in year t, taking into account travel by car and plane. *asinh* is the inverse hyperbolic sine of a given variable.

For the empirical analysis in this section, I re-code the underlying investment-level data on VC investment amounts into a dummy on whether an investment happened. In a second step, I then aggregate the number of investments to the county-to-county-by-year level. In other words, whereas Section 2.2 examines the determinants of the amounts of dollars invested at the county-pair-year level, this section studies the determinants of the *number of VC investments* at the same level of aggregation.

How can the extensive margin of investment be informative about the VC investment decision process? If the extensive margin were more important than the intensive margin, this could be interpreted as evidence that social connectedness matters more for the first two phases of the investment process, deal flow and deal selection. Social connectedness could in this case be understood to (i) foster the initial creation of links between VCs and entrepreneurs and/or (ii) increase the conditional likelihood of an investment happening during the selection phase. This result would be in line with Gompers et al. (2020), Nanda et al. (2020), and Burg et al. (2022). If, on the other hand, the intensive margin were more important than the extensive margin, this could be interpreted as evidence against the first two phases and in favor of the third phase, valuation. In this scenario, social connectedness could e.g. make more socially connected investors more confident or even exuberant, ceteris paribus, and lead to higher investment amounts.

The regression equation is as follows:

$$\#\text{VC Equity}_{ijt} = exp(\beta\Phi_{ijt} + \eta_{it} + \nu_{jt} + \mu_{ii} + \sigma_{ij} + \varepsilon_{ijt}) \tag{3}$$

where $\#\text{VC Equity}_{ijt}$ is the number of VC equity investments between counties i and j in year t. Otherwise, this regression resembles Equation (2). Table 4 presents the estimation results.

The results in Table 4 show that the extensive margin responds more to social connectedness than the aggregate amount of VC investment (Table 3). I interpret this result as evidence that social connectedness matters more for whether an investment happens than how much is being invested. Regarding the three phases of the investment process outlined in Gompers et al. (2020), it seems that social connectedness is more important for deal flow and deal selection rather than valuation.

Gompers et al. (2020) present survey evidence on how venture capitalists acquire deal flow (i.e. how they establish initial contact with the companies/founders that they consider investing in). They report that around 60% of deal flow is generated via existing social connections (31% via the VC firm's professional network, 20% is referred by other investors, and 8% is referred by portfolio companies), whereas around 40% is generated in other ways (10% inbound from company management, and 28% proactively self-generated by the VC firm). The results report in Table 3 and Table 4 are thus consistent with the survey evidence reported in Gompers et al. (2020); existing social connections seem to play an important role in generating potential VC investment relationships.

2.4 Investment Flows by Investment Stage

In order to make progress on understanding the mechanism behind the baseline results in Section 2.2, in this section I conduct a heterogeneity analysis. In particular, I explore whether social connectedness matters differentially in early or late stages of the VC investment process. Tian (2011) shows that staging by venture capitalists can be seen as a substitute for proximity, likely substituting for other methods of control. In this section I investigate whether social networks can function as a proxy for control as well.

Table 4: PPML Regressions of Number of VC Equity Investments

Dependent Variable →	# VC Equity			
	(1)	(2)	(3)	(4)
asinh(Distance)	-0.311***		0.022	0.085
	(0.043)		(0.039)	(0.077)
asinh(SCI)		0.544***	0.567***	0.506***
		(0.030)	(0.039)	(0.060)
asinh(Migration)				0.042**
				(0.015)
asinh(Commuters)				0.021
				(0.014)
asinh(Trade)				0.192**
				(0.064)
asinh(Travel Time)				0.089
				(0.084)
Observations	1,696,318	1,696,318	1,696,318	1,029,482
County×Year FEs	Yes	Yes	Yes	Yes
Same County FEs	Yes	Yes	Yes	Yes
Same State FEs	Yes	Yes	Yes	Yes

Note: Standard errors clustered at the county inbound and county outbound level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. *# VC Equity* is the number of VC equity investments from county i to county j in year t. *Distance* is the physical distance between two counties; *SCI* is the social connectedness index between two counties (as of August 2020); *Migration* is the amount of migrants moving from county i to county j in year t;*Commuters* is the amount of commuters from county i to county j in year t;*Trade* is the amount of trade from county i's state to county j's state in year t ;*Travel Time* is the shortest travel time between county i and county j in year t, taking into account travel by car and plane. *asinh* is the inverse hyperbolic sine of a given variable.

In order to examine the role of SCI for different investment stages, I build subset datasets for each investment stage. Analogously to how I construct the main sample from all individual investments, which I then aggregate up to the county-pair-year level, in this section I do the same, but for each investment stage separately. I.e. for each investment stage (Acquisition for Expansion, Bridge Loan, Early Stage, Expansion, Later Stage, Recap or Turnaround, Seed, and VC Partnership) I keep all investments made in that stage across the entire sample period, and then aggregate the dataset to the county-pair-year level. I then estimate Equation (2) for each of these stages separately. Table 5 presents the results.

The results indicate that investments at early stages of the company life cycle (columns 1 and 2) are more sensitive to social connectedness than investments at later stages (columns 3 and 4). The coefficient of SCI decreases monotonically across investment stages (although some of the coefficients are estimated rather imprecisely).

As a startup grows and receives subsequent rounds of VC financing, the uncertainty associated with its product, market, and management team arguably decreases substantially. Firms that receive further rounds of financing have arguably proven their worth and potential. Especially in the first months and years of a young company, uncertainties are very large. The fact that social connectedness matters more for early stages of investment than for late stages is therefore consistent with social connectedness being able to resolve some of that uncertainty. While it is also possible that social connectedness might reduce uncertainty around product and market, it seems much more plausible that it helps investors reduce uncertainty around the management team of the company they invest in.

Consistent with this interpretation, Bernstein et al. (2017) and Gompers et al. (2020) report that while VC firms frequently name the management team as the most important factor for deal selection in all investment stages (47% of VC firms), Gompers et al. (2020)

shows that it is a more decisive factor in early stages of investment (53% of VC firms name it as the most important factor in early stages versus just 39% in late stages). The fact that SCI matters more for early stages therefore seems consistent with the idea that SCI at least partially helps investors to reduce uncertainty around the management team. [13] However, note that the coefficient of SCI for later stages stay very significant. I interpret this as evidence that this channel is not the only way in which social connectedness matters for VC investments.

[13] This interpretation is also consistent with the findings of Garfinkel et al. (2021), who argue that social connections can be a substitute for other observable information. A related but slightly different interpretation can be found in Bottazzi et al. (2016), who investigate and emphasize the importance of trust in VC investment.

3 Social Access to VC and Local Entrepreneurship

Do social connectedness with locations that invest VC affect only the flow of VC, or do they have real impacts on the entrepreneurial and economic performance of counties? In Section 2 I document that venture capital investment flows between counties are strongly related to social connectedness. In this section I investigate whether social connectedness, through its impact on venture capital flows, has real impacts on local economies, in particular on entrepreneurship.

To investigate how social connectedness impacts local outcomes, I define a county's social access to venture capital (SAVC). This measure is a weighted sum over a county's social connectedness indices to all other counties, multiplied with the respective amounts of VC invested from these counties to all other counties. To account for potential endogeneity, I exclude all investments made to counties in the same MSA as the county under consideration. This measure of social access to venture capital thus intuitively captures how social close a given county in a given year is to counties that manage VC. If venture capital is indeed predicted by social connectedness, then higher values of this index should lead to higher levels of VC investment. This in turn should lead to better entrepreneurial outcomes, reflected in the number and quality of startups in the affected counties.

The estimation results indicate that counties with higher social access to venture capital (while controlling for physical access to venture capital) have better entrepreneurial outcomes. In particular, these counties have higher rates of start up foundation, i.e. they attract more startups, and they attract better startups (as measured by the entrepreneurial quality index, EQI).

These results are in line with those reported by Stuart and Sorenson (2003), who show that the rate of startup creation in the biotechnology sector is positively influenced by physical proximity to VC firms. In contrast to Stuart and Sorenson (2003), the results in this section demonstrate that social access to venture capital is an important predictor of startup creation, even conditional on physical proximity to VC firms. These results are also in line with results in Kuchler et al. (2021) and Rehbein and Rother (2022), who show that locations with better social access to institutional investors and banks, respectively, have better real economic outcomes.

3.1 Empirical Strategy

To measure a county's access to venture capital, I construct what I call the *social access to venture capital* (SAVC) index. The index is defined as follows:

$$SAVC_{i,t} = \sum_{j \in J} \theta_{ij} \cdot \sum_{k \notin M_i} VC_{jk,t} \tag{4}$$

where $\sum_{k \notin M_i} VC_{jk,t}$ is the sum of flows from county j to all other counties k that are not in M_i, the set of counties in the same MSA as county i. θ_{ij} is the SCI between counties i and j.[14]

Similarly, I define physical access to venture capital (PAVC) as

$$PAVC_{i,t} = \sum_{j \in J} \text{Distance}_{ij}^{-1} \cdot \sum_{k \notin M_i} VC_{jk,t} \tag{5}$$

Both physical and social access to venture capital are close in spirit to the concept of market potential (Harris, 1954).[15] Cf. also the concept of market access, which is frequently used in the spatial economics literature (e.g. Donaldson and Hornbeck (2016)).

[14]See Poelhekke and Wache (2023) for further discussion of this measure.

[15]See also Kuchler et al. (2021) and Rehbein and Rother (2022) for similar definitions, close to the concept of market potential.

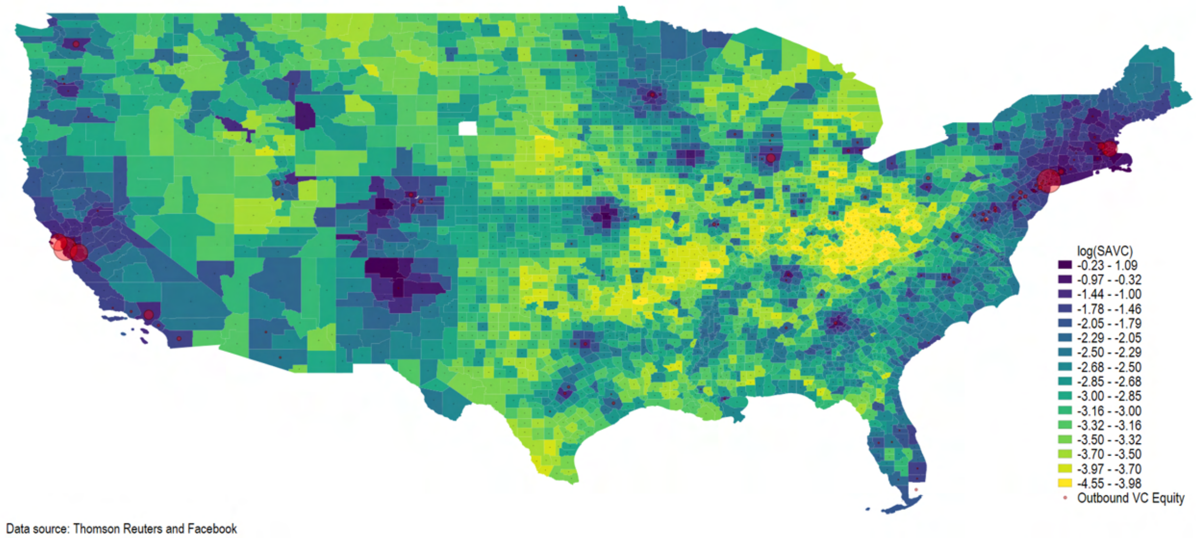

Figure 2: SAVC in 2018

Description: This figure plots SAVC for all US counties in 2018.

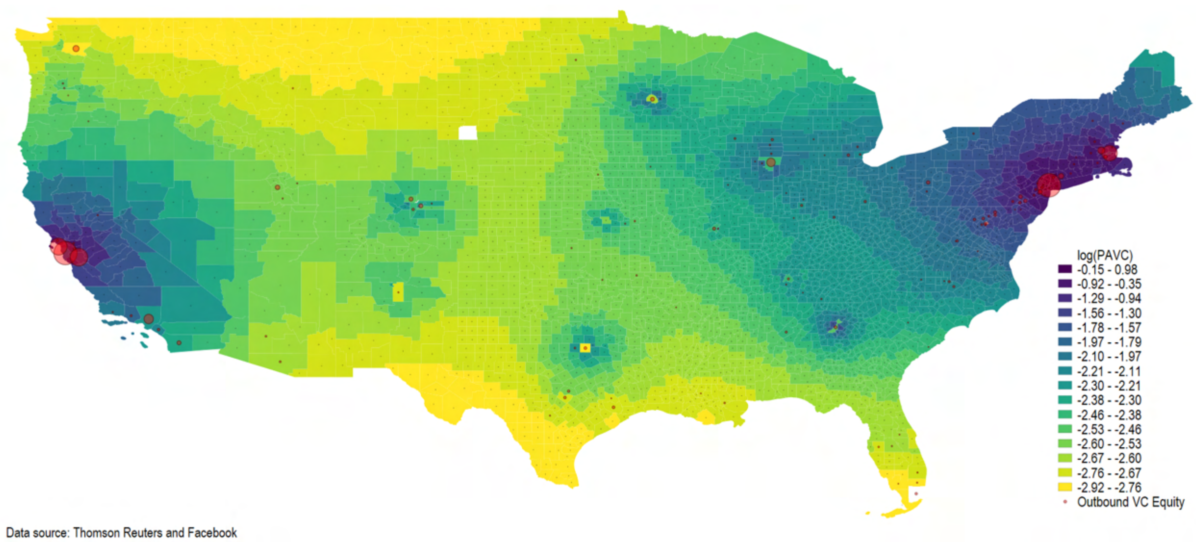

Figure 3: PAVC in 2018

Description: This figure plots PAVC for all US counties in 2018.

Equation (6) is the main regression equation in this section. I regress entrepreneurial outcomes on the county-by-year level on the social access to venture capital, while flexibly controlling for the level of physical access to venture capital.

$$log(Y_{i,t}) = \beta log(\text{SAVC}_{i,t}) + \eta_i + \nu_t + \sum_{j=1}^{100} I_j(\text{PAVC}_{i,t}) + \varepsilon_{i,t} \tag{6}$$

where $Y_{i,t}$ are entrepreneurial outcomes, $SAVC_{i,t}$ is the social access to venture capital index, $I_j(\text{PAVC}_{i,t})$ is an indicator variable that is equal to one if $\text{PAVC}_{i,t}$ is in the jth quantile of the distribution of PAVC, and η_i and ν_t and county and year fixed effects. Entrepreneurial outcomes at the county-by-year level include (Andrews et al., 2022): startup formation rate (SFR - the number of new startups), entrepreneurial quality index (EQI - the average growth potential of companies founded in a county in a given year), regional entrepreneurship cohort potential index (RECPI - the number of companies founded in a given county in a given year that are expected to experience a growth event), and regional entrepreneurship acceleration index (REAI - the ability of a county to live up to its expected amount of high growth companies, i.e. realized divided by expected growth events).

3.2 Results

This section empirically examines the influence of social access to VC on county-level entrepreneurial outcomes. Table 6 shows the main results of this analysis.

The results indicate that higher levels of SAVC are associated with significantly better entrepreneurial outcomes. In particular, counties with higher levels of SAVC (while controlling for 100 PAVC fixed effects) are host to more startups (column 1), and startups with higher expected quality (column 2). Interestingly, column 4 suggests that counties with higher

Table 5: VC Equity Investments, by Investment Stage

Dependent Variable →	VC Equity							
	Early Stages		Late Stages		Other Stages			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample →	Seed	Early Stage	Expansion	Later Stage	Bridge Loan	Recap or Turnaround	Acq. for Expansion	VC Partnership
asinh(Distance)	0.384*	0.063	0.062	0.010	0.352	-0.622	-0.073	0.336
	(0.180)	(0.035)	(0.041)	(0.042)	(0.223)	(0.386)	(0.111)	(0.182)
asinh(SCI)	0.598*	0.529***	0.507***	0.425***	0.979***	0.442	0.157	0.570*
	(0.244)	(0.066)	(0.054)	(0.049)	(0.268)	(0.452)	(0.154)	(0.244)
Observations	5,688	642,677	799,282	501,285	86,419	2,562	29,153	6,050
County×Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Same County FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Same State FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors clustered at the county inbound and county outbound level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. *VC Equity* is the total amount of VC equity invested in millions of dollars from county i to county j in year t. *Distance* is the physical distance between two counties; *SCI* is the social connectedness index between two counties (as of August 2020). *asinh* is the inverse hyperbolic sine of a given variable. Columns differ by the stage which the data are based on. For example, column 1 shows regression based on a sample of only seed stage investments, which are aggregated up to a county to county by year dataset, etc.

Table 6: OLS Regressions of Entrepreneurial Outcomes on Access to Venture Capital

Dependent Variable →	asinh(SFR)	log(EQI)	log(RECPI)	$asinh(REAI)$
	(1)	(2)	(3)	(4)
log(SAVC)	0.043*	0.052***	0.102***	-0.002
	(0.019)	(0.011)	(0.022)	(0.011)
Observations	87,926	87,926	86,164	74,442
Year FEs	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	Yes
PAVC Bucket FEs	100	100	100	100

Note: Standard errors clustered at the county level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. $SAVC$ is the social access to venture capital index; *PAVC buckets* are 100 fixed effects, one for each percentile of PAVC (physical access to venture capital index). *SFR* is the startup foundation rate, i.e. the number of startups founded; *EQI* is the entrepreneurial quality index, a measure of the average quality of startups in a county; *RECPI* is the regional entrepreneurship cohort potential index, i.e. the product of SFR and EQI; *REAI* is the regional entrepreneurship acceleration index, the ratio of realized to expected companies that experience growth events. All dependent variables in this table are defined for a given county in a given year, and are taken from Andrews et al. (2022). *asinh* is the inverse hyperbolic sine of a given variable.

social access to venture capital are not differentially better good at converting promising startups into high growth companies. In other words, counties with higher levels of SAVC receive more and better startups, which then achieve high growth-events at an ”expected” rate.

These results suggest that locations with higher levels of SAVC experience looser capital constraints for local entrepreneurs. What is harder to tell from these results is to what extent entrepreneurs are aware of these constraints and are able to adjust their location and/or social networks in order to access venture capital. These results are consistent with a theoretical world where entrepreneurs are completely immobile (Sorenson, 2018), and SAVC partially determines which business ideas in which locations receive funding. The results would also be consistent with a model where entrepreneurs are aware of the importance of SAVC for their businesses and migrate accordingly in order to have better chances of receiving funding. This second interpretation is in line with a literature studying entrepreneurs' decisions to migrate their company for better access to input, output, capital, and ownership markets (Guzman, 2018; Bryan and Guzman, 2021; Conti and Guzman, 2021).

In sum, this analysis suggests that social proximity to investors of risky capital is an important determinant of a location's ability to attract young companies with high growth potential.

4 Conclusion

The results in this paper show that the flow of venture capital investments across the economy crucially depends on social networks. After controlling for social connectedness, geographical distance does not affect the amount of VC investments. These results are robust to the inclusion of (time-varying) travel time, commuting patterns, migration, and physical trade across counties. I find evidence that the effect of social connectedness is stronger for early stage VC investments, and that the extensive margin of investment is more strongly impacted by it than the intensive margin.

In the second part of the paper, I analyze the effect of social access to venture capital on local entrepreneurial outcomes. I find that locations with higher social connectedness to locations that manage venture capital investments benefit from this by being host to more and better startups.

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A Venture Capital Flow Data

The county-to-county venture capital flows are constructed as follows: Between April and September 2021, I searched the ThomsonOne database for all observations of venture capital and private equity investment rounds with investor and recipient based in the US. I restricted the search dates to investment observations that happened between January 1, 1960 and December 31, 2019. I only include observations where the investing VC firm, as well as the receiving company are based in the mainland United States (i.e. excluding Alaska and Hawaii). In order to narrow these observations down to only venture capital investments, I excluded observations with the following entries for the investment stage: 'LBO', 'PIPE', 'Open Market Purchase', 'Acquisition', 'Acq. for Expansion', 'Secondary Buyout', 'Secondary Purchase', 'Recap or Turnaround'. Exceptions were made in cases where the investment security contained the words 'Series' and/or 'Venture'. So e.g. whereas observations at the investment stage 'PIPE' were generally excluded from the final sample, those with an investment security 'Series A' were included. During a given VC investment round, it is common that several VC firms invest into a company simultaneously. For every investment round I then create an individual observation for each VC firm that invests into a given company at a given time. This observation is thus at the VC-firm-to-company-at-time-t-level. I then geocode the address information for each company and each VC firm observed in the data and match them to the respective observation. Observations that lack information on either the firm, the company, the date, the counties, or the amount invested are discarded. This leaves me with a database of $240,978$ VC-firm-to-company-investment-at-time-t observations, between a total of $6,010$ VC investors and $41,487$ companies. Using the county information from the geocoded addresses, I then aggregate the data up to the county i to county j in year t flow level.

B Heterogeneity Analysis of VC Equity Investment Flows

This section explores different levels of heterogeneity of the main results presented in Section 2.2.

B.1 5-year Sub-sample Regressions

This section investigates whether social connectedness is likely to change quickly over time. Table B1 shows the same regression as in column 3 of Table 3, but with 5-year subsets of the full sample, between 1970-2019[16]. The results show that social connectedness as measured in August 2020 shows a robust and stable conditional correlation with VC investment over the whole sample period. This echoes the findings of Kuchler et al. (2021), who show a similar result in their sample of equity market investments. This result indicates that social networks across counties is likely highly persistent over time, and that social connectedness measured in 2020 is likely a good measure for social connectedness in previous years.

B.2 VC Equity Investment Flows by Industry

Do social networks impact the investment of venture capital differently across different industries? Burg et al. (2022) posit that social connectedness may play different roles in different industries. For example, a venture operating in a business-to-business industry, with a handful of large players dominating the market, may be susceptible to an embedded network, whereas a venture in a fast-moving consumer products industry may likely grapple

[16]Sub-samples for 1960-1964, and 1965-1969 are not shown due to very small sample sizes. Note that periods with very few or no non-zero observations will automatically be absorbed by County×Year fixed effects.

with cognitive network overload. This hypothesis can be tested by examining the Herfindahl index of the industries in which the ventures operate.

In this section I build sector level flow datasets in order to investigate this question.[17] Table B2 shows the same regression as column 6 from Table 3, but only taking into account investments in companies in specific industries.

The results in Table B2 show an interesting pattern. Whereas VC investments in the manufacturing, the transportation, the wholesale, and the services sectors are very much in line with the main results from Table 3, social networks seem to matter less for investments into companies from the retail and the finance sectors.[18] Interestingly, for both of these sectors, physical distance retains a significantly negative effect on investment after controlling for the strength of social ties. One reason for this pattern may be that startups in these two sectors are selected in a different way from other sectors, e.g. due to different capital requirements, or different access to capital.

B.3 VC Equity Investment Flows by Investor Type

In this section I split the VC investment flow sample by investor type., as the literature suggests that investor type and organizational structure may have important ramifications for their investment behaviour (see e.g. Hellmann et al. (2008)). I run regression Equation (2) on county to county investment flow samples taking into account only investments by certain investors. Results are presented in Table B3.

[17] In particular, I use the following subsets of industries and keep only flows where the receiving company is listed under one of the following two-digit SIC codes: Agriculture, Forestry, Fishing (01-09); Mining (11-14); Construction (15-17); Manufacturing (20-39); Transportation & Public Utilities (40-49); Wholesale Trade (50-51); Retail Trade (52-59); Finance, Insurance, Real Estate (60-67); Services (70-89); Public Administration (91-99).

[18] Due to very small sample sizes, I ignore the other four sectors (agriculture, mining, construction, and public administration) for now.

Table B1: PPML Regressions of VC Equity Investments in Companies

Dependent Variable →	VC Equity									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Sample Period →	1970-1974	1975-1979	1980-1984	1985-1989	1990-1994	1995-1999	2000-2004	2005-2009	2010-2014	2015-2019
asinh(Distance)	0.027	-0.101	-0.045	-0.133	0.075	-0.009	0.060	-0.003	0.070	0.102**
	(0.134)	(0.138)	(0.067)	(0.102)	(0.129)	(0.079)	(0.064)	(0.059)	(0.049)	(0.038)
asinh(SCI)	0.517**	0.170	0.373***	0.344**	0.541***	0.404***	0.471***	0.435***	0.470***	0.555***
	(0.178)	(0.215)	(0.086)	(0.117)	(0.135)	(0.096)	(0.086)	(0.067)	(0.103)	(0.079)
Observations	7,720	14,786	79,484	145,931	110,959	242,741	307,923	260,028	237,666	271,973
County×Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Same County FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Same State FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors clustered at the county inbound and county outbound level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. *VC Equity* is the total amount of VC equity invested in millions of dollars from county i to county j in year t. *Distance* is the physical distance between two counties; *SCI* is the social connectedness index between two counties (as of August 2020). *asinh* is the inverse hyperbolic sine of a given variable. Columns differ by the time period which the data are based on. For example, column 10 shows regressions based on a sample of only years 2015 - 2019, etc.

Table B2: VC Equity Investments, by Company Industry

Dependent Variable →	VC Equity									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Sample Companies →	Agriculture	Mining	Construction	Manufacturing	Transportation	Wholesale	Retail	Finance	Services	Admin
asinh(Distance)	0.643	0.387	-0.668	-0.031	0.250*	0.137	0.059	0.041	0.067	0.758
	(0.356)	(0.507)	(0.547)	(0.048)	(0.117)	(0.136)	(0.115)	(0.079)	(0.034)	(2.034)
asinh(SCI)	1.291**	0.843	0.104	0.356***	0.502***	0.632***	0.512**	0.214	0.569***	0.027
	(0.480)	(0.508)	(0.802)	(0.063)	(0.141)	(0.166)	(0.193)	(0.140)	(0.040)	(0.074)
Observations	1,333	2,664	1,618	742,257	110,090	26,855	43,710	57,015	812,664	96
County×Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Same County FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Same State FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors clustered at the county inbound and county outbound level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. *VC Equity* is the total amount of VC equity invested in millions of dollars from county i to county j in year t. *Distance* is the physical distance between two counties; *SCI* is the social connectedness index between two counties (as of August 2020). *asinh* is the inverse hyperbolic sine of a given variable. Columns differ by the company industry which the data are based on. For example, column 1 shows a regression based on a sample of only investments in companies active in the agricultural sector.

Table B3: VC Equity Investments, by Investor Type

Dependent Variable →	VC Equity														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Sample Investors →	Angel	Bank	Corporate	Endowment	Government	Incubator	Individuals	Insurance	Investment	Other	PE Advisor	PE Firm	SBIC	Service Provider	University
asinh(Distance)	-0.564*	0.032	0.096	-0.371	0.282	0.057	-0.841*	0.154	0.273	0.000	0.060	0.047	0.051	-0.170	-1.202*
	(0.240)	(0.095)	(0.080)	(0.217)	(0.353)	(0.120)	(0.395)	(0.321)	(0.159)	(0.000)	(0.207)	(0.049)	(0.114)	(0.422)	(0.517)
asinh(SCI)	0.935***	0.371*	0.330**	0.091	1.346**	0.510*	-0.635	0.436	0.748**	-293.177***	0.456	0.521***	0.641***	0.660	-0.262
	(0.243)	(0.188)	(0.122)	(0.290)	(0.420)	(0.221)	(0.786)	(0.310)	(0.277)	(0.166)	(0.243)	(0.066)	(0.118)	(0.506)	(0.789)
Observations	28,561	90,102	148,174	4,163	18,383	14,514	221	2,459	26,776	28	8,634	1,240,461	22,077	1,993	1,993
County×Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Same County FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Same State FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors clustered at the county inbound and county outbound level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. *VC Equity* is the total amount of VC equity invested in millions of dollars from county i to county j in year t. *Distance* is the physical distance between two counties; *SCI* is the social connectedness index between two counties (as of August 2020). *asinh* is the inverse hyperbolic sine of a given variable. Columns differ by the type of investor which the data are based on. For example, column 1 shows a regression based on a sample of only investments made by Angel investors.

B.4 VC Equity Investment Flows by Investor Age

In this section I split the VC investment flow sample in five investor age quantiles. Investor age is defined at time of investment. Investor age could interact with social connectedness, since older investors may have had more time to build up their own social networks. Alternatively, older investors may have higher recognition, so might be easier to 'find' by entrepreneurs. I estimate Equation (2) on sub-samples taking into account only investments by investors of a certain age at time of investment. Results are reported in Table B4. The estimation results indicate that the oldest investors differ from other investors. Specifically, VC investments by investors in the last (oldest) age quantile are most sensitive to social connectedness.

Table B4: VC Equity Investments, by Investor Age

Dependent Variable →	VC Equity				
	(1)	(2)	(3)	(4)	(5)
Sample Investors →	Q1	Q2	Q3	Q4	Q5
asinh(Distance)	0.017	-0.039	0.035	0.054	0.171**
	(0.043)	(0.050)	(0.049)	(0.063)	(0.056)
asinh(SCI)	0.499***	0.459***	0.488***	0.477***	0.561***
	(0.065)	(0.077)	(0.058)	(0.071)	(0.078)
Observations	549,015	361,094	384,718	295,859	246,604
County×Year FEs	Yes	Yes	Yes	Yes	Yes
Same County FEs	Yes	Yes	Yes	Yes	Yes
Same State FEs	Yes	Yes	Yes	Yes	Yes

Note: Standard errors clustered at the county inbound and county outbound level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. *VC Equity* is the total amount of VC equity invested in millions of dollars from county i to county j in year t. *Distance* is the physical distance between two counties; *SCI* is the social connectedness index between two counties (as of August 2020). *asinh* is the inverse hyperbolic sine of a given variable. Columns differ by the age of investors by the time of investment. For example, column 1 shows a regression based on a sample of only investors who are in the lowest of five quantiles at the time of investment.

C Venture Capital Debt Investment Flows

In this section I repeat the main estimation with VC debt investment flows, instead of VC equity investment flows. Results are reported in Table C1. The results indicate that VC debt investments are more sensitive to social connectedness than VC equity investments. However, note that the sample that these regressions are based on is roughly ten times smaller than the main sample of VC equity flows. Accordingly, standard errors are larger, so it is hard to draw decisive conclusions from these regressions. It is however notable that the point estimates are quite a bit larger than comparable estimates for VC equity flows.

Table C1: PPML Regressions of VC Debt Investments in Companies

Dependent Variable →	VC Debt			
	(1)	(2)	(3)	(4)
asinh(Distance)	-0.298***		0.133	0.537*
	(0.067)		(0.116)	(0.217)
asinh(SCI)		0.572***	0.712***	0.613**
		(0.073)	(0.147)	(0.196)
asinh(Migration)				0.045
				(0.086)
asinh(Commuters)				0.072*
				(0.037)
asinh(Trade)				0.206
				(0.192)
asinh(Travel Time)				-0.334
				(0.259)
Observations	146,851	146,851	146,851	109,578
County×Year FEs	Yes	Yes	Yes	Yes
Same County FEs	Yes	Yes	Yes	Yes
Same State FEs	Yes	Yes	Yes	Yes

Note: Standard errors clustered at the county inbound and county outbound level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. *VC Debt* is the total amount of VC debt invested in millions of dollars from county i to county j in year t. *Distance* is the physical distance between two counties; *SCI* is the social connectedness index between two counties (as of August 2020); *Migration* is the amount of migrants moving from county i to county j in year t;*Commuters* is the amount of commuters from county i to county j in year t;*Trade* is the amount of trade from county i's state to county j's state in year t ;*Travel Time* is the shortest travel time between county i and county j in year t, taking into account travel by car and plane. *asinh* is the inverse hyperbolic sine of a given variable.