

# Seed-Stage Success and Growth of Angel Co-investment Networks\*

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## Abstract

Using hand-collected data we show that co-investment is widespread in the angel investment market, even among seed-stage startups. Individual angels who demonstrate seed-stage success experience an increase in the quantity, quality, and geographic and industry spread of their co-investment connections relative to unsuccessful peers, and are rewarded with more deal flow. These results are stronger for less-established angels and for successes that are more indicative of the angel's ability. Success also begets more success, making it more likely that the angel's other portfolio companies receive follow-on financing, especially from VC firms. Our results highlight how angels grow their co-investment networks. (*JEL*: G24, L14, L26, M13)

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\*We thank two anonymous referees, Isil Erel (the editor), Bhagwan Chowdhry, Douglas Cumming, Matthew Denes (discussant), Radha Gopalan, Ravi Jagannathan, Sofia Johan (discussant), Praveen Kumar, Laura Lindsey, Elena Loutskina, Maurice McCourt (discussant), Debarshi Nandy, Paul Povel, Ramana Sonti (discussant), Kandarp Srinivasan (discussant), Krishnamurthy Subramanian, Richard Townsend (discussant), Jingyu Zhang (discussant), and seminar participants at the 29th Annual Conference on Financial Economics and Accounting 2018, the Australasian Finance and Banking Conference 2016, the Financial Management Association Annual Meeting 2017, the Indian School of Business Annual Summer Research Conference 2017, the Midwest Finance Association Conference 2017, the Paris December Finance Meeting 2016, the SFS Cavalcade 2017, and the University of Houston for their helpful comments or discussions on issues examined in the paper. All remaining errors are our responsibility. We are very grateful to Tim Li of CrunchBase and Joshua Slayton of AngelList for giving us access to their respective database. An earlier version of the paper was circulated under the title "How do Investors Accumulate Network Capital? Evidence from Angel Networks." Please send correspondence to Buvaneshwaran Venugopal at University of Central Florida, College of Business, BA1 417, Box 161400, Orlando, FL 32816, USA; telephone: +1 (407) 823-0896; email: eshwar@ucf.edu

Although startups and venture capital (VC) finance are often linked in the public eye, the most common source of equity finance for early-stage startups, especially those at the seed stage, are individual angel investors.<sup>1</sup> Unlike VCs and other institutional financial intermediaries, angels invest their own personal wealth in startups. Angels nurture early-stage startups in a variety of ways, which include screening and due diligence, providing strategic advice, and convincing other investors, such as VCs, to invest in later-stage funding rounds of their portfolio companies (Kerr, Lerner, and Schoar, 2014). Indeed, the funding path of growth-oriented startups typically involves some initial funding from angels, with subsequent funding coming from VCs (Hellmann and Thiele, 2015).

Despite their important role in nurturing early-stage startups, we know little about how angels source deal flow and how they are able to convince other investors to invest in later-stage funding rounds of their startups. It is well accepted in the entrepreneurial finance literature that venture capital (VC) networks affect deal flow and the performance of both VCs and their portfolio firms: in particular, well-networked VC firms appear to secure both more diverse (Sorenson and Stuart, 2001) and better-performing investment portfolios (Hochberg, Ljungqvist, and Lu, 2007).<sup>2</sup> However, as Stuart and Sorenson (2007) note, most of this literature treats network structures as *exogenous*. Thus, we know little about why or how some investors end up becoming central to their networks. Is network centrality itself determined because of reputation gained from good past performance? These questions are particularly relevant in case of the angel investment market because the vast majority of angels are *individual* investors who are not endowed with many network connections to begin with. In this paper we shed light on the co-investment behavior of angel investors, and examine whether angels are able to expand the quantity, quality, and geographic scope

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<sup>1</sup>In entrepreneurial finance, startups are generally classified into the following life-cycle stages: seed, series A, series B, series C, series D, and finally, exit via acquisition, IPO or failure (please see the Internet Appendix for the generally accepted definitions of these stage classifications in the industry).

<sup>2</sup>Sorenson and Stuart (2001) show that VC firms with axial positions in the network more frequently invest in target firms outside of their geographic regions and domain specializations than less advantageously positioned peers. Hochberg, Ljungqvist, and Lu (2007) show that target companies financed by these central VC firms go public (i.e., IPO) at higher rates.

of their network connections following the success of their seed-stage startups.

Empirical research on angels has been stymied by unavailability of structured data. Similar to [Bernstein, Korteweg, and Laws \(2017\)](#) and [Yu \(2020\)](#), we overcome this problem by collecting data on startups and angel investors from CrunchBase ([www.crunchbase.com](http://www.crunchbase.com)), which is the largest crowd-sourced database on startups and investors, and AngelList ([www.angel.co](http://www.angel.co)), which is the leading online fund-raising platform for startups. We use these databases to gather information on angel investors (e.g., biographical information, investment history, list of co-investors, etc.) and the performance of their portfolio firms in terms of their fund-raising activity and progression from one financing stage to the next; e.g., “seed” stage to “series A” stage, or from “series A” stage to “series B” stage, and so on.

Co-investment involves multiple investors participating jointly in the financing round of a startup. We first show that co-investment is widely prevalent in the angel market, even among seed-stage startups. Both the likelihood of co-investment and the number of investors increase monotonically from the seed stage through the Series D stage even after controlling for the startup’s age and size of the funding round, which is consistent with the idea that co-investment is more likely when informational problems are less severe ([Holmström and Tirole, 1997](#)). Startups in later stages are financed by co-investors that are *much closer* in terms of professional connections, and this effect intensifies as startups progress to later stages; but at the same time, these co-investors are also *more dispersed* in terms of educational connections and geographic similarity. These disparate patterns may reflect the importance of industry specialization in the entrepreneurial finance market, which can explain why co-investors in later stages are more likely to share professional connections. At the same time, geographic and educational ties among co-investors becomes less important as informational problems become less severe.

Our main focus is on understanding how individual angel investors improve their network connectedness over time. We hypothesize that successful performance by an angel investor enhances the markets’ beliefs about his investing abilities (“reputation”) and, hence, should

lead to an increase in his network connectedness — both in terms of the number and quality of connections — and increased deal flow relative to his unsuccessful peers. We refer to this as the *reputation hypothesis*. To measure successful performance, we define the dummy variable *Seed Success* for each angel-year combination to identify whether the angel successfully guided any of his seed-stage portfolio firms to series A stage during the year. We focus on seed-stage performance because of two important reasons, which we document below: (a) investments by angel investors, especially when angels invest alone, are more concentrated at the seed stage; and (b) the failure rate at the seed stage is much higher than at subsequent stages. Hence, we believe that *Seed Success* is likely to be most informative about an individual angel’s investing ability.

Of course, performance measures in this market are extremely noisy, and it is hard to distinguish skill from luck. Although successful transition from the seed to series A stage is an important sign of progress, considerable uncertainty remains about the fate of the startup, and more than 50% of startups at the series A stage fail to progress to the next stage. Moreover, given the perception that angels are “passive” investors, it is possible that the market may not credit the angel for the startup’s performance. Thus, it is not clear a priori that *Seed Success* will have a positive effect on the angel’s growth in network connections and deal flow. This is an empirical question that we hope to resolve.

The main empirical challenge is that seed success is endogenous and may itself depend on the angel’s skill or some other unobserved or omitted factor that also affects future network growth. While it is difficult to empirically isolate the causal effect of seed success on growth in network capital, we use the following approach to test the reputation hypothesis and rule out alternative explanations: First, we use propensity score matching to match each successful angel (“treated” group) with several unsuccessful angels during the same year and in the same state who are very similar in terms of observable characteristics that predict seed success (“control group”), such as the number and quality of their existing network connections, and past investment history. Then, we estimate difference-in-differences regressions with angel

fixed effects and year fixed effects to examine how the growth in network capital of successful angels in the treated group varies relative to their unsuccessful peers in the control group in the years before and after they experience success. As per the reputation hypothesis, the successful angels should experience higher growth relative to their unsuccessful peers *only after* the successful performance, but not before (i.e., the parallel trends assumption must hold). The inclusion of angel fixed effects ensures that our results cannot be explained by time-invariant angel characteristics, such as skill or entrepreneurial experience.

Using standard measures of network connectedness from the economic sociology literature (see [Jackson, 2010](#)), we show that angels that lead a seed-stage portfolio firm to series A stage see an improvement in both the quantity and quality of their co-investment connections compared to their unsuccessful peers in the following three years, although the two groups are very similar in the years before the success.<sup>3</sup> Angels that experience seed success are rewarded with more new investment opportunities compared to their unsuccessful peers. Moreover, they are able to expand the geographic scope of their co-investment network by forming more connections with out-of-state investors and by investing in more out-of-state startups compared to their unsuccessful peers.

Theoretical models of reputation predict that the gain in an agent’s reputation from good performance should be stronger for less-established agents, and when the good performance is more reflective of the agent’s ability and skill (see [Holmström, 1999](#)). Hence, we hypothesize that the positive effect of seed success will be stronger for angel investors with low existing network capital compared to those with high existing network capital, because angels in the former category are less established in the entrepreneurial finance market. Moreover, although ability and skill are not directly observable, we conjecture that seed successes that are less likely *ex ante*, based on founder characteristics and industry characteristics of the startup, should be more reflective of the angel’s ability and skill than seed successes that are

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<sup>3</sup>Because seed-stage success may lead to a mechanical increase in the angel’s network connections as new investors participate in the series-A financing of the successful startup, we only count the new co-investment connections that the angel generates through other portfolio firms not including the successful startup. The results are qualitatively similar if we ignore this requirement.

more likely ex ante even without the angel’s involvement; we hypothesize that the effect of seed success will be stronger in the former category. Our results are supportive of these two predictions of the reputation hypothesis.

If successful performance boosts an angel’s network connectedness, then it is logical to also expect a positive knock-on effect on his *other* existing portfolio companies (i.e., other than the company in which the angel first experienced success). Consistent with this idea, we find that angels that deliver seed success are more likely than their unsuccessful peers to lead their other seed-stage portfolio companies to the series A stage and to obtain venture capital financing for their other portfolio companies over the next three years. In other words, success begets more success for the angel investor.

An interesting feature of AngelList is that, just like other online communities, it allows investors to follow the activities of other investors without actually co-investing with them. We are able to obtain data on such “follower” networks for 733 individual angel investors over the time period August 2010 to February 2015. Consistent with the reputation hypothesis, we find the angels that experience seed success attract more new followers and also form more new co-investment connections with their existing followers relative to their unsuccessful peers in the year after they experience success. Successful angels are also more likely to start angel groups or join VC firms later in their careers.

Our paper contributes to the growing literature on the angel investment market (e.g., [Goldfarb, Triantis, Hoberg, and Kirsch, 2013](#); [Kerr, Lerner, and Schoar, 2014](#); [Bernstein, Korteweg, and Laws, 2017](#); [Lindsey and Stein, 2020](#)). In particular, we focus on individual angel investors who play a crucial role in the financing of seed-stage startups, and seek to understand how these investors grow their co-investment networks over time. The individual angel investor market is largely unorganized and fragmented by geography and industry, which makes it hard to provide a comprehensive picture of this market. Individual angels also operate differently compared to angel investment groups, which are institutions formed by groups of angel investors who work as a group instead of as solo investors ([Paul and](#)

Whittam, 2010). Our study complements some recent survey evidence on the angels market (e.g., Huang, Wu, Lee, and Bao, 2017; Denes, Howell, Mezzanotti, Wang, and Xu, 2020), although these studies acknowledge that they over-sample investors in angel investment groups and under-sample individual angel investors. Moreover, these papers do not address the question of how individual angel investors build their co-investment networks over time, which is the key focus of our study.

Our main contribution to the literature on financial networks is to highlight how individual angel investors leverage early success to improve the quantity, quality and geographic scope of their co-investment networks. We believe that the angel investment market is the ideal setting in which to study growth of co-investment networks and reputation effects. The vast majority of angels are individual investors who are not endowed with many network connections to begin with, which enables us to observe how they grow their co-investment networks over time and how performance affects the growth in networks.

By contrast, most of the literature on financial networks focuses on institutional investors, takes their network connectedness as given, and examines the effect of network connectedness on future performance. Most of the literature on investor reputation also focuses on institutional investors, and usually examines whether their reputation is damaged by poor performance. Such studies have been conducted in a variety of financial markets, such as loan syndication (Gopalan, Nanda, and Yerramilli, 2011) and venture capital (Atanasov, Ivanov, and Litvak, 2012; Tian, Udell, and Yu, 2015). We focus on the reputation gain to individual angel investors who demonstrate successful seed-stage performance, because failure is common and success is rare at the seed stage.

# 1 Theoretical and Institutional Background

## 1.1 The Angel Investment Market

Angel investments refer to investments in startup companies by wealthy individuals, some of whom are former entrepreneurs themselves. The vast majority of angels operate as individual investors, while a few are organized into institutional angel groups. Unlike VC funds, which mainly focus on funding later-stage startup firms, angels play a crucial role in the financing of early-stage startups (Kerr, Lerner, and Schoar, 2014; Hellmann and Thiele, 2015). In entrepreneurial finance, startups are generally classified into the following life-cycle stages: pre-seed, seed, series A, series B, series C, series D, and finally, exit via acquisition, IPO or failure (please see the Internet Appendix for the generally accepted definitions of these stage classifications in the industry). The academic literature (e.g., see Gompers, 1995) sometimes refers to seed and series A as “early stage,” series B as “expansion stage,” and series C and D as “late stage.” The vast majority of companies funded by angels tend to be at the seed stage or at the series A stage. It is relatively uncommon for angel-financed startups to undertake IPOs or to be acquired by other companies.

The angels market has flourished over the past decade, especially after the introduction of online fund-raising platforms such as AngelList ([www.angel.co](http://www.angel.co)). As per the 2014 report of the Angels Research Institute, US angels funded deals worth around \$24.8 billion whereas the corresponding figure for US VCs is estimated to be around \$29.6 billion. Despite their obvious importance, angel investors have received very little attention in the entrepreneurial finance literature, largely due to unavailability of structured data. In particular, although there is a large literature on syndication in the VC market (e.g., see Lerner, 1994; Sorenson and Stuart, 2001; Brander, Amit, and Antweiler, 2002; Tian, 2012; Bayar, Chemmanur, and Tian, 2020) and some work on angel groups (Paul and Whittam, 2010), we know little about the co-investment behavior of individual angel investors.



## 1.2 The Reputation Hypothesis

Despite the general perception of angels as passive investors (in contrast to VCs), both anecdotal evidence and recent empirical evidence (Kerr, Lerner, and Schoar, 2014) suggest that angel investors play a crucial role in the success of their portfolio companies in a variety of ways. This includes screening and due diligence, convincing other investors to invest in the portfolio companies, and directly adding value to the portfolio companies.

Given the high likelihood of failure among seed-stage startups (see Section 3), we hypothesize that an angel investor that successfully leads a seed-stage portfolio firm to the series A stage is likely to gain the attention of other investors and entrepreneurs, who will favorably update their beliefs about the angel’s ability to nurture startups (“reputation”). Hence, seed-stage success *should lead to* an increase in both the quantity and quality of the angel’s co-investment connections relative to his unsuccessful peers. Seed-stage success should also lead to more deal volumes and more lead opportunities for the angel investor because entrepreneurs like to secure funding from investors who they believe can add value to their firms (Hsu, 2004). It is also possible that seed-stage success boosts the angel’s confidence in his own abilities, and causes him to invest more of his personal wealth in startups. Moreover, the improvement in the angel’s network connectedness should also increase the likelihood that his other portfolio companies obtain more follow-on financing, especially from VC funds. We refer to this as the *reputation hypothesis*.<sup>4</sup>

Theoretical models of reputation predict that the gain in an agent’s reputation from good performance should be stronger for less-established agents, and when the good performance is

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<sup>4</sup>Anecdotal evidence suggests that angel investors prominently advertise their past successes to other investors and entrepreneurs through their profile pages on LinkedIn, AngelList, and CrunchBase. For example, Matt Johnson is an angel investor in San Francisco, and his profile pages on LinkedIn (<https://www.linkedin.com/in/matt-johnson-994267/>), AngelList (<https://angel.co/p/dukeblue>), and CrunchBase (<https://www.crunchbase.com/person/matt-johnson-16>) provide details about the stage and status of his past investments, as well as testimonials from founders of startups in which he has invested. A quick search on LinkedIn produces several such examples. Moreover, there are many articles that advise entrepreneurs on how to approach investors for fund-raising (e.g., see <https://www.forbes.com/sites/alejandrocramades/2018/09/02/7-ways-for-entrepreneurs-to-find-investors-and-raise-millions/>), and a common advice is to evaluate potential investors on platforms such as AngelList, CrunchBase, and LinkedIn.

more reflective of the agent’s ability and skill (see [Holmström, 1999](#)). Hence, we hypothesize that the positive effect of seed success will be stronger for angel investors with low existing network capital compared to those with high existing network capital, because angels in the former category are less established in the entrepreneurial finance market. Moreover, although ability and skill are not directly observable, we conjecture that seed successes that are less likely ex ante (based on founder characteristics and industry characteristics of the startup) should be more reflective of the angel’s ability and skill than seed successes that are more likely ex ante even without the angel’s involvement; we hypothesize that the effect of seed success will be stronger in the former category.

## 2 Data, Sample Collection, and Key Variables

### 2.1 Data Sources

Our analysis requires time-series information for a large sample of individual angel investors and the startups they invest in so that we can examine the evolution of their co-investment networks over time. Unfortunately, information on individual angel investors or early-stage startups funded by them is not readily available from commercial databases, because this market is largely unorganized and fragmented by geography and industry.

We overcome this problem by collecting data from CrunchBase ([www.crunchbase.com](http://www.crunchbase.com)), which is the largest crowd-sourced database on startups and investors, and AngelList ([angel.co](http://angel.co)), which is the leading on-line fund-raising platform for startups.<sup>5</sup> We discuss the coverage and limitations of these data sources in Section 2.2.

*CrunchBase*: CrunchBase is a graph database organized around several collection endpoints. We use the “People” endpoint to extract detailed information on individual an-

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<sup>5</sup>We access the data on CrunchBase and AngelList via their Application Programming Interfaces (APIs), which allows us to send requests for data on each investor and startup using a unique identifier. The output of requests is a JSON (JavaScript Object Notation) file that contains tags for data items such as name, location, role, jobs, etc., that are parsed using a Perl script to form data tables.

gel investors, and the “Organization” endpoint to extract detailed profiles of startups. For investors with complete profile pages, we are able to obtain data on personal information, education, employment history and investment history. A representative snapshot of the information available for Alexis Ohanian, who is the co-founder of Reddit and was the most active angel investor in 2014 (in terms of number of investments made), is available at <https://www.crunchbase.com/person/alexis-ohanian#section-overview>. Similarly, for startups with complete profile pages, we are able to extract data on the company’s founding date, website domain address, location, fund-raising dates, stage information on fund-raising rounds, amount of funds raised, status of the company, identity of investors who participated in various financing rounds, founding team and board members. A representative snapshot of the information available for Uber is available at <https://www.crunchbase.com/organization/uber>.

*AngelList:* AngelList is an online fund-raising platform where angel investors need to create profiles and undergo verification before they are allowed to invest in startups. Similar to CrunchBase, AngelList also provides biographical details and investment histories for investors, and information on fund-raising activities of startups. As of November 2017, the raw data from AngelList had information on 57,000 funding rounds and 38,000 investors.

After matching startup profiles listed in CrunchBase and AngelList based on their names and website domain address, we find an overlap of around 75% between the two datasets. In general, CrunchBase has better coverage on fund-raising dates and amounts raised by startups, whereas AngelList provides more details on the investors who participated in each round and the founding teams of startups. It is important to emphasize that although we have information on the total amount raised by a startup in a given financing round, we do not have the break-up of amounts invested by each investor in rounds financed by multiple investors.

After eliminating duplicates, the combination of CrunchBase and AngelList yields a sample of 56,749 North American startups for which we have information on fund-raising

dates, the identities of investors that participated in each fund-raising round, and information on the stage of the funding round (i.e., seed, series A, etc., which we need to evaluate the progress of startups and the performance of angels).<sup>6</sup> We use LinkedIn and S&P Capital IQ to verify and add missing profile information for investors and entrepreneurs. Overall, we believe that the combination of these data sets allows us to capture investment activity of a large and heterogeneous group of individual angel investors.

## 2.2 Data Coverage and Limitations

Although CrunchBase and AngelList are increasingly being used in the academic literature, there could be several concerns regarding the coverage and quality of these data sources. We note that these concerns apply more generally to all data sources used in entrepreneurial finance, including well-known databases in VC research (see [Kaplan and Lerner, 2017](#)). Compared to the VC market, the individual angel investor market is largely unorganized and fragmented by geography and industry, which makes it near impossible to assemble a comprehensive database of this market. Survey evidence is heavily weighted toward angel investment groups who are more likely to respond to surveys (e.g., see [Denes, Howell, Mezzanotti, Wang, and Xu, 2020](#); [Huang, Wu, Lee, and Bao, 2017](#)), but does not provide adequate coverage of individual angel investors who are the focus of our study.

CrunchBase provides broader coverage than existing databases because it collects data through multiple channels: crowd-sourcing from more than 80,000 contributors ([Freytag, 2014](#)); partnerships with more than 3,600 VCs, accelerators and incubators ([Crunchbase, 2018](#)); and by capturing information from Form-D filings, news articles, and industry announcements.<sup>7</sup> The data are authenticated manually and algorithmically ([Crunchbase,](#)

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<sup>6</sup>For around 1000 startups (mostly larger and later-stage startups), we are able to obtain information on the stage of the funding round from the Form D filings made by startups to the Securities and Exchanges Commission (SEC), which are available for download from SEC's FTP servers from the year 2008 onward. We also perform additional quality checks on our data by reading fund-raising announcements on news websites, such as [techcrunch.com](#) and [venturebeat.com](#), for a random sample of startups.

<sup>7</sup>As of November 2017, the raw CrunchBase data had information on 220,800 funding rounds, 551,300 individuals (including 47,400 investors), and 480,000 companies.

2017). This mitigates concerns relating to sample selection bias or coverage, and differentiates CrunchBase from commercially available databases—such as Refinitiv (SDC VentureXpert), Burgiss and PitchBook—which collect data from a smaller sample of limited/general VC fund partners. To mitigate concerns that successful investments are more likely to be back-filled than failed investments, we base our analysis only on startup performance after 2005, which is the year in which CrunchBase’s parent company, TechCrunch, was founded.

CrunchBase’s coverage is obviously tilted towards startups in technology-oriented industries and the investors who fund them, but this is an important sliver of the market for which CrunchBase provides more comprehensive coverage compared to other data sources.<sup>8</sup> It is also worth emphasizing that we do not rely on CrunchBase alone, and instead combine it with AngelList, which had more than 38,000 investor profiles as of 2017 (plus some other sources, such as Form D, LinkedIn, and S&P Capital IQ). We believe that the combination of CrunchBase and AngelList allows us to capture the investment activity of a large and heterogeneous group of individual angel investors. As we show in Section 3, there is substantial variation in terms of network size for angels in our sample, and the median investor is not endowed with a large network.

A few other limitations of our data are worth emphasizing. First, given the unorganized and fragmented nature of the angel investment market, we do not observe co-investment connections or social connections outside of CrunchBase and AngelList. Second, while we observe the total funds raised by a startup in a given financing round and the identity of all investors that participated in the round, we do not observe the amounts invested by each individual investor in a co-invested round. Third, we do not observe the valuations at which startups raise funds; hence, our success measure is based only successful transition from the seed to series A stage.

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<sup>8</sup>Block and Sandner (2009) and Wu (2017) compare CrunchBase with hand-collected data on startup creation in technology-oriented industries, and find that it captures more than 90% of startups. Moreover, Motoyama (2016), Dalle, den Besten, and Menon (2017), Raina (2019) and Jagannathan, Ouyang, and Yu (2020) compared CrunchBase data with traditional data sets—such as OECD Entrepreneurship Financing database, VentureXpert and PwC MoneyTree—and found that CrunchBase provides better coverage starting in mid- to late-2000s, which is the start of our sample period.

## 2.3 Mapping Co-Investor Networks

We define a co-investment connection as being formed between two investors when they invest together for the first time in the same funding round of a startup.<sup>9</sup> We use this definition along with our universe of startups and investors to map the co-investment networks each year. At any given point, the co-investment network reflects all the past interactions between investors since they first appear in our data, which in some cases, goes as far back as 1998. Please refer to the Internet Appendix for a more detailed and technical description of co-investment networks, and the methodology used to compute the network centrality measures.

We borrow two measures from graph theory – *Degree Centrality* and *Eigenvector Centrality* – to gauge the importance of investors in the co-investment network (see [Jackson, 2010](#), Chapter 2). Intuitively, both these measures can be seen as proxies for the pool of capital and expertise that an investor has access to. *Degree Centrality* is simply the number of connections an investor has with other investors as of year ‘t’. On the other hand, *Eigenvector Centrality* also measures the quality of connections an investor has in the network. It is a relative measure that is calculated using a recursive procedure where each investor’s centrality is the sum of ties to others weighted by their respective degree centrality. To facilitate comparisons in the quality of connections across years, we sort angel investors into deciles each year based on their *Eigenvector Centrality*.

## 2.4 Sample for our Analysis

Given our focus on individual angel investors, we exclude startups that are exclusively funded by institutional investors, such as angel groups and VC firms; there are 28,501 such startups. After this restriction, we have a sample of 28,248 startups funded by 12,147 individual investors and 7,453 institutional investors.

We restrict our analysis to time period from 2005 to 2014 because the coverage of Crunch-

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<sup>9</sup>A less stricter definition of a co-investment connection could include having invested in the same startup even if it is not in the same funding round (e.g., see [Hochberg, Ljungqvist, and Lu, 2007](#)). Using the less stricter definition does not change our qualitative results.

Base and AngelList is sparse in earlier years, and there may be concerns about back-filling bias in data from the 1990s. Within this time frame, we are mainly interested in angel investors who stay in the market to build a network and fund multiple companies rather than make a one-off investment in a startup founded by a family member or friend. Therefore, we restrict attention to individual angel investors who have invested in at least 3 different startups as of December 2014.<sup>10</sup> After this restriction, our final sample contains 4,108 individual angels who invested in 12,215 portfolio firms, alongside 1,797 institutional investors. For all these angels, we have network centrality measures from the first year they entered our sample. We use these 4,108 individual angels to create an investor-year panel that has one observation for each investor-year combination during the period 2005 to 2014. We identify the industry for the startups in our sample by manually matching the product market tags or descriptions in CrunchBase and AngelList to broad industry categories in SDC VentureXpert.

## 2.5 Key Variables

**Co-investment:** All the co-investment variables are defined at the financing round level. *Co-investment* is a dummy variable to identify financing rounds that are funded by more than one investor; hence,  $Co - investment = 0$  identifies financing rounds funded by a single investor. *No. of Investors* is simply a count of the number of investors funding that particular round.

For the sub-sample of financing rounds that are funded by more than one investor, we define measures of “closeness” among co-investors in terms of their past professional connections (based on having worked for the same employer together), past educational connections (based on having attended the same college together), and geographic closeness (based on being located in the same state). Specifically, we examine all co-investor pairs in a given financing round, and define *Professional Closeness* as the percentage of co-investor pairs

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<sup>10</sup>We show in Section 6.3 that our results are robust to this exclusion.

that share a past professional connection. We define *Educational Closeness* and *Geographic Closeness* along the same lines.

**Seed-Stage Success:** We define the dummy variable *Seed Success* for each angel-year combination to identify whether the angel led a seed-stage portfolio firm to series A stage during the year. There are a total of 2,913 startups in our sample that progressed from the seed to series A stage. Out of these, 2,444 startups (or 83.90%) obtained their seed-stage funding from a single angel investor, whereas the remaining 469 startups (or 16.10%) obtained their seed-stage funding from multiple investors. In the main body of the paper we define *Seed Success* using only the former subgroup of startups whose seed-stage rounds were financed by a single investor; we exclude the latter subgroup because it is not clear which among the multiple seed-stage investors should get the credit for the startup’s success. However, we show in the Internet Appendix that all our results hold if we also include these multi-investor seed-stage rounds in the analysis and attribute seed-stage success to all the co-investors when the startup successfully transitions to the series A stage.

As noted above, we focus on seed-stage success because investments by angel investors, especially solo investments, are more concentrated at the seed stage, and the failure rate at seed stage is much higher than at subsequent stages. Hence, we believe that *Seed Success* is likely to be the most informative about the angel’s ability. Nonetheless, we show in the Internet Appendix that our qualitative results also hold for the following alternative success measures: *Other Stage Success*, which is a dummy variable that identifies if any non-seed-stage portfolio firm successfully progressed to the next financing stage during the year; and *Successful Exit*, which is a dummy variable that identifies if any portfolio firm underwent an IPO or was acquired during the year.

**Growth in Network Connectedness:** We use the following variables to measure the growth in network connectedness of angel ‘i’ in year ‘t’: *New Connections<sub>i,t</sub>* is number of new co-investment connections the angel investor forms in year ‘t’, *excluding* the new co-investment connections that arise from any existing portfolio firm that progressed from seed



stage to series A stage during the year;  $\Delta(\textit{Eigenvector Centrality Decile})_{i,t}$  is the change in the angel’s *Eigenvector Centrality Decile* from year ‘t-1’ to ‘t’, and measures the improvement in the quality of the angel’s network connections over the previous year; and *New Investments* $_{i,t}$  is the number of new startups in which the angel has invested for the first time in year ‘t’ either as the lead investor or as a participant.

### 3 Descriptive Statistics and Preliminary Results

#### 3.1 Descriptive Statistics

**Break-up of Data by Time, Industry, and Geography:** We provide a year-wise summary of our sample in Panel A of Table 1, where each row shows the number of startups that raised funds, number of funding rounds along with a stage-wise breakdown, number of startups that exited via acquisition or IPO, total funds raised by these startups from both individual angel investors and other institutional investors, and the number of individual angels involved in these funding rounds (“Angels”). Consistent with the idea that angels fund very early-stage startups, we can see that more than 50% of the total rounds funded during the 2005–2014 period are seed-stage rounds, and that exits through acquisition or IPO are relatively uncommon. The increase in all the numbers over the 2005–2014 period is consistent with the overall growth of the angels market during this time. In Panel B, we provide a breakdown of our data for the top 10 industries. Similarly, we provide a state-wise breakdown for the top 10 states in Panel C.

We provide round-level average values of our key variables in Table 2. The first column in each row lists the average value of that variable across all the financing rounds, whereas the second through fifth columns provide the averages for each funding stage. As expected, the average value of *Funds Raised* increases monotonically as we move from seed rounds to series D rounds. Recall that we only have information on the total amount raised by a startup in a given financing round, but do not have the break-up of amounts invested by each investor

in rounds financed by multiple investors. Of course, in case of financing rounds funded by a single investor (i.e., rounds with  $Co - investment = 0$ ) which constitute 68% of our sample, the size of the investment round is the same as the amount invested by the single investor. For seed-stage rounds funded by a single investor, the average investment size is \$0.281M.

The statistics on *%Individual Angel* and *%VC* indicate that early-stage startups are more likely to be funded by angels whereas later-stage startups are more likely to be financed by VCs, as predicted by [Chemmanur and Chen \(2014\)](#) and [Hellmann and Thiele \(2015\)](#). Examining co-investment characteristics, we find that 32% of all rounds are funded by multiple investors, including 20.5% of seed-stage rounds. Both the likelihood of co-investment and the number of co-investors increase monotonically as we go across the columns from seed to series D stage. Moreover, co-investors become closer in terms of professional connections but more dispersed in terms of educational and geographic connections as we go across the columns from seed to series D stage.

**Startup Survival and Transition Probabilities:** According to the 2014 annual report of the Angel Capital Association, most startups fail within first three years of operation. In panel A of table 3, we report the unconditional probabilities of a startup surviving till each funding stage. Out of the 12,215 startups in our sample, only 23.85% reached Series A, and less than 10% progressed to series B and further in their life cycle. This suggests that the performance measures we employ are fairly stringent.<sup>11</sup>

In Panel B of table 3, we report the average transition probabilities between the various sequential stages at different time horizons. This panel highlights that the transition from seed stage to series A stage is the toughest transition, with only around 24% of startups successfully making this transition. Moreover, most of the startups that make this transition successfully do so within 3 years: 15.1% make the successful transition within a year, 20.48% within 2 years, and 22.47% within 3 years. It is also clear from Panel B that the odds of a

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<sup>11</sup>Note that 2.7% of startups in our sample exited via an acquisition or IPO which is greater than number of firms that reached series D. This is because some of the firms got acquired at earlier stages in their life cycle.

startup succeeding improve significantly if it makes it to the series A stage. As can be seen, 44.6% of startups at series A successfully transition to series B, 47.5% of startups at series B successfully transition to series C, and so on. Of course, despite the improvement in success probabilities, more than half the startups fail at each stage.

**The Angel-Year Panel:** Table 4 provides summary statistics of key variables in our investor-year panel over the years 2005 to 2014. The unbalanced panel consists of one observation for each angel-year combination. As can be seen, there is substantial cross-sectional variation among angels in terms of the number of startups and rounds they invest in each year, as well as the quantity and quality of their co-investment connections, as proxied by *Degree Centrality* and *Eigenvector Centrality*, respectively.

The mean value of the *Seed Success* dummy is 0.096, which indicates that, on average, only 9.6% of angels successfully transition at least one of their seed-stage portfolio firms to the series-A stage during the year. Similarly, the statistics on *Other Stage Success* and *Successful Exit* indicate that, on average, only 5.8% of angels successfully transition at least one non-seed-stage firm in their portfolio to the next financing stage during the year, and only 1.9% of angels successfully exit a portfolio firm through an IPO or M&A during the year.

## 4 Co-investment in the Angel Investment Market

We estimate variants of the following regression at the level of the individual financing round to examine how co-investment varies with startup characteristics and investor characteristics:

$$y_{rt} = \alpha + \beta X_s + \gamma X_i + \mu_{mkt} + \mu_{state} + \mu_t + \epsilon_r \quad (1)$$

The dependent variable  $y$  in equation (1) is either the indicator variable for co-investment or a continuous variable that captures characteristics of co-investment structure; subscript

‘r’ denotes the financing round; subscript ‘s’ denotes the startup, subscript ‘i’ denotes the angel investor, subscript ‘mkt’ denotes the industry, and subscript ‘t’ denotes the year. Apart from startup characteristics ( $X_s$ ) and angel investor characteristics ( $X_i$ ), we also include industry fixed effects ( $\mu_{mkt}$ ) and state fixed effects ( $\mu_{state}$ ) to control for time-invariant industry characteristics and geographic location characteristics, and year fixed effects ( $\mu_t$ ) to control for time trends that affect the likelihood of co-investment and co-investment structure. The results of our estimation are presented in Table 5.

The dependent variable in columns (1) and (2) is *Co-investment*, which is a dummy variable that identifies if there are multiple investors financing the round. The specification in column (1) only includes startup characteristics. Not surprisingly, the likelihood of co-investment increases with the size of the financing round. Co-investment is more likely in older startups and in startups founded by serial entrepreneurs. The coefficients on the stage dummies, *Series A* through *Series D*, capture the likelihood of co-investment in each stage relative to the seed stage, which is the omitted category. These coefficients indicate that the propensity of co-investment increases monotonically from the seed stage through the Series D stage even after controlling for the startup’s age and size of the funding round. Given that the level of information asymmetry reduces as the startup progresses from the seed stage to later stages, these findings are consistent with the idea that co-investment is more likely when informational problems are less severe.

The specification in column (2) also controls for key investor characteristics. Co-investment is more likely when the startup is financed by well-connected investors (positive coefficient on  $\ln(\text{Degree Centrality})$ ). Agency conflicts and information asymmetry between the investors and the startup are likely to be less severe when the startup’s founder and investors share a past professional or educational connection and when the investors are located in the same geographic location as the startup. We find that co-investment is more likely when either of these conditions is met (positive coefficients on *Connected Founder-Investor* and *Same Location Investor*), which lends further support to the idea that co-investment is more likely

when agency conflicts and informational problems are less severe.

In columns (3) and (4), we estimate regression (1) with  $\ln(\text{No. of Investors})$  as the dependent variable. As can be seen, the general thrust of the results in columns (3) and (4) is very similar to those in columns (1) and (2). All else equal, the number of co-investors is higher for startups in later stages, when the startup’s founder and investors share a past professional or educational connection, and when the investors are located in the same geographic location as the startup.

In the remaining columns, we focus on the sub-sample of financing rounds that are funded by more than one investor (i.e., for which  $\text{Co-investment} = 1$ ) and examine how the “closeness” among co-investors varies with startup and investor characteristics. The dependent variable is *Professional Closeness* in columns (5) and (6), *Educational Closeness* in columns (7) and (8), and *Geographic Closeness* in columns (9) and (10). Examining the coefficients on the stage dummies across these columns reveals a very interesting pattern: all else equal, startups in later stages are financed by co-investors that are *much closer* in terms of professional connections, and this effect intensifies as startups progress to later stages (positive coefficients of increasing magnitude on *Series A* through *Series D* in columns (5) and (6)); but at the same time, the co-investors are *more dispersed* in terms of educational connections and geographic similarity (negative coefficients on *Series A* through *Series D* in columns (7) through (10)). These disparate patterns may reflect the importance of industry specialization in the entrepreneurial finance market, which can explain why co-investors in later stages are more likely to share professional connections. At the same time, geographic ties and educational ties becomes less important as the startup progresses to later stages and informational problems become less severe.

## 5 Effect of Performance on Network Connectedness

Having established that co-investment is widely used in the angel investor market, we now examine how individual angel investors build their co-investment connections over time. Recall that our main hypothesis is that seed-stage success by an angel leads to an increase in his network connectedness— both in terms of the number and quality of connections— and increased deal flow relative to his unsuccessful peers.

### 5.1 Empirical Methodology

While it is difficult to empirically isolate the causal effect of seed success on growth in network capital, we use the following approach to test the reputation hypothesis and rule out alternative explanations: First, we use propensity score matching to match each successful angel (“treated” group) with at least three unsuccessful angels (“control group”) during the same year and in the same state who are very similar in terms of observable characteristics that predict seed success, such as no. of rounds invested, years of experience, entrepreneurship experience and degree centrality.<sup>12</sup> We use a caliper of 0.1 for the propensity score match.

Table 6 provides a univariate comparison of key characteristics of the angels in the treated and control groups in their respective year of seed-stage success. As can be seen, the two groups are very similar in terms of no. of rounds and startups invested, entrepreneurship experience and network centrality. The only exception being that angels that experience seed-stage success (i.e., treated group) actually have less average experience (0.23 years) in angel investing than their unsuccessful peers. Next, we estimate two difference-in-differences regression specifications on a sample that only includes the successful angels and the corresponding control group of unsuccessful angels.

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<sup>12</sup>Seed success is relatively rare, which means that there are significantly more unsuccessful angels than successful angels. Therefore, we match each successful angel in the year of seed success with at least three unsuccessful angels so that we get a better average match and do not lose lot of valuable information.

The first specification is the [Bertrand, Duflo, and Mullainathan \(2004\)](#) estimator. Specifically, for each successful angel and its corresponding control group of angels, we condense all the pre-success observations into a single observation and all the post-success observations into a single observation by averaging all the variables. We then estimate the following regression on the condensed panel:

$$y_i = \alpha + \beta \times SeedSuccess + \psi \times Post + \gamma \times Post \times SeedSuccess + \mu_i \quad (2)$$

In equation (2),  $y_i$  is a measure of improvement in network connectedness for angel ‘i’ (see [Section 2.5](#)), and  $Post$  is a dummy variable that identifies the post-success observations for the successful angel and its control group of angels. The key coefficient of interest is  $\gamma$  which captures the change in  $y$  after seed-stage success for the successful group of angels relative to the control group of angels. The reputation hypothesis predicts that  $\gamma > 0$ .

The second specification verifies that the *parallel trends* assumption holds in our setting. We create three dummy variables indexed  $Post_\tau$  for  $\tau \in \{1, 2, 3\}$  to indicate the year  $\tau$  after the success year, and three dummy variables indexed  $Pre_\tau$  for  $\tau \in \{-3, -2, -1\}$  to indicate the year  $\tau$  before the success year. Let  $PostSuccess_\tau$  and  $PreSuccess_\tau$  denote the interaction of *Seed Success* with  $Post_\tau$ , and  $Pre_\tau$ , respectively. Then, we estimate the following difference-in-differences regression on a panel that includes all the successful angels and their corresponding control group of unsuccessful angels.

$$y_{i,t} = \alpha + \sum_{\tau=-3}^{\tau=-1} \beta_\tau \times PreSuccess_\tau + \sum_{\tau=1}^{\tau=3} \gamma_\tau \times PostSuccess_\tau + \delta \times Seed\ Success + \sum_{\tau=-3}^{\tau=-1} \zeta_\tau \times Pre_\tau + \sum_{\tau=1}^{\tau=3} \eta_\tau \times Post_\tau + \mu_i + \mu_t + \epsilon_{i,t} \quad (3)$$

Apart from controlling for observable determinants of success using our matching procedure, we also include angel fixed effects ( $\mu_i$ ) to control for all time-invariant angel characteristics

(e.g., inherent skill) and year fixed effects ( $\mu_t$ ) to control for market-wide factors.<sup>13</sup> The inclusion of year fixed effects and the fact that the control group of unsuccessful angels is similar to the successful angel at the time of its success ensures that our results cannot be driven by macroeconomic time trends, such as boom and bust cycles in the entrepreneurial finance market.<sup>14</sup> The standard errors are robust to heteroskedasticity and are clustered at the angel investor level.

The key coefficient of interest is  $\gamma_\tau$ , which denotes the change in  $y$  for the successful angel between the year it experiences success and in year  $\tau$  after the success event, after adjusting for any changes experienced by its control group of unsuccessful angels. As per the reputation hypothesis, the successful angels must experience significantly higher improvement in network capital compared to their unsuccessful peers in the years after they experience success (i.e.,  $\gamma_\tau \geq 0$  for  $\tau \in \{1, 2, 3\}$  with at least one of the inequalities being strict), but there should be no discernible difference in the years prior to success (i.e.,  $\beta_\tau = 0$  for  $\tau \in \{-3, -2, -1\}$ ). While the findings that  $\gamma_\tau \geq 0$  and  $\beta_\tau = 0$  may not fully rule out the alternative explanations based on time-varying omitted characteristics, they do provide some comfort that these omitted characteristics did not generate significant differences between the successful angels and their control group in the years leading up to success. Nonetheless, we conduct a variety of alternative specifications to test for the robustness of our results, which are described in Section 6.3.

As per the reputation hypothesis, the effect of successful performance should be stronger for angels with less-established angels with low existing network capital because of greater uncertainty regarding their abilities. To test this, we divide our angels into two groups each year based on whether their degree centrality exceeds the sample median (“high network

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<sup>13</sup>We do not include angel characteristics in the above equation because our matching procedure adjusts for similarities in angel characteristics. In an unreported table we find that including angel characteristics as controls in equation (3) does not have any material effect on our results.

<sup>14</sup>For example, one concern could be that a large inflow of funds into the angel investor market leads to both successful performance of existing startups as well as increase in future deal flow for the angel investors. However, such a macro trend should affect both the successful angel and the control group of unsuccessful angels, and hence, cannot drive the  $\gamma_\tau$  coefficient because it captures the *difference* in the change in the  $y$ -variable between the two groups.



capital”) or not (“low network capital”). We then estimate the regressions separately for the low-network-capital group and the high-network-capital group, and test whether the effects of success are statistically different across the two groups.<sup>15</sup>

The reputation hypothesis also predicts that the positive effect of seed success should be stronger for seed success that are less likely *ex ante* versus those that more likely *ex ante* even without the angel’s involvement, because less likely successes should be more reflective of the angel’s ability and skill at nurturing early-stage startups. Accordingly, we use founder characteristics and industry characteristics to classify seed successes into two groups as follows: we classify a seed-stage success as “more likely” if the startup’s founder is a serial entrepreneur or if startup is in a “hot market” *before* the angel’s investment (i.e., in a industry and state where lots of seed-stage startups have progressed to the series A stage in year before the angel invested in it); and “less likely” otherwise.<sup>16</sup> We then estimate the regressions separately for the less expected and more expected groups, and test whether the effects of success are statistically different across the two groups.

## 5.2 Effect on Quantity and Quality of Connections

We begin by examining the effect of seed success on the *quantity* and *quality* of new co-investment connections formed by the angel investor. The results of our analysis are presented in Table 7.

The dependent variable in Panel A is  $\ln(1+New\ Connections)$ , which proxies for the quantity of new connections. Recall that our definition of *New Connections* excludes new co-investment connections directly on account of the portfolio firm that progressed to the series A stage during the year. We estimate regression (2) in column (1) and regression (3)

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<sup>15</sup>A related concern could be that angel investors who are former entrepreneurs or VC fund partners may have pre-existing connections in the entrepreneurial financing market even before making an angel investment, and do not need the reputation boost from seed-stage success. As a robustness check, we exclude such investors from our sample and show that our results are qualitatively similar (see Table IA.7 in the Internet Appendix).

<sup>16</sup>We show in Table IA.1 in the internet appendix that seed-stage startups founded by serial entrepreneurs and those in “hot markets” are more likely to progress to series A stage.

in column (2) on the full sample of all successful angels and their corresponding group of unsuccessful angels; in column (2), we suppress the coefficients on the  $Post_\tau$  and  $Pre_\tau$  dummies to conserve space. The results are broadly consistent with the reputation hypothesis. In particular, the results in column (2) indicate that angels that successfully transition a seed-stage portfolio company to the series A stage are more likely to form new co-investment connections compared to their peer group of unsuccessful angels in each of the three years following the success (positive and significant coefficients on  $PostSuccess_\tau$  for  $\tau \in \{1, 2, 3\}$ ), although there are no significant differences between the two groups in the three years prior to the success (insignificant coefficient on  $PreSuccess_\tau$  for  $\tau \in \{-3, -2, -1\}$ ). The effects are also economically significant: the coefficient estimates in column (2) indicate that an angel investor that successfully transitions one of his seed-stage portfolio firms to the series-A stage is rewarded with a total of 9.7 more new co-investment connections compared to his unsuccessful peers over the next three years.

In columns (3) and (4), we estimate regression (3) separately for the low-network-capital angels and the high-network-capital angels, respectively. The last row in the table reports the  $p$ -value of the  $\chi^2$ -test to reject the null hypothesis that the effects are not statistically different across the two subgroups. Consistent with the reputation hypothesis, we find that although the effect of successful performance is present among both the groups, the effects are significantly stronger among the subgroup of angels with low existing network capital. The  $p$ -value listed in the last row of the table indicates that the sum of coefficients on the  $PostSuccess_\tau$  terms in column (3) is significantly different from the corresponding sum in column (4).

In columns (5) and (6), we estimate regression (3) separately for seed successes classified into two groups based on the ex-ante likelihood of success: the less-likely successes and the more-likely successes, respectively. As can be seen from the  $p$ -value listed in the last row, the coefficients on the  $PostSuccess_\tau$  for  $\tau \in \{1, 2, 3\}$  are larger in column (6) compared to column (5), which suggests that effects are stronger when the seed-stage success is less likely

ex ante.<sup>17</sup>

The dependent variable in Panel B is  $\Delta$ *Eigenvector Centrality Decile*, which is a proxy for the change in quality of the angel’s network connections. As in Panel A, we first estimate the regressions on the full sample in columns (1) and (2), and find that the quality of an angel’s network connections improve significantly in the years following seed-stage success compared to its peer group of unsuccessful angels, although there are no differences between the two groups prior to success. In terms of economic significance, the coefficient estimates in column (2) indicate that an angel investor that successfully leads one of his seed-stage portfolio companies to the series A stage improves his *Eigenvector Centrality Decile* by 0.24 compared to his unsuccessful peers over the next three years. This effect is significantly stronger for low-network-capital angels compared to high-network-capital angels (columns (3) vs. (4)), and for less-likely successes compared to more-likely successes (columns (5) vs. (6)).

The dependent variable in Panel C is  $\ln(1+New\ Outside\ Connections)$ , which is a measure of the expansion of the geographic scope of the angel’s network connections. The empirical specification and control variables in each column are identical to those in the corresponding columns in Panel A. We find that angels that experience seed-stage success are more likely to form new out-of-state network connections relative to their unsuccessful peers in the following years, although there are no differences between the two groups in the years preceding success (columns (1) and (2)). This effect is significantly stronger among angels with low existing network capital compared to those with high existing network capital (columns (3) vs. (4)), and for seed success that are less likely ex ante compared to those that are more likely ex ante (columns (5) vs. (6)).

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<sup>17</sup>In Table IA.8 in the internet appendix, we analyze the effect of seed success after splitting the number of new connections into (i) new co-investment connections from new portfolio companies and (ii) new co-investment connections from existing portfolio companies, excluding startups that successfully moved from seed to series A stage in the current year. We find that angels that successfully transition a seed-stage portfolio company to series A stage form more co-investment connections in the following three years both from new portfolio companies and from existing portfolio companies.

### 5.3 Effect on New Deal Flow

In this section we examine the effect of seed-stage success on the new deal flow that the angel gains access to. Accordingly, we define *New Investments* as the number of new startups in which the angel invests for the first time during the year, either as a solo investor or as a co-investor. Moreover, to investigate whether successful performance allows angels to broaden the geographic scope of their deal flow, we define *New Outside Investments* to denote the number of new out-of-state startups in which the angel invests for the first time during the year, either as a solo investor or as a co-investor. Similarly, to investigate whether successful performance allows angels to broaden the industry scope of their deal flow, we define *New Industry Investments* to denote the number of new-industry startups (i.e., startups in industries that the angel hasn't invested in the past) in which the angel invests for the first time during the year, either as a solo investor or as a co-investor. The results of our estimation are presented in Table 8.

The dependent variables are  $\ln(1+New\ Investments)$  in Panel A,  $\ln(1+New\ Outside\ Investments)$  in Panel B, and  $\ln(1+New\ Industry\ Investments)$  in Panel C. The results are very similar across all three panels. We find that angels who successfully lead a seed-stage portfolio company to series A stage are rewarded with more new investment opportunities (1.25 more new startup companies as per coefficient estimates in column (2) of Panel A), more new out-of-state investment opportunities (Panel B), and more investment opportunities in new industries (Panel C) relative to their unsuccessful peers in the following three years, although there are no differences between the two groups in the three years preceding success. In each panel, the effect is stronger among angels with low existing network capital compared to those with high existing network capital (columns (3) vs. (4)) and for less-likely successes compared to more-likely successes (columns (5) vs. (6)). These results show that seed-stage success allows angel investors to expand the quantity, geographic scope, and industry scope of their new deal flow.

## 5.4 Effect on Angels' Other Portfolio Companies

We have shown that successful performance by an angel investor allows to him attract not just more co-investors but also more influential co-investors in the following years. If so, it is logical to expect a knock-on effect on the performance of the successful angel's *other* portfolio companies (i.e., other than the company in which the angel experienced success). To test this, we define the following dummy variables to measure the success of other portfolio companies in the angels' portfolio: *Other Seed Success* is a dummy variable that identifies if the angel leads another seed-stage portfolio company to the series A stage; and *VC Financing* is a dummy that identifies if another portfolio company in which the angel is a lead investor receives venture capital financing. We then estimate regressions (2) and (3) with each of these variables separately as the dependent variable.<sup>18</sup> The results of our estimation are presented in Table 9.

The dependent variable in Panel A is *Other Seed Success*. We find that angels that deliver successful seed-stage performance are 41.9% more likely (as per coefficient estimates in column (2)) than their unsuccessful peers to lead their *other* seed-stage portfolio companies to series A stage in the following three years, but there are no differences between the two groups in the three years preceding the seed success. When we estimate the regressions separately for the low-network-capital group (column (3)) and the high-network-capital group (column (4)), we find that the effects are actually stronger among the latter group. This is partly because angels with high network capital are likely to have several more companies in their portfolio at the same time compared to angels with low network capital, which makes it more likely to detect a knock-on effect of success in the former group. In columns (5) and (6), we find that the effects are stronger for the less-likely successes compared to the more-likely successes.

The dependent variable in Panel B is *VC Financing*. We find that angels that deliver

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<sup>18</sup>Given that we have several indicator variables and investor fixed effects on the right-hand side of equation (3), we estimate a linear probability model instead of a Logit model to avoid the incidental parameter problem (see Neyman and Scott, 1948; Hausman, Hall, and Griliches, 1984).

successful performance are 41.6% more likely (as per coefficient estimates in column (2)) than their unsuccessful peers to obtain VC financing for their *other* portfolio companies in the following three years, but there are no differences between the two groups in the three years preceding success. Interestingly, this effect seems to be largely confined to the subsample of angels with high existing network capital (column (4)). This may be because VCs are more likely to invest in late-stage startups, and angels with high network capital are significantly more likely to have late-stage startups in their portfolio. Another interesting finding is that this effect is stronger for the more-likely successes (column (5)) compared to the less-likely successes (column (6)). This may be because well-established angels are more likely to invest in seed-stage startups with a higher ex-ante probability of success and are also more likely to obtain financing from VC funds.

## 6 Additional Tests and Robustness of Results

### 6.1 Effect of Success on Angels’ “Follower” Networks

An interesting feature of AngelList is that, just like other online communities, it allows investors to follow the activities of other investors without actually co-investing with them. We are able to obtain data on such follower networks for 733 individual angel investors over the time period August 2010 to February 2015. As per the reputation hypothesis, it is natural to expect that an angel that has delivered seed-stage success will not only attract more followers subsequently, but also that more of his followers will co-invest with him. We test this hypothesis using a framework very similar to regression (3); the only difference is that we use only a one year lead and a one year lag, instead of three each, because our follower network data spans a shorter time period. The results of our estimation are presented in Table 10.

The dependent variable in column (1) is  $\ln(1 + Followers_{i,t})$ , where  $Followers_{i,t}$  denotes the number of new investors that become followers of angel ‘i’ in year ‘t’. The positive and

significant coefficient on  $PostSuccess_{+1}$  and the insignificant coefficient on  $PreSuccess_{-1}$  indicate that successful angels attract more new followers than their unsuccessful peers in the next year, but the two groups are similar in the year before success.

To test if seed-stage success also affects the propensity of an angel’s followers to co-invest with him, we define the following dummy variables for all possible cross-products of investors ‘i’ and ‘j’ in each year ‘t’:  $Followed_{ij,t}$  identifies if investor ‘j’ is a follower of angel ‘i’ in year ‘t’; and  $Co-invested_{ij,t}$  identifies if ‘i’ and ‘j’ co-invested for the first time in year ‘t’. In column (2), we examine how the effect of  $Followed_{ij,t}$  on  $Co-invested_{ij,t}$  varies with seed-stage success, which we capture using the interaction terms of  $Followed_{ij,t}$  with the  $PreSuccess_{-1}$  and  $PostSuccess_{+1}$  indicators. The positive and significant coefficient on  $Followed_{ij,t} \times PostSuccess_{+1}$ , combined with the insignificant coefficient on  $Followed_{ij,t} \times PreSuccess_{-1}$ , indicates that successful performance by an angel makes it more likely that his followers begin co-investing with him next year.

## 6.2 Effect of Success on Angels’ Career Paths

It is possible that successful performance also enhances the future career prospects of angel investors, in terms of their ability to join angel groups, co-invest with angel groups, or get employed by venture capital firms. To test this prediction, we define the following dummy variables:  $Belongs\ to\ Angel\ Group_t$  to identify angels who belong to an angel group in year  $t$ ,  $Co-invest\ with\ Angel\ Group/VC_t$  to identify angels who co-invest with an angel group or VC firm for the first time in year  $t$ , and  $Employed\ by\ VC_t$  to identify angels who are employees of a VC firm in year  $t$ . We then estimate logit regressions on the angel-year panel data to investigate how an angel’s outcome in year  $t$  varies with the angel’s cumulative performance record with seed-stage startups till year  $t - 1$ .

Accordingly, the key independent variable of interest is  $Seed\ Success\ Ratio_{i,t-1}$ , which is defined as the number of seed successes the angel has experienced divided by total number of seed-stage investments made by the angel as of year ‘t-1’. We control for the following other

possible determinants of the angel’s propensity to belong to an angel group (or be employed by a VC firm): a dummy variable *Entrepreneur* to identify whether the angel founded a startup in the past; *Degree Centrality*; *Years of Experience*; and the total amount of funds raised by all of the angel’s portfolio companies. We also include year fixed effects in these regressions and report the marginal effects for each regressor in Table 11.

The positive and significant coefficients on *Seed Success Ratio* $_{i,t-1}$  in columns (1), (2) and (3) indicate that angels who have led a large fraction of their seed-stage portfolio firms to the series A stage are significantly more likely to join angel groups, co-invest with angel groups/VCs and be employed by VC firms, respectively. The coefficients on control variables in column (1) indicate that network connections, years of experience, and funds raised by portfolio companies have a positive effect on the propensity to join an angel group, but entrepreneurial experience does not matter. According to column (2), past entrepreneurial experience and network size increase the probability of an angel getting to co-invest with angel groups or VC firms. On the other hand, the coefficient estimates in column (3) indicate that entrepreneurial experience is crucial for being employed by a VC firm. We obtain qualitatively similar results if we include angel fixed effects in the specification, which will subsume the *Entrepreneur* dummy.

### 6.3 Robustness Tests

We conduct several additional robustness tests, which we report in the Internet Appendix to conserve space in the paper. We provide a brief description of these results in this section.

In Table IA.2 we replicate our main results with *Other Stage Success* (Panel A) and *Successful Exit* (Panel B) as alternative measures of success, and show that our qualitative results are unchanged.

To address the concern that our results are driven by macro trends in the angel investor market, we implement a falsification test by creating a variable called *PlaceboSuccess* as follows. For each angel that actually experiences a seed success, we randomly assign *Place-*



$boSuccess=1$  to one of the angels in its control group and assign  $PlaceboSuccess=0$  to the successful angel and all other angels in its control group. We then repeat our estimation with  $PlaceboSuccess$  instead of  $Seed Success$  as the treatment variable, the results of which are presented in Table IA.3. We find that the  $\gamma_\tau$  coefficients on the  $PostPlaceboSuccess_\tau$  terms are all insignificant, which shows that our results in Section 5.2 are capturing the causal effect of successful performance.

In Table IA.4 we estimate equation (3) using only the first  $Seed Success$  of every angel investor, and show that our results are mostly unchanged. In Table IA.5 we show that all our main results hold even if we expand the sample to include angel investors that have invested in less than 3 portfolio companies during the period 2005–2014.

Our propensity score matching methodology did not control for the past seed successes or exit performance of angels. This is because seed success and exit via IPO and M&A are rare for individual angels in our sample. Nonetheless, as a robustness check, we re-do our analysis after controlling the matching procedure for angels’ past seed successes, IPOs and M&A exits. Table IA.6 reports the results of these analyses, which are qualitatively similar to those in the paper.

## 7 Conclusion

We use unique hand-collected data to examine the co-investment behavior of individual angel investors, and to understand how individuals build their co-investment connections and improve their network connectedness. We show that co-investment is common among angel investors. Consistent with the idea that co-investment is more likely when informational problems are less severe, we find that the likelihood of co-investment and the number of co-investors increase monotonically from the seed stage through Series D stage, all else equal. Moreover, startups in later stages are financed by co-investors that are *much closer* in terms of professional connections, but are also *more dispersed* in terms of educational connections

and geographic similarity.

Angel investors that successfully transition one of their seed-stage portfolio companies to the series-A stage are rewarded with more new co-investment connections and see an improvement in the quality and geographic scope of their network connections compared to their unsuccessful peers in the following three years. Successful angels are also rewarded with more new investment opportunities, both as a lead investor and as a participant, in the following three years when compared to their unsuccessful peers. These results are particularly strong for small angels with low existing network capital, and for seed-stage success that are less expected *ex ante*, and hence, are more likely to be attributed to the angels' ability and skill.

Angels that deliver seed-stage success are also more likely than their unsuccessful peers to lead their other seed-stage portfolio companies to the series A stage and to obtain venture capital financing for their other portfolio companies over the next three years. In other words, success begets more success for the angel investor. Finally, seed-stage success also expands the online followership of angels, and makes it more likely that their existing followers establish a new co-investment connection. Overall, our results highlight that reputation for good performance enhances the network connectedness of angel investors.

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**Table 1** Distribution of Start-ups and Funding Rounds

This table presents summaries of the number of start-ups, funding rounds and individual angels in our sample. Panel A provides a year-wise summary. Panels B and C provide the distributions of startups in the top 10 industry categories and top 10 states respectively, sorted based on the funds raised. We manually match startups in our sample to industries in SDC VentureXpert based on the startup description in Crunchbase and Angellist. We only include individual angels that invested in at least three portfolio firms by December 2014. *Startups* and *Rounds* are the number of start-up firms and the number of funding rounds, respectively, that these individual angels invested in. *Rounds* are further classified into *Seed*, *Series A*, *Series B*, *Series C*, and *Series D* to identify the different financing stages in the life-cycle of the start-ups. *Acquired/IPO* is the number of start-ups that exited via IPO or acquisition. *Funds Raised* is the total amount (in billion dollars) raised by the start-ups in all the funding rounds combined, both from the individual angels in our sample as well as from other investors. *Angels* is the number of unique angel investors who participated in at least one funding round in the given year.

*Panel A: Year-wise Distribution*

Year	Startups	Rounds	Seed	Series A	Series B	Series C	Series D	Acquired /IPO	Funds Raised	Angels
2005	345	530	144	172	120	63	31	8	0.705	545
2006	517	796	234	249	171	94	48	9	1.076	702
2007	731	1124	345	359	224	128	68	14	1.599	843
2008	852	1311	429	368	276	143	95	16	1.781	971
2009	1256	1933	869	373	305	207	179	26	1.363	1002
2010	1698	2612	1179	564	348	269	252	35	1.849	1248
2011	2019	3106	1465	673	413	253	302	41	2.248	1555
2012	2841	4370	2506	787	437	276	364	57	2.178	1818
2013	3286	5055	3051	882	471	277	374	66	2.125	1929
2014	2866	4409	2583	777	443	265	341	58	2.847	1775
Total	12215	25246	12805	5204	3208	1975	2054	330	17.769	4018

*Panel B: Industry-wise Distribution*

Industry	Startups	Rounds	Funds Raised
Software	1014	2103	1.626
Social Media	839	1752	1.321
Advertising	682	1742	1.278
Biotechnology	29	47	1.215
Mobile	1202	2259	1.123
Media & Entertainment	770	1428	0.678
Analytics	404	808	0.649
Messaging & Telecommunications	530	1225	0.582
Health Care	395	927	0.530
Financial Services	302	733	0.530
Top 10 Total	6167	13024	9.531

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*Panel C: Geography-wise Distribution*

Location	Startups	Rounds	Funds Raised
California	3404	5578	5.017
New York	1617	3284	2.066
Massachusetts	902	1244	1.502
Texas	883	1102	1.155
Florida	544	1013	0.935
Washington	515	943	0.474
Illinois	499	769	0.366
Pennsylvania	456	683	0.275
Colorado	433	695	0.328
Georgia	408	557	0.510
Top 10 Total	9660	15868	12.627

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**Table 2** Round-Wise Summary of Co-investment Activity

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This table presents round-wise summary of startup characteristics and co-investment activity. All variables are defined in the appendix.

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	All Rounds	Seed	Series A	Series B	Series C	Series D
Startup Age	1.686	0.757	1.658	2.311	3.409	4.912
Serial Entrepreneur	0.075	0.086	0.075	0.056	0.047	0.040
Funds Raised	0.851	0.371	1.010	1.317	1.676	1.919
Connected Founder-Investor	0.228	0.253	0.215	0.233	0.190	0.128
Same Location Investor	0.225	0.375	0.134	0.042	0.015	0.007
Round with Co-investors	0.320	0.205	0.337	0.486	0.453	0.608
Funds Raised (Co-investment=0)	0.536	0.281	0.521	0.701	1.053	1.411
% Individual Angel	0.701	0.941	0.722	0.444	0.161	0.068
% VCs & Angel Groups	0.299	0.059	0.278	0.556	0.839	0.932
No. of Investors	1.568	1.213	1.592	1.963	2.092	2.598
No. of Investors with Experience	0.839	0.687	0.957	0.720	1.121	1.401
No. of Investors (Co-investment=1)	2.773	2.037	2.755	2.979	3.413	3.630
No. of Individual Angels	1.099	1.141	1.149	0.872	0.337	0.177
No. of VCs & Angel Groups	0.469	0.072	0.443	1.091	1.755	2.421
Professional Closeness	0.317	0.174	0.314	0.447	0.520	0.562
Educational Closeness	0.167	0.230	0.175	0.105	0.082	0.056
Geographic Closeness	0.173	0.297	0.092	0.016	0.009	0.009
Total Rounds	25246	12805	5204	3208	1975	2054

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**Table 3** Survival and Transition Probabilities

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Panel A of this table presents the average unconditional probability of a start-up in our sample surviving till each of the financing stages in its life cycle: *Seed*, *Series A*, *Series B*, *Series C*, *Series D*, and *Successful Exit*. Panel B presents the conditional probability of a successful transition to the next financing stage in the life cycle for different financing stages: the first column lists the overall probability of making a successful transition, whereas the second, third and fourth columns show probabilities of making a successful transition within 1, 2 and 3 years, respectively.

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*Panel A: Proportion of total firms surviving at each stage*

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	Seed	Series A	Series B	Series C	Series D	Successful Exit
% of startups at funding stage	100.000	23.852	8.914	4.228	2.011	2.703

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*Panel B: Probability of transition to next funding stage*

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	$t \leq \text{May 2015}$	$t \leq 1$	$t \leq 2$	$t \leq 3$
Seed to Series A	23.852	15.097	20.480	22.472
Series A to B	44.638	26.802	38.569	42.179
Series B to C	47.535	24.844	39.277	44.510
Series C to D	47.589	26.324	39.929	44.159

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**Table 4** Summary of Angel Investor Characteristics

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This table reports summary statistics of the key variables for our sample of individual angels. Each observation in the panel data corresponds to an angel-year combination. The data spans the time period 2005–2014, and only includes individual angels that invested in at least three portfolio firms by December 2014. All variables are defined in the Appendix.

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Variable	Mean	Stdev.	Percentile Distribution			N
			10 <sup>th</sup>	50 <sup>th</sup>	90 <sup>th</sup>	
<b><i>Angel Characteristics:</i></b>						
Start-ups invested	1.972	3.881	0.000	1.000	5.000	25868
Rounds invested	2.078	4.884	0.000	1.000	5.000	25868
Years of Experience	5.118	3.374	0.980	4.000	7.500	25868
Entrepreneur	0.142	0.349	0.000	0.000	1.000	25868
Degree centrality	17.367	34.934	1.000	7.000	42.000	25868
New connections	8.013	17.429	0.000	5.000	20.000	25868
Eigenvector centrality	5.990	10.570	0.045	2.253	15.451	23979
Eigenvector centrality Decile	5.433	2.953	1.000	5.000	9.000	23979
$\Delta(\text{Eigenvector decile})$	0.184	1.438	-1.000	0.000	2.000	21964
New outside connections	4.093	9.560	0.000	2.000	10.000	25868
New investments	1.811	3.422	0.000	1.000	5.000	25868
New outside investments	0.997	1.954	0.000	0.000	2.000	25868
<b><i>Performance Measures:</i></b>						
Seed Success	0.088	0.284	0.000	0.000	0.000	25868
No. of seed Successes	0.161	0.635	0.000	0.000	0.000	25868
Other stage Success	0.072	0.259	0.000	0.000	0.000	25868
No. of Other stage Successes	0.124	0.586	0.000	0.000	0.000	25868
Successful Exit	0.028	0.165	0.000	0.000	0.000	25868
No. of Successful Exits	0.052	0.399	0.000	0.000	0.000	25868

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**Table 5** Co-investment Likelihood and Co-investor Characteristics

In this table we present the results of regressions (1) aimed at understanding how co-investment likelihood and co-investor characteristics vary with startup and investor characteristics. In columns (1) through (4) we estimate the regression on all financing rounds. In columns (5) through (10) we estimate the regression on the subsample of rounds with more than one investor. All regressions include fixed effects for state, industry category and funding year. Standard errors reported in parentheses are robust to heteroskedasticity. We use \*\*\*, \*\*, and \* to denote statistical significance at 1%, 5% and 10% levels, respectively. All variables are defined in the Appendix

	Co-investment		Ln(No. of Investors)		Professional Closeness		Educational Closeness		Geographic Closeness	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
<i>Startup Characteristics</i>										
Serial Entrepreneur	0.092*** (0.015)	-0.005 (0.013)	0.100*** (0.013)	0.006 (0.011)	-0.010 (0.016)	-0.037** (0.015)	0.015 (0.012)	0.007 (0.012)	0.003 (0.007)	-0.003 (0.007)
Ln(Startup Age)	0.040*** (0.005)	0.019*** (0.005)	0.031*** (0.005)	0.011*** (0.004)	0.012* (0.007)	0.009 (0.006)	-0.009* (0.005)	-0.009 (0.005)	-0.003 (0.003)	-0.002 (0.003)
Series A	0.099*** (0.010)	0.033*** (0.009)	0.073*** (0.009)	0.033*** (0.008)	0.091*** (0.014)	0.008 (0.013)	-0.050*** (0.010)	-0.038*** (0.011)	-0.039*** (0.006)	-0.012** (0.006)
Series B	0.153*** (0.012)	0.066*** (0.011)	0.132*** (0.011)	0.084*** (0.010)	0.198*** (0.018)	0.089*** (0.017)	-0.088*** (0.014)	-0.071*** (0.014)	-0.036*** (0.008)	-0.004 (0.008)
Series C	0.181*** (0.015)	0.094*** (0.014)	0.194*** (0.013)	0.147*** (0.012)	0.260*** (0.023)	0.162*** (0.021)	-0.100*** (0.017)	-0.081*** (0.018)	-0.030*** (0.010)	0.004 (0.010)
Series D	0.182*** (0.018)	0.104*** (0.016)	0.203*** (0.016)	0.163*** (0.013)	0.293*** (0.027)	0.208*** (0.024)	-0.108*** (0.020)	-0.087*** (0.020)	-0.025** (0.012)	0.008 (0.011)
Ln(Funds Raised)	0.009** (0.004)	0.000 (0.004)	0.007* (0.004)	0.001 (0.003)	0.045*** (0.007)	0.016** (0.007)	-0.023*** (0.006)	-0.018*** (0.006)	-0.025*** (0.003)	-0.009*** (0.003)
<i>Investor Characteristics</i>										
Ln(Degree Centrality)		0.028*** (0.003)		0.031*** (0.003)		0.017*** (0.005)		0.002 (0.004)		-0.004* (0.002)
Connected Founder-Investor		0.049*** (0.009)		0.046*** (0.008)		0.011 (0.01)		0.002 (0.008)		0.003 (0.005)
Same Location Investor		0.100*** (0.011)		0.098*** (0.009)		-0.003 (0.012)		0.018* (0.01)		0.025*** (0.005)
Ln(Market Funds Flow)	0.015*** (0.004)	0.010*** (0.003)	0.018*** (0.003)	0.012*** (0.003)	-0.021*** (0.005)	-0.013*** (0.005)	-0.002 (0.004)	-0.005 (0.004)	0.006*** (0.002)	0.001 (0.002)
Observations	25246	25246	25246	25246	8084	8084	8084	8084	8084	8084
Adj. R <sup>2</sup>	0.158	0.343	0.140	0.395	0.197	0.340	0.172	0.182	0.247	0.317
Location, Industry & Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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**Table 6** Summary of Matched Angel Investor Characteristics

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This table reports a univariate comparison of the treatment (Successful angels) and control (Unsuccessful angels) groups obtained through the propensity score matching method in the year of *Seed Success*. The last column reports the *t-statistic* of the tests for difference between treatment and control samples. All variables are defined in the Appendix.

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Variable	Successful Angels (A: Treatment Group)			Unsuccessful Angels (B: Control Group)			(A-B) t-stat
	Mean	Stdev.	N	Mean	Stdev.	N	
<b><i>Angel Characteristics</i></b>							
Start-ups invested	2.182	4.457	2024	2.199	5.257	6575	-0.144
Rounds Invested	3.022	6.331	2024	3.202	7.635	6575	-1.063
Years of Experience	3.072	4.179	2024	3.299	4.907	6575	-2.048
Entrepreneur	0.158	0.369	2024	0.143	0.355	6575	1.615
Degree Centrality	12.272	21.868	2024	11.524	24.178	6575	1.312
Eigenvector Centrality	6.364	8.886	1916	6.198	12.198	6380	0.653

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**Table 7** Effect of Success on New Co-investment Connections

In this table we examine the effect of *Seed Success* on the quantity and quality of new co-investment connections formed by the angel. The dependent variable is  $\ln(1 + \text{New Connections}_{i,t})$  in Panel A,  $\Delta(\text{Eigenvector Centrality Decile})_{i,t}$  in Panel B, and  $\ln(1 + \text{New Outside Connections}_{i,t})$  in Panel C. In each panel, we estimate regression (2) in column (1), and regression (3) in columns (2) through (6). We estimate the regressions on the entire sample in columns (1) and (2); separately for low-network-capital angels and high-network-capital angels in columns (3) and (4), respectively; and separately for more-likely successes and less-likely successes in columns (5) and (6), respectively. For the sample splits in columns (3) versus (4), and for columns (5) versus (6), we also report  $p$ -values of  $\chi^2$ -tests to examine whether the total post-period effect of success is the same across the two groups. All variables are defined in the Appendix. Standard errors reported in parentheses are robust to heteroskedasticity and are clustered by angels. We use \*\*\*, \*\*, and \* to denote statistical significance at 1%, 5% and 10% levels, respectively.

*Panel A: Effect of Success on Quantity of New Co-investment Connections*

	$\ln(1 + \text{New Connections}_{i,t})$					
	All angels		Low network capital angels	High network capital angels	More likely success	Less likely success
	(1)	(2)	(3)	(4)	(5)	(6)
Seed Success	0.020 (0.014)	0.017 (0.016)	0.019 (0.020)	0.017 (0.028)	0.016 (0.023)	0.020 (0.018)
Post	0.020** (0.008)					
<i>Seed Success</i> $\times$ <i>Post</i>	0.093*** (0.018)					
<i>PreSuccess</i> <sub>-3</sub>		-0.041 (0.028)	-0.031 (0.030)	-0.053 (0.060)	-0.034 (0.021)	-0.030 (0.025)
<i>PreSuccess</i> <sub>-2</sub>		-0.021 (0.022)	-0.017 (0.021)	-0.031 (0.043)	-0.021 (0.019)	-0.026 (0.023)
<i>PreSuccess</i> <sub>-1</sub>		-0.015 (0.020)	-0.011 (0.021)	0.020 (0.038)	-0.011 (0.017)	-0.019 (0.020)
<i>PostSuccess</i> <sub>+1</sub>		0.141*** (0.026)	0.181*** (0.026)	0.099*** (0.033)	0.075*** (0.025)	0.196*** (0.021)
<i>PostSuccess</i> <sub>+2</sub>		0.079*** (0.021)	0.101*** (0.025)	0.016 (0.028)	0.045* (0.027)	0.079*** (0.024)
<i>PostSuccess</i> <sub>+3</sub>		0.059** (0.024)	0.111*** (0.032)	0.031 (0.030)	0.040 (0.029)	0.082*** (0.027)
Obs.	17198	49335	26355	22980	22103	27232
<i>Adj. R</i> <sup>2</sup>	0.356	0.379	0.378	0.368	0.456	0.401
Investor F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	No	Yes	Yes	Yes	Yes	Yes
<i>p-value of difference</i>			0.044		0.051	

Panel B: Effect of Success on Quality of New Co-investment Connections

	$\Delta(\text{Eigenvector Centrality Decile})_{i,t}$					
	All angels		Low network capital angels	High network capital angels	More likely success	Less likely success
	(1)	(2)	(3)	(4)	(5)	(6)
Seed Success	0.009 (0.021)	-0.016 (0.012)	-0.021 (0.017)	-0.012 (0.016)	-0.011 (0.030)	-0.014 (0.032)
Post	0.019* (0.010)					
<i>Seed Success</i> × <i>Post</i>	0.164*** (0.032)					
<i>PreSuccess</i> <sub>-3</sub>		-0.027 (0.018)	-0.036* (0.020)	-0.020 (0.020)	-0.021 (0.039)	-0.036 (0.050)
<i>PreSuccess</i> <sub>-2</sub>		-0.020 (0.016)	-0.021 (0.021)	-0.019 (0.018)	-0.025 (0.035)	-0.036 (0.042)
<i>PreSuccess</i> <sub>-1</sub>		0.021 (0.013)	0.023 (0.020)	0.020 (0.016)	0.022 (0.031)	0.030 (0.035)
<i>PostSuccess</i> <sub>+1</sub>		0.189*** (0.024)	0.272*** (0.029)	-0.013 (0.038)	0.073** (0.031)	0.259*** (0.036)
<i>PostSuccess</i> <sub>+2</sub>		0.190*** (0.024)	0.314*** (0.026)	0.065* (0.039)	0.055 (0.034)	0.365*** (0.041)
<i>PostSuccess</i> <sub>+3</sub>		0.092*** (0.025)	0.142*** (0.031)	0.096** (0.042)	0.064 (0.039)	0.078 (0.048)
Obs.	15363	44072	23543	20529	19745	24327
<i>Adj. R</i> <sup>2</sup>	0.271	0.144	0.242	0.122	0.135	0.196
Investor F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	No	Yes	Yes	Yes	Yes	Yes
<i>p-value of difference</i>			0.000		0.001	

Panel C: Effect of Success on Geography of New Connections

	Ln(1+New Outside Connections <sub>i,t</sub> )					
	All angels		Low network capital angels	High network capital angels	More likely success	Less likely success
	(1)	(2)	(3)	(4)	(5)	(6)
Seed Success	0.020 (0.013)	0.020 (0.024)	0.015 (0.028)	0.028 (0.031)	0.042** (0.021)	0.013 (0.022)
Post	0.018** (0.007)					
<i>Seed Success</i> × <i>Post</i>	0.175*** (0.018)					
<i>PreSuccess</i> <sub>-3</sub>		-0.026 (0.025)	-0.029 (0.041)	-0.027 (0.032)	-0.024 (0.033)	-0.035 (0.039)
<i>PreSuccess</i> <sub>-2</sub>		-0.017 (0.023)	-0.018 (0.040)	-0.010 (0.030)	-0.018 (0.029)	-0.033 (0.036)
<i>PreSuccess</i> <sub>-1</sub>		0.021 (0.024)	0.019 (0.034)	0.031 (0.029)	0.018 (0.029)	0.017 (0.033)
<i>PostSuccess</i> <sub>+1</sub>		0.164*** (0.023)	0.226*** (0.028)	0.073** (0.035)	0.138*** (0.026)	0.156*** (0.024)
<i>PostSuccess</i> <sub>+2</sub>		0.239*** (0.021)	0.275*** (0.029)	0.142*** (0.036)	0.124*** (0.034)	0.310*** (0.029)
<i>PostSuccess</i> <sub>+3</sub>		0.115*** (0.025)	0.121*** (0.031)	0.076* (0.039)	0.044 (0.032)	0.179*** (0.029)
Obs.	17198	49335	26355	22980	22103	27232
<i>Adj. R</i> <sup>2</sup>	0.635	0.462	0.434	0.472	0.473	0.401
Investor F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	No	Yes	Yes	Yes	Yes	Yes
<i>p-value of difference</i>			0.017		0.009	

**Table 8** Effect of Success on New Deal Flow

In this table we examine the effect of *Seed Success* on the angel's ability to generate new investment opportunities. The dependent variables is  $\ln(1 + \text{New Investments}_{i,t})$  in Panel A,  $\ln(1 + \text{New Outside Investments}_{i,t})$  in Panel B, and  $\ln(1 + \text{New Industry Investments}_{i,t})$  in Panel C. In each panel, we estimate regression (2) in column (1), and regression (3) in columns (2) through (6). We estimate the regressions on the entire sample in columns (1) and (2); separately for low-network-capital angels and high-network-capital angels in columns (3) and (4), respectively; and separately for more-likely successes and less-likely successes in columns (5) and (6), respectively. For the sample splits in columns (3) versus (4), and for columns (5) versus (6), we also report  $p$ -values of  $\chi^2$ -tests to examine whether the total post-period effect of success is the same across the two groups. All variables are defined in the Appendix. Standard errors reported in parentheses are robust to heteroskedasticity and are clustered by angels. We use \*\*\*, \*\*, and \* to denote statistical significance at 1%, 5% and 10% levels, respectively.

<i>Panel A: Effect of Success on New Investments</i>						
	$\ln(1 + \text{New Investments}_{i,t})$					
	All angels		Low network capital angels	High network capital angels	More likely success	Less likely success
	(1)	(2)	(3)	(4)	(5)	(6)
Seed Success	-0.006 (0.009)	-0.015 (0.010)	-0.012 (0.014)	-0.017 (0.016)	-0.017 (0.015)	-0.014 (0.015)
Post	0.011** (0.005)					
<i>Seed Success</i> × <i>Post</i>	0.152*** (0.010)					
<i>PreSuccess</i> <sub>-3</sub>		-0.027 (0.019)	-0.030 (0.031)	-0.020 (0.023)	-0.028 (0.022)	-0.032 (0.020)
<i>PreSuccess</i> <sub>-2</sub>		-0.012 (0.017)	-0.020 (0.029)	-0.019 (0.021)	-0.018 (0.021)	-0.022 (0.019)
<i>PreSuccess</i> <sub>-1</sub>		0.011 (0.015)	0.011 (0.026)	0.014 (0.020)	0.038* (0.021)	0.033 (0.022)
<i>PostSuccess</i> <sub>+1</sub>		0.196*** (0.017)	0.194*** (0.023)	0.136*** (0.020)	0.134*** (0.021)	0.245*** (0.020)
<i>PostSuccess</i> <sub>+2</sub>		0.138*** (0.018)	0.245*** (0.024)	0.040* (0.023)	0.105*** (0.019)	0.124*** (0.018)
<i>PostSuccess</i> <sub>+3</sub>		0.036* (0.019)	0.105*** (0.021)	0.062** (0.026)	0.006 (0.021)	0.065*** (0.020)
Obs.	17198	49335	26355	22980	22103	27232
<i>Adj. R</i> <sup>2</sup>	0.622	0.554	0.482	0.518	0.506	0.416
Investor F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	No	Yes	Yes	Yes	Yes	Yes
<i>p-value of difference</i>			0.002		0.028	



Panel B: Effect of Success on Geography of New Deal Flow

	Ln(1+New Outside Investments <sub>i,t</sub> )					
	All angels		Low network capital angels	High network capital angels	More likely success	Less likely success
	(1)	(2)	(3)	(4)	(5)	(6)
Seed Success	0.011 (0.008)	0.019* (0.011)	-0.005 (0.012)	0.021 (0.015)	0.020 (0.015)	0.019 (0.016)
Post	0.007 (0.005)					
<i>Seed Success</i> × <i>Post</i>	0.126*** (0.010)					
<i>PreSuccess</i> <sub>-3</sub>		-0.026 (0.017)	-0.029 (0.029)	-0.018 (0.021)	-0.020 (0.022)	-0.029 (0.024)
<i>PreSuccess</i> <sub>-2</sub>		-0.015 (0.015)	-0.019 (0.027)	-0.010 (0.019)	-0.011 (0.017)	-0.018 (0.022)
<i>PreSuccess</i> <sub>-1</sub>		-0.009 (0.014)	-0.010 (0.022)	-0.010 (0.018)	-0.009 (0.018)	-0.011 (0.020)
<i>PostSuccess</i> <sub>+1</sub>		0.215*** (0.015)	0.249*** (0.026)	0.169*** (0.017)	0.171*** (0.019)	0.252*** (0.019)
<i>PostSuccess</i> <sub>+2</sub>		0.168*** (0.015)	0.182*** (0.023)	0.156*** (0.019)	0.099*** (0.016)	0.201*** (0.017)
<i>PostSuccess</i> <sub>+3</sub>		0.111*** (0.016)	0.139*** (0.021)	0.043** (0.020)	0.088*** (0.017)	0.102*** (0.019)
Obs.	17198	49335	26355	22980	22103	27232
<i>Adj. R</i> <sup>2</sup>	0.594	0.466	0.454	0.542	0.489	0.426
Investor F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	No	Yes	Yes	Yes	Yes	Yes
<i>p-value of difference</i>			0.024		0.008	

Panel C: Effect of Success on Industry of New Deal Flow

	Ln(1+New Industry Investments <sub>i,t</sub> )					
	All angels		Low network capital angels	High network capital angels	More likely success	Less likely success
	(1)	(2)	(3)	(4)	(5)	(6)
Seed Success	0.010 (0.011)	0.009 (0.010)	0.010 (0.018)	0.011 (0.016)	0.021* (0.011)	0.013 (0.012)
Post	0.008 (0.010)					
<i>Seed Success</i> × <i>Post</i>	0.018** (0.009)					
<i>PreSuccess</i> <sub>-3</sub>		-0.026** (0.012)	-0.020** (0.011)	0.007 (0.012)	-0.024 (0.015)	-0.022 (0.014)
<i>PreSuccess</i> <sub>-2</sub>		-0.012 (0.011)	-0.016 (0.010)	0.010 (0.013)	-0.018 (0.013)	-0.010 (0.016)
<i>PreSuccess</i> <sub>-1</sub>		0.011 (0.013)	0.013 (0.012)	0.024* (0.013)	0.018 (0.014)	0.011 (0.013)
<i>PostSuccess</i> <sub>+1</sub>		0.024** (0.011)	0.034*** (0.012)	0.026** (0.012)	0.010 (0.016)	0.058*** (0.014)
<i>PostSuccess</i> <sub>+2</sub>		0.033*** (0.011)	0.045*** (0.015)	0.010 (0.012)	0.030** (0.014)	0.035** (0.015)
<i>PostSuccess</i> <sub>+3</sub>		0.015 (0.012)	0.011 (0.011)	0.016 (0.014)	0.017 (0.012)	0.017 (0.016)
Obs.	17198	49335	26355	22980	22103	27232
<i>Adj. R</i> <sup>2</sup>	0.203	0.121	0.143	0.174	0.132	0.106
Investor F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	No	Yes	Yes	Yes	Yes	Yes
<i>p-value of difference</i>			0.000		0.000	

**Table 9** Effect of Success on Angel's Other Portfolio Companies

In this table we examine the effect of *Seed Success* on the performance of the angels' *other* portfolio companies. The dependent variable is *Other Seed Success<sub>i,t</sub>* in Panel A and *VC Financing<sub>i,t</sub>* in Panel B. In each panel, we estimate regression (2) in column (1), and regression (3) in columns (2) through (6). We estimate the regressions on the entire sample in columns (1) and (2); separately for low-network-capital angels and high-network-capital angels in columns (3) and (4), respectively; and separately for more-likely successes and less-likely successes in columns (5) and (6), respectively. For the sample splits in columns (3) versus (4), and for columns (5) versus (6), we also report  $p$ -values of  $\chi^2$ -tests to examine whether the total post-period effect of success is the same across the two groups. All variables are defined in the Appendix. Standard errors reported in parentheses are robust to heteroskedasticity and are clustered by angels. We use \*\*\*, \*\*, and \* to denote statistical significance at 1%, 5% and 10% levels, respectively.

*Panel A: Effect of Success on angel's other seed-stage portfolio firms*

	<i>Other Seed Success<sub>i,t</sub></i>					
	All angels		Low network capital angels	High network capital angels	More likely success	Less likely success
	(1)	(2)	(3)	(4)	(5)	(6)
Seed Success	0.004 (0.013)	0.016 (0.014)	0.018 (0.014)	0.022 (0.015)	0.018 (0.014)	0.014 (0.014)
Post	0.006 (0.012)					
<i>Seed Success</i> × <i>Post</i>	0.152*** (0.015)					
<i>PreSuccess</i> <sub>-3</sub>		-0.026* (0.015)	-0.020 (0.016)	-0.025 (0.017)	-0.020 (0.014)	-0.031** (0.014)
<i>PreSuccess</i> <sub>-2</sub>		-0.012 (0.012)	-0.012 (0.015)	-0.016 (0.017)	-0.010 (0.015)	-0.011 (0.015)
<i>PreSuccess</i> <sub>-1</sub>		-0.002 (0.014)	0.022 (0.016)	-0.031* (0.017)	0.011 (0.014)	-0.018 (0.015)
<i>PostSuccess</i> <sub>+1</sub>		0.139*** (0.016)	0.090*** (0.020)	0.156*** (0.018)	0.082*** (0.015)	0.169*** (0.015)
<i>PostSuccess</i> <sub>+2</sub>		0.180*** (0.015)	0.106*** (0.019)	0.186*** (0.018)	0.092*** (0.020)	0.153*** (0.018)
<i>PostSuccess</i> <sub>+3</sub>		0.100*** (0.016)	0.052** (0.021)	0.082*** (0.017)	0.059*** (0.019)	0.050*** (0.017)
Obs.	17198	49335	26355	22980	22103	27232
<i>Adj. R</i> <sup>2</sup>	0.452	0.302	0.34	0.311	0.302	0.268
Investor F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	No	Yes	Yes	Yes	Yes	Yes
<i>p-value of difference</i>			0.028		0.045	

Panel B: Effect of Success on angel's other portfolio firms attracting VC financing

	<i>VC Financing<sub>i,t</sub></i>					
	All angels		Low network capital angels	High network capital angels	More likely success	Less likely success
	(1)	(2)	(3)	(4)	(5)	(6)
Seed Success	-0.011 (0.014)	-0.011 (0.013)	-0.018 (0.017)	-0.011 (0.013)	-0.017 (0.014)	-0.020 (0.015)
Post	0.050*** (0.012)					
<i>Seed Success</i> × <i>Post</i>	0.138*** (0.016)					
<i>PreSuccess</i> <sub>-3</sub>		-0.026* (0.015)	-0.020 (0.019)	-0.028* (0.016)	-0.018 (0.017)	-0.030* (0.018)
<i>PreSuccess</i> <sub>-2</sub>		-0.011 (0.016)	-0.011 (0.019)	-0.007 (0.016)	-0.010 (0.016)	-0.020 (0.017)
<i>PreSuccess</i> <sub>-1</sub>		-0.004 (0.015)	0.009 (0.016)	0.010 (0.016)	0.004 (0.016)	-0.007 (0.015)
<i>PostSuccess</i> <sub>+1</sub>		0.165*** (0.018)	0.092*** (0.018)	0.194*** (0.020)	0.202*** (0.019)	0.099*** (0.016)
<i>PostSuccess</i> <sub>+2</sub>		0.132*** (0.019)	0.075*** (0.017)	0.170*** (0.023)	0.154*** (0.021)	0.084*** (0.018)
<i>PostSuccess</i> <sub>+3</sub>		0.119*** (0.016)	0.072*** (0.019)	0.134*** (0.021)	0.092*** (0.023)	0.105*** (0.021)
Obs.	17198	49335	26355	22980	22103	27232
<i>Adj. R</i> <sup>2</sup>	0.456	0.399	0.401	0.409	0.411	0.405
Investor F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	No	Yes	Yes	Yes	Yes	Yes
<i>p-value of difference</i>			0.002		0.037	

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**Table 10** Effect of Success on Angels’ “Follower” Networks
 

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This table reports the results of regressions investigating the effect of successful performance on the angels’ followership networks on the AngelList platform, and the likelihood of a follower co-investing with the angel. The sample for these regressions only includes 773 individual angel investors listed on the AngelList platform, for whom we have data on followership networks for the 2010–2014 period. The measure of successful performance is *Seed Success*. We use the same propensity score matching method as before but with one pre- and post- period. In column (1), we estimate regression (3).  $Followers_{i,t}$  is the number of followers for angel  $i$  in year  $t$  on the AngelList platform. In column (2), we estimate the likelihood of an angel’s follower becoming a co-investor after seed success. The sample for this regression is obtained by taking the cross-product of 773 individual angels and all other investors in the AngelList universe. The dependent variable  $Co-invest_{ijt}$  is a dummy variable that identifies if angel  $i$  and investor  $j$  co-invested together in year  $t$ , whereas the regressor  $Followed_{ijt}$  is a dummy variable that indicates whether investor  $j$  is a follower of angel  $i$  on AngelList in year  $t$ . We estimate the following difference-in-differences regression on all the angel-year observations in the treated and control groups.

$$\begin{aligned}
 y_{ij,t} = & \alpha + \beta \times PreSuccess_{-1} + \gamma \times PostSuccess_{+1} + \delta \times Successful_i + \zeta \times Pre_{-1} + \eta \times Post_{+1} \\
 & + \theta Followed_{ijt} + \kappa \times PreSuccess_{-1} \times Followed_{ijt} + \lambda \times PostSuccess_{+1} \times Followed_{ijt} \\
 & + \mu_i + \mu_t + \epsilon_{ij,t}
 \end{aligned}$$

All variables are defined in the Appendix. Standard errors reported in parentheses are robust to heteroskedasticity and are clustered by angels. We use \*\*\*, \*\*, and \* to denote statistical significance at 1%, 5% and 10% levels, respectively.

	$Ln(1 + Followers_{i,t})$	$Co-invest_{ijt}$
	(1)	(2)
$Followed_{ijt}$		0.016 (0.013)
$PreSuccess_{-1}$	0.021 (0.028)	0.021 (0.018)
$PostSuccess_{+1}$	0.069** (0.029)	0.012 (0.015)
$PreSuccess_{-1} \times Followed_{ijt}$		0.027 (0.021)
$PostSuccess_{+1} \times Followed_{ijt}$		0.055*** (0.021)
Observations	1398	1092602
Adj. $R^2$	0.412	0.148
Investor & Year F.E.	Yes	Yes

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**Table 11** Effect of Success on Angels' Career Paths

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This table reports marginal effects of Logit regressions investigating the effect of successful performance on the probability an angel joins an angel group (column 1), co-invests with an angel group (column 2), or gets employed by a VC (column 3). *Seed Success Ratio*<sub>*t*-1</sub> is defined as the number of seed successes divided by the total number of seed-stage investments the angel made as of year 't-1' before joining an angel group or getting employed by a VC in year 't'. Entrepreneur takes a value 1 if the angel was an entrepreneur in the past; 0 otherwise. All variables are defined in the Appendix. We use \*\*\*, \*\*, and \* to denote statistical significance at 1%, 5% and 10% levels, respectively.

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	Belongs to Angel Group <sub><i>t</i></sub>	Co-invest with Angel Group/VC <sub><i>t</i></sub>	Employed by VC <sub><i>t</i></sub>
	(1)	(2)	(3)
<i>Seed Success Ratio</i> <sub><i>i,t</i>-1</sub>	0.096*** (0.007)	0.110*** (0.011)	0.032*** (0.004)
<i>Entrepreneur</i> <sub><i>i</i></sub>	0.007 (0.013)	0.035** (0.015)	0.068*** (0.007)
<i>Ln(Degree)</i> <sub><i>i,t</i>-1</sub>	0.015*** (0.005)	0.018** (0.009)	0.004 (0.003)
<i>Ln(Years of Experience)</i> <sub><i>i,t</i>-1</sub>	0.028*** (0.008)	0.012 (0.010)	-0.005 (0.004)
<i>Ln(Amt Raised by Portfolio Companies)</i> <sub><i>i,t</i>-1</sub>	0.004** (0.002)	0.001 (0.012)	0.002* (0.001)
Obs.	25868	25868	25868
Pseudo <i>R</i> <sup>2</sup>	0.087	0.098	0.095
Year F.E.	Yes	Yes	Yes

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## Appendix: Variable Definitions

### Start-up Characteristics:

- *Startup Age* is the age of startup in years.
- *Serial Entrepreneur* is a dummy variable that identifies whether one of the startup's founders is a repeat entrepreneur.
- *Connected Founder-Investor* is a dummy variable that identifies whether one of the founders has a past professional or educational connection with one of the startup's investors. Professional connections include having worked for the same employer together or a past founder-investor relationship on a previous venture.
- *Same Location Investor* indicates whether at least one of the investors in a funding round is from the same state as the startup.
- *Co-investment* indicates whether a financing round has more than one investor (i.e.,  $\text{Co-investment}=1$ ).
- *Professional Closeness* is the fraction of co-investor pairs in a syndicate who share a prior professional connection.
- *Educational Closeness* is the fraction of co-investor pairs in a syndicate who share a prior educational connection.
- *Geographic Closeness* is the fraction of co-investor pairs in a syndicate who are located in the same state.
- *Market Fund Flow* is the aggregate funding (in \$ billion) received by startups in the same industry and state during the previous year.

### Network Measures:

Please refer to the Internet Appendix for a more detailed and technical description of co-investment networks, and the methodology used to compute the following network measures:

- *Degree Centrality $_{i,t}$*  denotes the total number of co-investment connections that an investor has as of year  $t$ .
- *Eigenvector Centrality $_{i,t}$*  measures the relative importance of each investor in the network. It is a recursive degree measure where each investor's eigenvector centrality is the sum of his ties to others weighted by their respective degree centrality.
- *Eigenvector Centrality Decile $_{i,t}$*  represents the decile of *Eigenvector Centrality* to which the individual angel belongs in year  $t$ .  $\Delta(\text{Eigenvector Centrality Decile})_{i,t}$  represents change in *Eigenvector Centrality Decile* of angel  $i$  from year  $t - 1$  to  $t$ .
- *New Connections $_{i,t}$*  is the number of new co-investment connections formed by an investor in year  $t$  excluding the new-co-investment connections that arise from any existing portfolio firm that progressed from seed stage to series A stage.
- *New Outside Connections $_{i,t}$*  is the number of new out-of-state co-investment connections formed by an investor in year  $t$ .

## Performance measures:

To create our performance measures for angel ‘i’ in year ‘t’, we first identify all start-ups for which the angel has acted as a lead investor in the past. When there are multiple investors in a funding round, we designate the investor with the highest degree centrality (i.e., the most prominent investor) as the lead investor. Then, we create the following performance measures for each angel investor-year combination:

- *Seed Success<sub>it</sub>* is a dummy variable that identifies if any seed-stage portfolio firm of angel *i* successfully progressed to Series A stage during year *t*. *No. of Seed Successes<sub>it</sub>* is the number of such seed successes experienced by angel *i* in year *t*.
- *Other stage Success<sub>it</sub>* is a dummy variable that identifies if any non-seed-stage portfolio firm of angel *i* successfully progressed to the next financing stage during year *t*; e.g., from series A stage to series B stage. *No. of Other stage Successes<sub>it</sub>* is the number of such non-seed-stage successes angel *i* has experienced in year *t*.
- *Successful exit<sub>it</sub>* is a dummy variable that identifies if any portfolio firm of angel *i* underwent an IPO or was acquired during year *t*. *No. of Successful Exits<sub>it</sub>* is the number of successful exits for angel *i* in year *t*.
- *Pre<sub>τ</sub>* for  $\tau \in \{-3, -2, -1\}$  indicate the year  $\tau$  before the *Seed Success* year.
- *Post<sub>τ</sub>* for  $\tau \in \{1, 2, 3\}$  indicate the year  $\tau$  after the *Seed Success* year.
- *PreSuccess<sub>τ</sub>* denote the interaction of *Seed Success* with *Pre<sub>τ</sub>* for  $\tau \in \{-3, -2, -1\}$ .
- *PostSuccess<sub>τ</sub>* denote the interaction of *Seed Success* with *Post<sub>τ</sub>* for  $\tau \in \{1, 2, 3\}$ .

## Angel Characteristics:

- *Start-ups invested<sub>it</sub>* is the number of start-ups in which angel *i* invested in year *t*, either as a lead investor or as a participant.
- *New investments<sub>it</sub>* is the number of new start-ups in which angel *i* invested for the first time in year *t* either as a solo investor or co-investor.
- *New outside investments<sub>it</sub>* is the number of new out-of-state start-ups in which angel *i* invested for the first time in year *t* either as a solo investor or co-investor.
- *New Industry Investments<sub>it</sub>* is the number of new industries in which angel *i* invested for the first time in year *t* either as a solo investor or co-investor.
- *Rounds invested<sub>it</sub>* is the number of funding rounds in which angel *i* invested in year *t*, either as a lead investor or as a participant.
- *Years of Experience<sub>it</sub>* is the difference (in years) between year *t* and the first year in which angel *i* made an investment reported on CrunchBase or AngelList.
- *Entrepreneur<sub>i</sub>* identifies angel investors who have previous entrepreneurial experience.
- *Other Seed Success<sub>it</sub>* is a dummy variable that identifies if the angel had lead another seed-stage portfolio company to the series A stage in year *t*.
- *VC Financing<sub>it</sub>* is a dummy variable that identifies if any portfolio firm, for which angel *i* acted as lead investor, receives venture capital financing in year *t*.



- *Belongs to Angel Group* $_{i,t}$  is a dummy variable that identifies whether angel  $i$  belongs to an angel group as of year ‘t’.
- *Co-invest with Angel Group/VC* $_{i,t}$  is a dummy variable that identifies whether angel  $i$  has co-invested with an angel group or VC firm for the first time in year ‘t’.
- *Employed by VC* $_{i,t}$  is a dummy variable that identifies whether angel  $i$  was employed by a VC firm as of year ‘t’.
- *Low network capital angels* $_{i,t}$  identifies angels whose Degree Centrality in year ‘t’ is below the sample median in year ‘t’.
- *High network capital angels* $_{i,t}$  identifies angels whose Degree Centrality in year ‘t’ is above the sample median in year ‘t’.
- *More likely success group angel* $_{i,t}$  identifies angels whose seed-stage success in year ‘t’ came from a startup that was either founded by a serial entrepreneur or was in a hot market in the year before the angel’s seed investment. We classify a state and industry combination as “hot market” if it experienced above-average number of seed-stage successes in a given year.
- *Less likely success group angel* $_{i,t}$  identifies angels whose seed-stage success in year ‘t’ came from a startup that was neither founded by a serial entrepreneur nor was in a hot market in the year before the angel’s seed investment.
- *Amt. Raised by Portfolio Companies* $_{i,t}$  is the amount (in millions) raised by all portfolio companies of angel ‘i’ as of year ‘t’.

### **AngelList Social Network Analysis Variables:**

- *Followers* $_{it}$ : Number of new investors that become followers of angel  $i$  on the AngelList platform in year  $t$ .
- *Followed* $_{ijt}$  is a dummy variable that identifies if investor  $j$  is a follower of angel  $i$  on the AngelList platform in year  $t$ .
- *Co-invested* $_{ijt}$  is a dummy variable that identifies if angel  $i$  and investor  $j$  co-invested for the first time in year  $t$ .