How do Investors Accumulate Network Capital? Evidence from Angel Networks*

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Abstract

Using unique hand-collected data on start-ups financed by individual angel investors, we show that angels that successfully lead a start-up to the next financing stage, especially from seed to series-A stage, experience an increase in the quantity and quality of co-investment connections relative to their unsuccessful peers, and are rewarded with more new investment opportunities, both as lead investors and participants. Success begets more success, making it more likely that other seed-stage start-ups of the successful angel also progress to the next financing stage. Our results highlight that reputation for good performance enhances the network capital of angel investors.

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Introduction

Financial institutions are often bound by their current and past investments into webs of relationships ("networks") with other financial institutions. Such networks are widespread in financial markets, and play a crucial role in the transmission of information and mitigation of agency conflicts.[1] Networks are all the more important in entrepreneurial finance, both among venture capital funds (e.g., see Lerner (1994), Hsu (2004) Hochberg et al. (2007), and Hochberg et al. (2010)) and angel investors (Kerr et al. (2014)), because valuation uncertainty and agency conflicts are particularly severe in case of young start-up firms. Hochberg et al. (2007) highlight the importance of venture capital (VC) networks by showing that, all else equal, VC funds with higher *network centrality* (i.e., better-networked VC funds) deliver better future performance, in terms of the proportion of their portfolio investments that are successfully exited through an IPO or sale to another company.

While the existing literature has examined the relationship between investors' network centrality and future performance, it is still not clear 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? Do social network connections translate into more future co-investment connections? In general, we know little about how networks are formed and how investors accumulate network capital over time (Allen and Babus (2009)). Any empirical investigation of these questions faces the following challenges: First, most financial markets are highly concentrated in nature and are dominated by a few large institutions, which themselves came into existence due to a series of consolidations over time. Therefore, it is near impossible to examine how these institutions' networks evolved over time. Second, in most financial markets, it is difficult to measure the performance and network connections of individuals within the institutions. Given that individuals can, and often do, move across institutions, the true relationship between individual performance and network connectedness may not be reflected in institution-level metrics of performance and network connectedness.[2] In this paper, we overcome these challenges by using *angel investor*

[1] For instance, investment banks use their connections with institutional investors to issue and underwrite securities (e.g., see Cornelli and Goldreich (2001) and Morrison and Wilhelm, Jr. (2007)), banks use their syndication networks to underwrite new loans, and so on.

[2] Institutions may be able to limit the damage to reputation from poor performance by firing the employees or

networks to understand how investors accumulate network capital over time. Angel investments refer to investments in start-up companies by wealthy individuals, who play a crucial role in the financing of early-stage start-ups (see Section 1.1 for a detailed background of this market).

The angel investor market is the ideal setting in which to understand how investors acquire network capital. Most importantly, it allows us the opportunity to focus on *individual* investors rather than institutions, and to examine how their position in the network changes over time with their performance. This is crucial because, unlike institutional investors, such as VC funds or private equity groups, individual angels are not endowed with large network capital to begin with, and have to build their connections from the ground up. Moreover, the network structure plays an important role in the angel investor market. Kerr et al. (2014) note that angel investors are part of semiformal networks that meet at regular intervals to hear pitches from aspiring entrepreneurs, and to decide whether to invest in these deals. Given the high rate of failure among start-up companies, it is plausible to expect that angels who successfully guide their portfolio companies to the next stage of financing will subsequently become more important within angel networks.

Despite their obvious importance, angel investors have received very little attention in the entrepreneurial finance literature, largely due to unavailability of structured data. We overcome this problem by collecting data on start-ups and angel investors from CrunchBase (`www.crunchbase.com`), which is the largest crowd-sourced database on start-ups and investors, and AngelList (`www.angel.co`), which is the leading online fund-raising platform for start-ups. We use these databases and other sources to gather information both on the 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 stage to the next. We provide a detailed description of our data collection in Section 2. Our data spans the period 2005–2014. We focus our analysis on angels that have invested in at least 3 portfolio companies during this period. Based on this criterion, our final sample comprises 4,108 individual angels who invested in 12,215 portfolio firms over the period 2005–2014.

divesting the divisions responsible for the poor performance. Conversely, they may be able to gain reputation by hiring employees or acquiring businesses with a track record of good performance. Therefore, it is hard to identify the true effects of good or bad performance using institution-level metrics.

We measure the performance of angel investors based on whether portfolio companies for which they acted as lead investor successfully progressed from one financing stage in their life cycle to the next; e.g., "seed" stage to "series A" stage, or from "series A" stage to "series B" stage, and so on. For each angel-year combination, we define three indicator variables for success to identify whether the angel successfully lead any of his portfolio companies to the next stage during the year (*Success*), whether he successfully guided any of his seed-stage portfolio firms to the series A stage during the year (*Seed Success*), and whether one of his portfolio companies underwent an IPO or was acquired during the year (*Successful Exit*). Note that all measures of performance are only based on portfolio firms for which the angel acted as lead investor, because the lead investor is primarily involved in screening the start-up and setting the terms of the deal. As expected, success is relatively rare in this market because most start-up firms, especially those at the seed stage, fail to progress to the next stage. We follow the economic sociology literature (see Jackson (2008)) to create measures of network connectedness, such as *Degree Centrality*, which captures the number of network connections, and *Eigenvector Centrality*, which captures the importance or quality of connections. We rank angels into deciles based on their *Eigenvector Centrality* each year, and use the year-on-year changes in *Eigenvector Centrality Decile* as a proxy for improvement in the quality of connections.

Our main hypothesis is that, all else equal, 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, relative to his unsuccessful peers. The growth in network connections should, in turn, result in better future performance of the angel's existing portfolio companies as well as lead to new funding opportunities for the angel. We refer to this as the *reputation hypothesis*. Of course, successful performance is not exogenous, and may itself depend on the angel's existing network capital (Hochberg et al. (2007)). Therefore, an obvious concern is that the angel's existing network capital may be driving both his current success as well as future growth. We refer to this alternative hypothesis as the *network capital hypothesis*.

Of course, the two hypotheses are not mutually exclusive because the causation between performance and network capital can go both ways. Nonetheless, we use the following approach to try and identify the causal effect of successful performance on network capital: First, we use the nearest neighbor matching procedure to match each successful angel ("treated" group) with several unsuccessful angels during the same year ("control group") who are very similar in terms of their degree centrality, number of rounds invested and years of experience. Then, we estimate difference-in-differences regressions to examine how the growth in network capital of successful angels varies relative to their unsuccessful peers 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.

Our results are broadly consistent with the reputation hypothesis. For all three measures of success, we find that angels that deliver a successful performance are rewarded with more new co-investment connections and see an increase in the quality of their network connections compared to their unsuccessful peers in the following three years, although the two groups are very similar in the years before the success. 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 effects are economically significant: for instance, an angel that successfully leads one of its seed-stage portfolio firms to the series A stage is rewarded with 9.95 more new co-investment connections, improves his *Eigenvector Centrality Decile* by 0.24, invests in 1.19 more new start-up companies, and acts as lead investor in 0.53 more new start-up companies compared to his unsuccessful peers over the next three years.

We also estimate these regressions separately on the sub-samples of investors with low and high existing network capital (i.e., less established vs. better established investors). As per the reputation hypothesis, the link between success and future network growth should be stronger for less established investors because of higher uncertainty about their investing abilities (see Holmström (1999)); the network capital hypothesis predicts the opposite. Consistent with the reputation hypothesis, we find that the effects are indeed significantly stronger among angels with low existing network capital.

If successful performance boosts an angel's network capital, 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 a successful performance 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 portfolio companies over the next three years. In other words, success begets more success for the angel investor. When we separately examine angels with high and low existing network capital, we find that the knock-on effect is actually stronger among angels with high network capital. This is likely because angels with high network capital are likely to have several more companies in their portfolio, especially late-stage start-ups, at the same time compared to angels with low network capital, which makes it more likely to detect a knock-on effect in the former group.

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. We then examine how success affects an angel's ability to attract new followers and the propensity of his existing followers to co-invest with him. Consistent with the reputation hypothesis, we find successful angels attract more new followers relative to their unsuccessful peers in the year after they experience success, and that an angel's existing followers are more likely to establish a new co-investment connection with him in the year after he delivers a successful performance.

Our paper contributes to the small but growing literature on angel investors (Goldfarb et al. (2013) and Bernstein et al. (2016)) and to the literature on financial networks by highlighting how successful performance by individual angel investors, especially in their seed-stage startups, leads to significant improvement in their network capital and future deal flow. These effects are particularly strong for angel investors with low existing network capital. By contrast, most of the literature on financial networks takes the network structure as given, and focuses on the effect of network centrality on future performance. In the context of entrepreneurial finance, Hochberg et al. (2007) show that better-connected VC funds deliver better future performance, all else equal.[3] Interestingly, and in contrast to our results, they fail to find any relationship between the past performance of VCs and their current network centrality. These contrasting results may have to do with the fact that we focus on individual angel investors that are not endowed with large network capital to begin with, and have to build their connections from the ground up, whereas Hochberg et al. (2007) focus on institutional VC funds that may already have long track records and connections.

Our main contribution to the literature on reputation of financial intermediaries is that we focus on individual angel investors that have little reputation to begin with, instead of well-established financial institutions that the extant literature has mostly focused on. In terms of empirical strategy, our paper is similar to Gopalan et al. (2011) who examine the loss of reputation to banking institutions in the loan syndication market resulting from poor performance.[4] By contrast, we focus on the reputation gain to individual angel investors who demonstrate successful performance, because, unlike in the loan market, failure is common whereas success is rare in the angel investor market. Reputation effects have also been studied at the institution level in a variety of other financial markets, such as IPO underwriting (Beatty and Ritter (1986), Carter and Manaster (1990), and Nanda and Yun (1997)), bond underwriting (Fang (2005)), and venture capital (Krishnan et al. (2007), Atanasov et al. (2012), and Tian et al. (2015)).

1 Theoretical and Institutional Background

In this section, we provide a short overview of the angel investment market, and outline the reputation hypothesis and the network capital hypothesis, both of which have predictions for the relationship between current performance of angel investors and their future network growth.

[3] There is also a large literature that focuses on social network connections of investors and executives, and examines the performance consequences of such network connections (e.g., see Cohen et al. (2008), Cohen et al. (2010), Shue (2013), and Ishii and Xuan (2014)).

[4] There is also a related literature that examines how performance affects mutual fund flows (Gruber (1996), Sirri and Tufano (1998), and Zheng (1999)), and job terminations of mutual fund managers (Chevalier and Ellison (1999)) and security analysts (Hong and Kubik (2003)).

1.1 The Angel Investment Market

Angel investments refer to investments in start-up companies by wealthy individuals, who are often former entrepreneurs themselves. Although a few large angel investors are structured as angel groups, most angel investors are individual investors. Unlike VC funds, which mainly focus on funding later-stage start-up firms, angels play a crucial role in the financing of early-stage start-ups (Hellmann and Thiele (2015)). In entrepreneurial finance, start-ups 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 Appendix for the generally accepted definitions of these stage classifications in the industry).[5] 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 start-ups to undertake IPOs or to be acquired by other companies.

Kerr et al. (2014) show that the early stage market is an important place for experimentation and quick failure without which innovation process would stagnate. Therefore, the funding path of growth-oriented start-ups typically involves some initial funding from angels. Kerr et al. (2014) show that angels have a real impact on the firms in which they invest. They also note that angel investors are part of semi-formal networks that meet at regular intervals to hear pitches from aspiring entrepreneurs, and to decide whether to invest in these deals.

The angels market has flourished over the past decade, especially after the introduction of online fund-raising platforms such as AngelList (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.

[5] The academic literature (e.g., see Gompers (1995)) sometimes refers to series A as "early stage," series B as "expansion stage," and series C and D as "late stage."

1.2 Reputation Hypothesis

Both anecdotal evidence and recent empirical evidence (Kerr et al. (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 that most start-up ventures fail, an angel investor with a successful track record of leading his portfolio companies to the next funding stage is likely to gain reputation and the attention of other investors and entrepreneurs. Therefore, successful performance by an angel investor *should lead to* an increase in his network centrality, both in terms of the number and quality of connections, relative to his unsuccessful peers. This, in turn, should 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)). Moreover, the increase in the angel's network centrality should also increase the likelihood that his other portfolio companies will progress to the next funding round. We refer to this as the *reputation hypothesis*.

Theoretical models of reputation predict that the gain in an agent's reputation from good performance should be stronger when there is greater uncertainty about the agent's abilities (see Holmström (1999)). Therefore, as per the reputation hypothesis, the positive relationship between success and future network growth should be stronger for angel investors with low existing network capital compared to those with high existing network capital.

1.3 Network Capital Hypothesis

Of course, successful performance is not exogenous, and may itself depend on the angel's existing network capital. Therefore, an obvious alternative hypothesis is that an investor's existing network capital may be driving both his current success as well as future network growth. That is, if the investor is already well-known and well-connected in the network, then his existing portfolio companies are more likely to succeed because his existing connections allow him to deliver funding to them (see Hochberg et al. (2007)), and also more investors would want to associate with him going forward in order to participate in his network. We refer to this alternative hypothesis as the *network capital hypothesis.*

In general, it is hard to distinguish between the reputation hypothesis and the network capital hypothesis because both effects may be present simultaneously. However, our unique setting with its focus on individual angel investors allows us to develop a difference-in-differences regression framework to distinguish between the reputation hypothesis and the network capital hypothesis. We describe this methodology in Section 4.1.

2 Data, Sample Collection, and Construction of Variables

2.1 Data Sources

In order to map the co-investment networks of angel investors, we need information on all start-up companies in their portfolio, as well as the complete fund-raising histories of the portfolio firms including the identity of all investors that participate in each funding round. Moreover, in order to measure the performance of angel investors, we need information on the progress of their portfolio firms from one stage in their life cycle to the next. Unfortunately, information about angel investors or early-stage start-ups funded by them is not readily available from commercial databases. Similar to Bernstein et al. (2016) and Yu (2016), we overcome this problem by collecting data from CrunchBase (`www.crunchbase.com`), which is the largest crowd-sourced database on start-ups and investors, and AngelList (`angel.co`), which is the leading on-line fund-raising platform for start-ups.[6] We obtain supplementary data from a variety of other sources, such as the SEC's notice of exempt offering of securities (Form D), and news websites. We describe these data sources in detail below.

CrunchBase

CrunchBase is a graph database organized around several collection endpoints. We use the "People" endpoint to extract detailed information on individual angel investors identified in Crunch-

[6]We access the data on CrunchBase and AngelList via their Application Programming Interface (API), which allows us to send requests for data on each investor and start-up 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.

Base. Apart from personal information, such as date of birth, gender, location and education, we are also able to obtain their employment and investment history, and links to news articles. Figure 1 provides 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). As can be seen, the investment history lists 117 investments that Alexis Ohanian has made, including the names of start-ups, dates the investments were made, the amount raised by the start-up in each round he participated, and the stage of investment rounds.

We use the "Organization" endpoint to extract detailed profiles of start-ups. Although there are many missing variables, for start-ups 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. Figure 2 provides a representative snapshot of the information available for Uber.

Using CrunchBase's Organization endpoint, we are able to identify 70,157 North American start-ups for which we have information on all their fund-raising dates. For a subset of 47,730 start-ups, we also have information on the identities of investors that participated in each funding round. These start-ups are funded by 24,132 investors, of which 10,017 are individual angel investors, and the rest are institutions such as venture capital funds, angel groups, accelerators and incubators. That still leaves 22,427 start-ups for which we are unable to obtain fund-raising information from Crunchbase. Therefore, we turn to alternative data sources to augment our data.

AngelList

AngelList is the leading on-line fund-raising platform for start-ups. Similar to CrunchBase, AngelList also provides the biographical details and investment histories for investors, and information on fund-raising activities of start-ups.[7] We are able to identify 38,814 North American start-ups on AngelList with non-missing information on fund-raising dates and the identities of investors

[7] After matching start-up profiles listed in CrunchBase and AngelList based on their names and website domain address, we found an overlap of around 75% between the two datasets. In general, CrunchBase provides better coverage on the fund-raising dates and amounts raised by start-ups, whereas AngelList provides more detail on the investors who participated in each round and the founding teams of start-ups.

that participated in each round. These start-ups are funded by 13,376 investors, out of which 7,324 are individual angel investors, whereas the rest are angel groups and VCs. Next, we match the CrunchBase and AngelList to eliminate duplications. We find that AngelList sample includes 11,854 start-ups that were not covered by CrunchBase, and 8,300 start-ups that were covered by CrunchBase but for which we could not find investor information on CrunchBase.

Other Data Sources

Overall, the combination of CrunchBase and AngelList yields a sample of 67,884 start-ups for which we have complete information on fund-raising dates and the identities of investors that participated in each fund-raising round. Crucial information on the stage of each funding round for the start-up (which we need to evaluate success of start-ups and performance of angels) is only available for 57,897 start-ups. To further augment and verify our data, we turn to Form D filings made by start-up companies to the SEC, which are available for download from SEC's FTP servers from the year 2008 onward.[8] We download the Form D filings using CIK numbers in the Edgar Company Index file and funding round dates obtained from Crunchbase and AngelList, and use the description field under "Type(s) of Securities Offered" to identify the stage of the funding round. This exercise yields the stage information for 1,027 additional start-ups.[9] Overall, we have information on the stage of each funding round for 58,924 start-ups.

2.2 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 start-up.[10] We use this definition along with our universe of start-ups and investors to map the co-investment networks each year. At

[8]As per Regulation D of the Securities Act of 1933, some companies are allowed to offer their securities for sale without having to register with the SEC. This is intended to make access to capital markets possible for small companies that could not otherwise bear the costs of a normal SEC registration. Such companies are required to file a Form D with the SEC after making the first sale, which, among other things, contains information on the type of security sold, date of first sale and the amount sold.

[9]We 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 start-ups.

[10]A less stricter definition of a co-investment connection could include having invested in the same start-up even if it is not in the same funding round (as used in Hochberg et al. (2007)). Using the less stricter definition does not change our qualitative results.

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 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 Chapter 2 of Jackson (2008)). 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*.

2.3 Sample for our Analysis

Given our focus on individual angel investors, we exclude start-ups that are exclusively funded by institutional investors, such as angel groups and VCs; there are 28,501 such start-ups. Next, we require that we have the complete funding history for each start-up, and stage information for all the funding rounds. If either of these conditions is violated, then we remove the start-up and all angel investors associated with the start-up from our analysis. As a result of these restrictions, we drop 2,175 start-ups thus reducing our sample size to 28,248 start-ups funded by 12,147 individual investors and 7,453 institutional investors for whom we have complete investment history.

We restrict our analysis to time period from 2005 to 2014 because the coverage of CrunchBase and AngelList is sparse in earlier years. 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 start-up founded by a family member or friend. Therefore, we restrict attention to individual angel investors who have invested in at least 3 different start-ups as of December 2014.[11] After this restriction, our final sample comprises 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, which goes back to 1998 in some cases. We use these 4,108 individual angels to create an investor-year panel that has one observation for each investor-year combination and spans the time period from the first year they entered the market to 2014.

2.4 Key Variables

Performance of Angel Investors

We measure of performance of angel investors based on whether portfolio companies for which they acted as lead investor successfully progress from one financing stage in their life cycle to the next stage; e.g., from the seed stage to series A stage, or from series A stage to series B stage, and so on. This is reasonable because a start-up moving from one stage to the next is considered to be a significant show of progress for both the start-up and the lead investor involved.[12]

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.[13] Then, we create the following performance measures for each angel investor-year combination: *Success* is a dummy variable that identifies if any portfolio firm, for which the angel acted as lead investor, successfully progressed to the next financing stage during the year; *Seed Success* is a dummy variable that identifies if any seed-stage portfolio firm, for which the angel acted as lead investor, successfully progressed to Series A stage during the

[11] We show in Section 5.3 that our results are robust to this exclusion.

[12] In the VC literature, it is common to measure the performance of VCs using the number of their portfolio firms that have successfully exited via an acquisition or IPO. However, exits via acquisition or IPO are relatively less common in angel markets because angel investors are more likely to invest in early-stage start-ups.

[13] Academic literature has defined lead investor using different methods, where the choice is usually driven by data constraints. For example, Gompers (1996) classified the investor who has served longest on the company's board as the lead investor. On the other hand, Hochberg et al. (2007) classify the investor who has invested the maximum amount in a given round as the lead investor of that round. Since we do not know the amounts invested by each individual investor in each round, we designate the investor with the highest degree centrality (i.e., the most prominent investor) as the lead investor. This is reasonable for our purposes, because other investors are more likely to attribute the success or failure of the deal to the most prominent investor behind the deal.

year; and *Successful Exit* is a dummy variable that identifies if any portfolio firm, for which the angel acted as lead investor, underwent an IPO or was acquired during the year.

Growth in Network Capital

We use the following variables to measure the growth in network capital of angel 'i' in year 't': $New\ Connections_{i,t}$ is number of new co-investment connections the angel investor forms in year 't', which also equals the increase in the angel's *Degree Centrality* from year 't-1' to year 't'; $\Delta(Eigenvector\ Centrality\ Decile)_{i,t}$ 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; $New\ Investments_{i,t}$ is the number of new start-ups in which the angel has invested for the first time in year 't' either as the lead investor or as a participant; and $New\ Lead\ Investments_{i,t}$ is the number of new start-up deals in which the angel has participated as the lead investor for the first time in year 't'.

3 Descriptive statistics and Preliminary Results

3.1 Descriptive Statistics

As noted above, we restrict attention to angel investors that have invested in at least 3 different start-ups as of December 2014. There are 4,108 angel investors that meet this requirement, who funded 12,215 start-ups over the years 2005 to 2014. We provide a year-wise summary of our sample in Table 1, where each row shows the number of start-ups that raised funds, number of funding rounds along with a stage-wise breakdown, number of start-ups that exited via acquisition or IPO, total funds raised by these start-ups 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 start-ups, 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.

According to the 2014 annual report of the Angel Capital Association, most start-ups fail within first three years of operation. In panel A of table 2, we report the unconditional probabilities of a start-up surviving till each funding stage. Out of the 12,215 start-ups 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.[14]

In Panel B of table 2, 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 start-ups successfully making this transition. Moreover, most of the start-ups 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 start-up succeeding improve significantly if it makes it to the series A stage. As can be seen, 44.6% of start-ups at series A successfully transition to series B, 47.5% of start-ups at series B successfully transition to series C, and so on. Of course, despite the improvement in success probabilities, more than half the start-ups fail at each stage.

Table 3 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. On average, individual angels invest in 1.97 start-ups via 2.08 funding rounds each year, although there is substantial cross-sectional variation in these numbers as evidenced by their 10^{th} and 90^{th} percentile values. The average angel acts as lead investor in 0.99 deals each year, or roughly half the number of deals he invests in. Moreover, the average angel invests in 1.8 new start-ups each year, out of which he acts as lead investor in 0.9 deals.

In terms of network centrality, the average angel has 17.4 co-investor connections (*Degree Centrality*) although there is substantial cross-sectional variation in this measure, as well as in *Eigenvector Centrality*, which measures the quality of connections. This shows that even among individual angels, there are big investors with more than 42 co-investment connections (the

[14]Note that 2.7% of start-ups 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.

$90^{th}-$percentile value) and small investors with only 1 co-investment connection (the $10^{th}-$percentile value). The average angel gains around 12 new connections each year.

Panel B summarizes the performance measures discussed in section 2.4. The mean value of the *Success* dummy is 0.149, which indicates that, on average, only 14.9% of angels successfully transition at least one of their portfolio firms to the next financing stage during the year. Similarly, the statistics on *Seed Success* and *Successful Exit* indicate that, on average, only 9.6% of angels successfully transition at least one seed-stage firm in their portfolio to Series-A stage during the year, and only 1.9% of angels successfully exit a portfolio firm through an IPO or M&A during the year.

3.2 Univariate Results

Angel characteristics and performance measures may vary significantly based on their existing network capital. To understand these relationships, we sort the angels into five quintiles each year based on their degree centrality. We then report the mean values of angel characteristics and performance measures separately for each quintile in Table 4; the last column reports the difference in means between the highest and lowest quintile subsamples and the corresponding $t-$statistic. As expected, the network centrality measures – *Degree Centrality* and *Eigenvector Centrality* – increase significantly as we move from the lowest to the highest quintile.

Table 4 shows that investors with high network capital (those in top quintile) invest in and lead more deals, and acquire more new connections and new investments. Examining the performance measures, it is also clear that investors with high existing network capital are more likely to successfully transition their portfolio firms to the next financing stage in any given year, especially from the seed stage to the series-A stage, and are more likely to successfully exit their portfolio firms through an M&A or IPO. These differences are consistent with both the reputation hypothesis and the network capital hypothesis. We attempt to distinguish between these hypotheses in the subsequent multivariate analysis, where we can better control for the differences in existing network capital.

4 Main Empirical Results

4.1 Empirical Methodology

We use a difference-in-differences regression framework to distinguish between the reputation hypothesis and the network capital hypothesis. Our methodology involves the following steps:

First, for all of our success measures, we use the nearest neighbor matching procedure to match each successful angel investor (the "treated" group) with at least 3 unsuccessful angels during the same year (the "control" group) that are similar in terms of degree centrality, number of rounds invested and years of experience. This ensures that we explicitly control for these important observable determinants of success.[15]

Next, for each successful angel and its corresponding control group of unsuccessful angels during the same year, we create three dummy variables indexed $PostSuccess_\tau$, for $\tau \in \{1, 2, 3\}$, to indicate the year τ *after* the success year, and three dummy variables indexed $PreSuccess_\tau$, for $\tau \in \{-3, -2, -1\}$, to indicate the year τ *before* the success year. Then, for each of our success measures, 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.

$$y_{i,t} = \alpha + \sum_{\tau=-3}^{\tau=-1} \beta_\tau \times \text{PreSuccess}_\tau + \sum_{\tau=1}^{\tau=3} \gamma_\tau \times \text{PostSuccess}_\tau + \mu_i + \mu_t + \epsilon_{i,t} \tag{1}$$

In equation (1), $y_{i,t}$ is a measure of the angel's growth in network capital (see Section 2.4). Apart from controlling for observable determinants of success using our matching procedure, we also include angel fixed effects (μ_i) to control for any time-invariant angel characteristics and year fixed effects (μ_t) to control for market-wide factors. The standard errors are robust to heteroskedasticity and are clustered at the angel investor level.

The above specification omits a dummy variable for the year in which a successful angel experiences success, but includes six dummy variables to identify the three years before and three years after the success year. Therefore, the coefficient γ_τ denotes the change in y for the successful

[15]We use a caliper of 0.1 to ensure that the control group is very similar to the treated group in terms of the matching characteristics. As a result of this restriction, we are unable to find matches for 647 out of 3855 instances of *Success*, 422 out of 2,484 instances of *Seed Success*, and 84 out of 492 instances of *Successful Exit*.

angel between the year it experiences success and in year τ 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 growth 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 $\tau \in \{-3, -2, -1\}$).

Note that 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.[16]

Of course, a shortcoming of the matching approach is that we cannot control for any other unobservable differences between the treated group and the control group of angels that may be driving the successful performance as well as growth in network capital, but are uncorrelated with our matching characteristics (degree centrality, number of rounds invested and years of experience). However, we note that any such unobserved factor will likely also lead to differences in the years preceding the success; i.e., it should cause the β_τ coefficient to be positive. Nonetheless, we conduct a variety of alternative specifications to test for the robustness of our results, which are described in Section 5.3.

4.2 Effect of Success on Growth in Network Capital

4.2.1 Effect of Success on New Co-investment Connections

We begin our empirical analysis by examining the effect of success on new co-investment connections formed by the angel investor. Accordingly, we estimate regression (1) with *Ln(1+New Connections)* as the dependent variable, separately for each of the three measures of success.[17]

[16] For example, one concern could be that a large inflow of funds into the angel investor market leads to both successful performance of existing start-ups 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 γ_τ coefficient because it captures the *difference* in the change in the $y-$variable between the two groups.

[17] We add one to *New Connections* before taking the natural logarithm to ensure that the dependent variable in the regression is bounded below by zero.

The results of our estimation are presented in Table 5.

In Panel A, we estimate the regression on the full sample of all successful angels and their corresponding group of unsuccessful angels. We examine the effect of *Success* in column (1), *Seed Success* in column (2), and *Successful Exit* in column (3). The results in column (1) indicate that angels that successfully transition one of their portfolio companies to the next financing 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 $\tau \in \{-3, -2, -1\}$). We obtain similar results when we examine the effect of *Seed Success* in column (2) and *Successful Exit* in column (3), although the effect of *Successful Exit* seems to be weaker than that of *Seed Success*.

Overall, the results in Panel A are consistent with the reputation hypothesis, and indicate that successful performance by a portfolio firm, especially a seed-stage firm, leads to more co-investment connections for the angel investor in the following years. The effects are also economically significant: for instance, 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 9.95 more new co-investment connections compared to his unsuccessful peers over the next three years.

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 (Holmström (1999)). To test this, we divide our angels into two groups each year: angels whose degree centrality is lower than the sample median ("low network capital") and those whose degree centrality exceeds the sample median ("high network capital"). We then estimate the regressions in Panel A separately on these two groups.

These results are presented in Panel B, where columns (1) through (3) correspond to the group with low network capital, and columns (4) through (6) correspond to the group with high network capital. The last row in Panel B reports the $p-$value of the χ^2-test to reject the null hypothesis that the sum of coefficients on the $PostSuccess_\tau$ terms for the low-network-capital group is not statistically different from the corresponding sum for the high-network-capital group. The results in Panel B indicate that, while 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.

4.2.2 Effect of Success on Quality of Connections

Next, we examine the effect of success on the *quality* of an angel's network connections (*Eigenvector Centrality*). To do this, we estimate regression (1) with Δ*Eigenvector Centrality Decile*$_{i,t}$ as the dependent variable, separately for each of the three measures of success. The results of our estimation are presented in Table 6. As in the earlier table, we estimate the regression on the full sample in Panel A, and separately for low-network-capital group and the high-network-capital group in Panel B.

The results in Panel A indicate that quality of an angel's network connections improve significantly in the three years following successful performance, for all three measures of success. In terms of economic significance, the coefficient estimates in column (1) (column (2)) indicate that an angel investor that successfully leads one of his (seed-stage) portfolio companies to the next financing stage (series A stage) improves his *Eigenvector Centrality Decile* by 0.35 (0.24) compared to his unsuccessful peers over the next three years.

The results in Panel B indicate that the effect of successful performance on the quality of network connections is significantly stronger among the group with low network capital (columns (1) through (3)) compared to the group with high existing network capital (columns (4) through (6)).

4.3 Effect of Success on New Deals

An angel investor may grow his network either by inviting new investors to invest in his existing portfolio companies or by investing in new start-up companies. In this section, we examine the effect of successful performance on the angels' ability to generate new investment opportunities, which may arise either because the angel is the lead investor for a new start-up or because the angel is invited to participate in deals lead by other investors. Therefore, we use regression (1) to separately examine the effect of success on total new investments (*New Investments*) and the number of new investments in which the angel is the lead investor (*New Lead Investments*). The results of our estimation are presented in Table 7.

We estimate the regressions on the full sample in Panel A. The dependent variable in columns (1) through (3) is *Ln(1+New Investments)*, whereas the dependent variable in columns (4) through (6) is *Ln(1+New Lead Investments)*. The results in Panel A indicate that, regardless of the measure of success, angels which deliver successful performance are rewarded with more total investment opportunities and more lead investment opportunities relative to their unsuccessful peers in the following three years. In terms of economic significance, the coefficient estimates in column (2) (column (5)) indicate that angels that successfully lead one of their seed-stage portfolio firms to the series A stage invest in (act as lead investors for) 1.19 more (0.53 more) new start-up companies relative to their unsuccessful peers over the next three years.

In Panels B and C, we examine the effect of successful performance on *New Investments* and *New Lead Investments*, respectively, separately for angels with low network capital (columns (1) though (3)) and angels with high network capital (columns (4) through (6)). Once again, the subsample analysis confirms that the effect of successful performance are stronger for angels with low existing network capital, which is consistent with the reputation hypothesis.

4.4 Effect of Success 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 regression (1) with each of these variables separately as the dependent variable.[18] The results of our estimation are presented in Table 8.

We estimate the regressions on the full sample in Panel A. The dependent variable in columns (1) through (3) is *Other Seed Success*. The results indicate that, regardless of the measure of performance, angels that deliver successful performance are more likely than their unsuccessful peers to lead their other seed-stage portfolio companies to the series A stage in the following three years. Similarly, the results in columns (4) through (6) indicate that angels that deliver successful performance are more likely than their unsuccessful peers to see their other portfolio companies receive venture capital financing in the following three years. In terms of economic significance, the coefficient estimates in columns (2) and (5) indicate that, in comparison to their unsuccessful peers, angels that successfully lead one of their seed-stage portfolio firms to the series A stage are 25.6% more likely to lead another seed-stage portfolio company to the series A stage, and 35.8% more likely to lead another portfolio company to venture capital financing over the following three years, respectively.

In Panels B and C, we examine the effect of successful performance on *Other Seed Success* and *VC Financing* separately for angels with low network capital (columns (1) though (3)) and angels with high network capital (columns (4) through (6)). In contrast to our earlier subsample analysis, we find that the effect of successful performance on the performance of other portfolio companies in the angels' portfolio is actually stronger among angels with high network capital. This is partly because, as we showed in the univariate comparison in Table 4, 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. Angels with high network capital are also more likely to have late-stage companies in their portfolio, which are more likely to receive venture capital financing.

[18] Given that we have several indicator variables and investor fixed effects on the right-hand side of equation (1), we estimate a linear probability model instead of a Logit model to avoid the incidental parameter problem (see Neyman and Scott (1948) and Hausman et al. (1984)).

5 Additional Tests and Robustness of Results

5.1 Effect of Success on Angels' Future Career Path

Although most angels operate as individual investors, some go on to form angel groups while others gain employment in VC firms. Angel groups allow individuals to pool their funds, thus allowing them to diversify their risks by investing in more deals, and bargain for better terms with founders while maintaining control over their investments. On the other hand, employment at a VC firm allows angels to graduate to larger deals at later-stage start-ups. In this section, we examine if success affects angels' likelihood of forming angel groups or joining VC firms. To test this, we define dummy variables to identify if angel 'i' forms an angel group in year 't' ($Formed\ Angel\ Group_{i,t}$) or joins a VC firm in year 't' ($Joined\ VC_{i,t}$), and then estimate regression (1) with each of these as the dependent variable.

The results of our estimation are presented in Table 9. The results in columns (1) and (3) indicate that successful angels are more likely to form angel groups relative to their unsuccessful peers in the following three years, although columns (1) and (2) also indicate that two groups differ in their likelihood of forming angel groups even one year prior to the successful performance (positive and significant coefficient on $PreSuccess_{-1}$). Thus, these results are only weakly supportive of the idea that success affects angels' likelihood of forming angel groups. On the other hand, the insignificant coefficients on all the $PostSuccess_{\tau}$ terms in columns (4) through (6) indicate that there is no significant effect of success on angels' likelihood of joining VC firms.

5.2 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 a successful angel will not only attract more followers, but also that more of his followers will co-invest with him. We test this hypothesis using a framework very similar to regression (1); the only difference is that we use one lead term and one lag term, 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 columns (1) through (3) 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.

Next, we examine if success also affects the propensity of an angel's followers to co-invest with him. To test this, we define the following dummy variable 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 columns (4) through (6), we examine how the effect of $Followed_{ij,t}$ on *Co-invested*$_{ij,t}$ varies with 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 $Followed_{ij,t} \times PostSuccess_{+1}$ in all three columns (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.

5.3 Robustness Tests

In this section, we provide a brief description of additional robustness tests which we report in the Internet Appendix to conserve space.

Instrumenting for success: As we noted in Section 4.1, a shortcoming of the matching approach is that we cannot control for any other unobservable differences between the treated group and the control group of angels that may be driving the successful performance as well as growth in network capital, but are uncorrelated with our matching characteristics (degree centrality, number of rounds invested and years of experience). To address this concern, we estimate an instrumental variables regression where we use the number of competing start-ups funded in an angel's industry during the year as an instrument for *Seed Success*. The idea here is that a large number of competing start-ups makes it less likely that the angel's seed-stage portfolio firms progress to the next stage, but is otherwise unrelated to the angels' ability or existing network capital.

The results of the 2SLS estimation are presented in Table IA.1 in the Internet Appendix. The results of the first-stage regression are presented in column (7), and show that *Seed Success* is indeed less likely when *Ln(No. Competing firms funded)* is high. The results of the second-stage regressions for the various outcome variables are presented in columns (1) through (6), and broadly confirm the findings in Section 4, with the exception of column (2) where we fail to detect a significant relation between *Seed Success* and Δ*Eigenvector Centrality Decile*.

Falsification test: Another concern could be that our results are driven by macro trends, such as large inflow of funds into the angel investor market, that lead to both successful performance of existing start-ups as well as increase in future deal flow for the angel investors. We note that our empirical specification should ameliorate such concerns because such a macro trend should affect both the successful angel and the control group of unsuccessful angels, and hence, cannot drive the γ_τ coefficient which captures the *difference* in the change in the $y-$variable between the two groups. Nonetheless, to further address this concern, 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 *PlaceboSuccess*$= 1$ 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.2 in the Internet Appendix. As can be seen, the γ_τ coefficients on the $PostPlaceboSuccess_\tau$ terms are all insignificant, which shows that our results in Section 4 are capturing the causal effect of successful performance.

Dealing with multiple successes: One concern with the diff-in-diff specification (1) is that if an investor experiences multiple successes within a gap of a few years, then it complicates the identification of the causal effect of success on y, because a *PostSuccess* term corresponding to the first success may overlap with a $PreSuccess$ term on account of the second success. We note that this is not a serious concern in our setting because only a few investors experience more than one success during the 2005–2014 time period. Nonetheless, to alleviate this concern, we estimate equation (1) using only the first *Seed Success* of every angel investor, and show that our results are mostly unchanged (see Table IA.3 in the Internet Appendix).

Other tests: Next, to address the Bertrand et al. (2004) critique of difference-in-differences estimators, for each 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 examine how the key outcome variables change after treatment for the treated group vs. the control group of angels (see Table IA.4 in the Internet Appendix), and find that the results are qualitatively similar to those in Section 4.

Recall that we conducted our analysis only on angel investors that invested in at least 3 portfolio companies during the period 2005–2014. The idea behind this restriction was to eliminate angel investors that make one-off investments in start-ups founded by their family members or friends. We now ease this restriction, and repeat all our tests with *Seed Success* as the measure of success after including all individual angels in the analysis. The results are presented in Table IA.5, and show all our main results hold even without the restriction.

6 Conclusion

We use angel investor networks to examine the causal effect of successful performance on the network connectedness of individual angel investors. To this end, we assemble a unique dataset of 4,108 individual angels who invested in 12,215 portfolio firms over the period 2005–2014. We find that angel investors that successfully move one of their portfolio companies to the next financing stage, especially from the seed stage to the series A stage, are rewarded with more new co-investment connections and see an improvement in the quality 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.

The improvement in angels' network centrality following successful performance also has a knock-on effect on the performance of the angels' other portfolio companies. In particular, we find that angels that deliver successful performance are more likely than their unsuccessful peers to lead their other seed-stage portfolio companies to the series A stage in the following three years. That is, success begets more success. Finally, successful performance 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 capital of angel investors.

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Figure 1 Sample Investor Profile on CrunchBase

The figure below is an excerpt of Alexis Ohanian's (Co-founder of Reddit and most active angel in 2014) profile on CrunchBase.

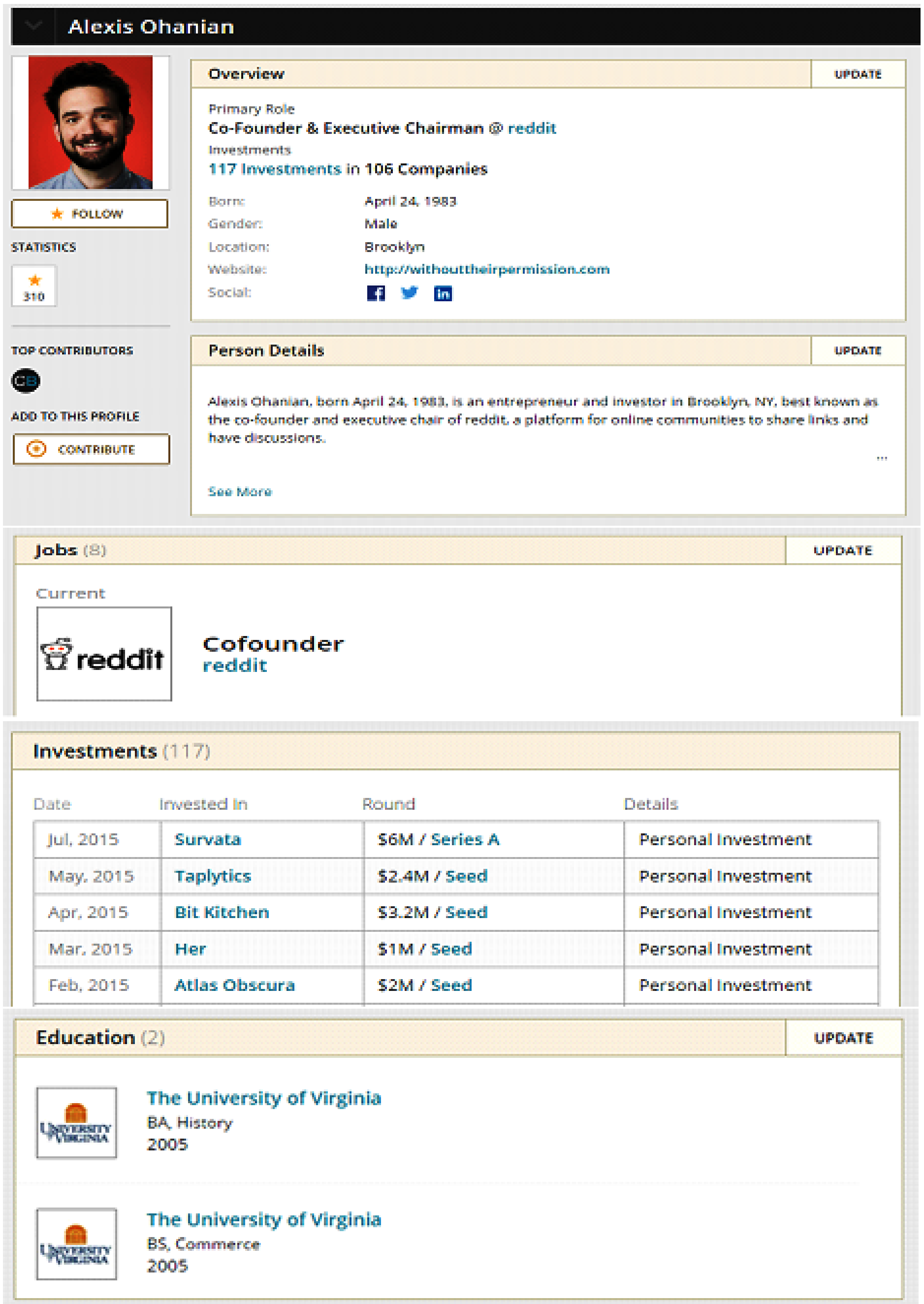


Figure 2 Sample start-up Profile on CrunchBase

The figure below is an excerpt from UBER's profile on CrunchBase.

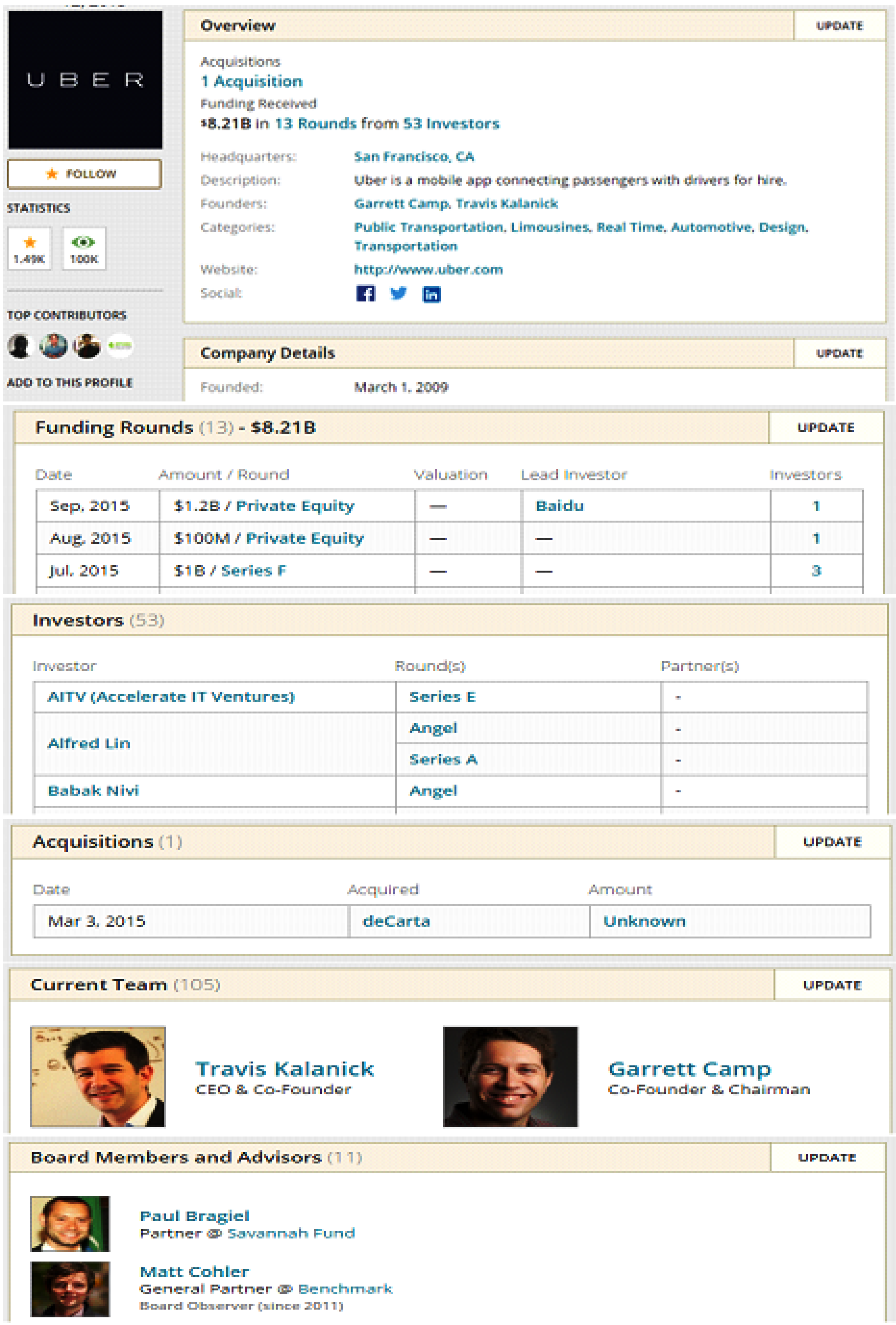


Table 1 Year-Wise Distribution of Start-ups and Funding Rounds

This table presents a year-wise summary of the number of start-ups, funding rounds and individual angels in our sample. We only include individual angels that invested in at least three portfolio firms by December 2014; *Angels* is the number of individual angels that satisfy this requirement. *Start-ups* 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. *Funds Raised* is the total amount raised (in billion dollars) by the start-ups in all the funding rounds combined, both from the individual angels in our sample as well as from other investors. *Acquired/IPO* is the number of start-ups in the angels' portfolios that exited via IPO or acquisition.

Year	Start-ups	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

Table 2 Survival and Transition Probabilities

Panel A of this table presents the average unconditional probability (expressed as a percentage) 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 list the probabilities of making a successful transition within 1, 2 and 3 years, respectively.

Panel A: Proportion of total firms surviving at each stage

	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

Panel B: Probability of transition to next funding stage

	$t <= May\,2015$	$t <= 1$	$t <= 2$	$t <= 3$
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

Table 3 Summary Statistics

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 panel 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.

			Percentile Distribution			
Variable	Mean	Stdev.	10^{th}	50^{th}	90^{th}	N
Angel Characteristics:						
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
Rounds lead	0.993	3.572	0.000	0.000	2.000	25868
Degree Centrality	17.367	34.934	1.000	7.000	42.000	25868
New connections	12.066	22.585	1.000	6.000	27.000	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
$\Delta(Eigenvector\ decile)$	0.184	1.438	-1.000	0.000	2.000	21964
New investments	1.811	3.422	0.000	1.000	5.000	25868
New lead investments	0.901	3.181	0.000	0.000	2.000	25868
Experience	5.118	3.374	0.980	4.000	7.500	25868
Performance Measures:						
Success	0.149	0.357	0.000	0.000	1.000	25868
No. of successes	0.254	1.204	0.000	0.000	1.000	25868
Seed Success	0.096	0.294	0.000	0.000	0.000	25868
No. of seed Successes	0.168	0.668	0.000	0.000	0.000	25868
Successful Exit	0.019	0.139	0.000	0.000	0.000	25868
No. of successful exits	0.040	0.359	0.000	0.000	0.000	25868

Table 4 Univariate Comparison by Degree Centrality

This table presents a univariate comparison of the mean values of the key variables in our angel-year panel across the five sub-samples that correspond to the five quintiles of *Degree Centrality*, where "Low (Q1)" and "High (Q5)" correspond to the lowest and the highest quintile, respectively. The last column lists the difference between the "High" and "Low" groups, along with the corresponding $t-$statistic (in brackets). Each observation in the panel data corresponds to an angel-year combination. The panel 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.

Variable	Low(Q1)	Q2	Q3	Q4	High(Q5)	High-Low [t-stat]
Angel Characteristics:						
$Degree\ Centrality_{t-1}$	0.219	3.389	7.86	15.913	61.614	61.394
						[69.668]
$Eigenvector\ Centrality_{t-1}$	3.004	3.907	4.986	6.439	11.614	8.610
						[31.816]
$\Delta(Eigenvector\ Centrality\ decile)_{t-1}$	0.753	0.584	0.131	-0.094	-0.162	-0.915
						[-27.307]
Start-ups invested	1.809	2.005	2.354	3.843	11.825	10.016
						[16.649]
Rounds Invested	2.036	2.441	3.048	5.135	17.425	15.388
						[17.666]
Rounds lead	1.538	1.552	1.588	2.089	8.778	7.240
						[10.516]
New Connections	6.438	6.12	7.32	10.331	28.006	21.568
						[28.508]
New Investments	1.194	1.198	1.201	1.75	4.799	3.606
						[17.954]
New Lead Investments	0.666	0.498	0.469	0.683	2.499	1.833
						[11.857]
Performance Measures:						
Success	0.111	0.141	0.133	0.169	0.187	0.076
						[14.385]
No. of seed successes	0.174	0.238	0.188	0.313	0.355	0.181
						[5.833]
Seed Success	0.081	0.089	0.075	0.096	0.136	0.055
						[10.164]
No. of seed successes	0.123	0.142	0.109	0.164	0.267	0.143
						[8.194]
Successful Exit	0.014	0.019	0.022	0.022	0.025	0.011
						[4.566]
No. of successful exits	0.022	0.025	0.038	0.036	0.042	0.021
						[2.796]

Table 5 Effect of Success on New Co-investment Connections

This table reports the results of regressions investigating the effect of successful performance on angels' ability to generate new co-investment connections. The measure of successful performance is *Success* in column (1), *Seed Success* in column (2), and *Successful Exit* in column (3). For each measure of success, we use the nearest neighbor matching procedure to match each successful angel-year observation (the "treated" group) with at least three unsuccessful angels during the same year that are similar in terms of *Degree Centrality*, *Rounds Invested*, and *Experience* (the "control" group). For each treated angel-year observation and its corresponding control group, the dummy variables $PostSuccess_\tau$ identify the year $\tau \in \{1, 2, 3\}$ *after* the success year, whereas the dummy variables $PreSuccess_\tau$ identify the year $\tau \in \{-3, -2, -1\}$ *before* the success year. We then estimate the following difference-in-differences regression on all the angel-year observations in the treated and control groups.

$$Ln(1 + New\ Connections)_{i,t} = \alpha + \sum_{\tau=-3}^{\tau=-1} \beta_\tau \times \text{PreSuccess}_\tau + \sum_{\tau=1}^{\tau=3} \gamma_\tau \times \text{PostSuccess}_\tau + \mu_i + \mu_t + \epsilon_{i,t}$$

We include angel fixed effects (μ_i) and year fixed effects (μ_t) in all specifications. We estimate the regression on the entire sample in Panel A. In Panel B, we divide our sample into two categories based on whether the angels' *Degree Centrality* is below ("Low network capital") or above ("High network capital") the sample median during the year. We then estimate the regression in Panel A separately on these two groups in Panel B. The last row in Panel B reports the $p-$value of the χ^2-test to reject the null hypothesis that $\sum_{\tau=1}^{\tau=3} \gamma_\tau$ for the group with low network capital is not statistically different from the corresponding sum for group with high network capital.
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: Full sample

	$Ln(1 + New\ Connections_{i,t})$		
	$Success_{i,t}$ (1)	$Seed\ Success_{i,t}$ (2)	$Successful\ Exit_{i,t}$ (3)
$PreSuccess_{-3}$	-0.027	-0.052	-0.051
	(0.037)	(0.034)	(0.036)
$PreSuccess_{-2}$	0.034	0.057	0.053
	(0.037)	(0.036)	(0.039)
$PreSuccess_{-1}$	0.054	0.023	0.060
	(0.033)	(0.033)	(0.037)
$PostSuccess_{+1}$	0.281***	0.283***	0.148*
	(0.040)	(0.047)	(0.087)
$PostSuccess_{+2}$	0.266***	0.279***	0.140
	(0.042)	(0.050)	(0.097)
$PostSuccess_{+3}$	0.079**	0.162***	0.017
	(0.040)	(0.049)	(0.090)
Observations	23936	20102	23198
Adj. R^2	0.150	0.142	0.117
Investor & Year F.E.	Yes	Yes	Yes

Panel B: Low vs. High network capital angels

	$Ln(1 + New\,Connections_{i,t})$					
	Low network capital angels			High network capital angels		
	$Success_{i,t}$ (1)	$Seed\,Success_{i,t}$ (2)	$Successful\,Exit_{i,t}$ (3)	$Success_{i,t}$ (4)	$Seed\,Success_{i,t}$ (5)	$Successful\,Exit_{i,t}$ (6)
$PreSuccess_{-3}$	-0.074	-0.069	-0.068	-0.036	-0.038	-0.066
	(0.049)	(0.043)	(0.046)	(0.062)	(0.065)	(0.064)
$PreSuccess_{-2}$	0.008	0.042	0.041	0.098	0.098	0.104
	(0.048)	(0.046)	(0.051)	(0.060)	(0.062)	(0.064)
$PreSuccess_{-1}$	0.073	0.065	0.050	0.033	0.017	0.065
	(0.044)	(0.043)	(0.049)	(0.069)	(0.097)	(0.114)
$PostSuccess_{+1}$	0.329***	0.285***	0.209*	0.189***	0.208***	0.197***
	(0.052)	(0.058)	(0.123)	(0.053)	(0.054)	(0.056)
$PostSuccess_{+2}$	0.288***	0.319***	0.207	0.246***	0.129	0.062
	(0.055)	(0.061)	(0.139)	(0.071)	(0.098)	(0.120)
$PostSuccess_{+3}$	0.072	0.130**	0.009	0.032	0.014	0.028
	(0.051)	(0.059)	(0.127)	(0.074)	(0.104)	(0.116)
Observations	11988	9950	11943	11948	10152	11255
Adj. R^2	0.165	0.162	0.139	0.105	0.087	0.107
Investor & Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
$\sum_{\tau=1}^{\tau=3} \gamma_{\tau,Low} = \sum_{\tau=1}^{\tau=3} \gamma_{\tau,High} : p - value$	0.000	0.000	0.000			

Table 6 Effect of Success on Quality of Connections

This table reports the results of regressions investigating the effect of successful performance on the improvement in the angels' quality of connections. The measure of successful performance is *Success* in column (1), *Seed Success* in column (2), and *Successful Exit* in column (3). For each measure of success, we use the nearest neighbor matching procedure to match each successful angel-year observation (the "treated" group) with at least three unsuccessful angels during the same year that are similar in terms of *Degree Centrality*, *Rounds Invested*, and *Experience* (the "control" group). For each treated angel-year observation and its corresponding control group, the dummy variables $PostSuccess_\tau$ identify the year $\tau \in \{1,2,3\}$ *after* the success year, whereas the dummy variables $PreSuccess_\tau$ identify the year $\tau \in \{-3,-2,-1\}$ *before* the success year. We then estimate the following difference-in-differences regression on all the angel-year observations in the treated and control groups.

$$\Delta(Eigenvector\ Centrality\ Decile)_{i,t} = \alpha + \sum_{\tau=-3}^{\tau=-1} \beta_\tau \times \text{PreSuccess}_\tau + \sum_{\tau=1}^{\tau=3} \gamma_\tau \times \text{PostSuccess}_\tau + \mu_i + \mu_t + \epsilon_{i,t}$$

We include angel fixed effects (μ_i) and year fixed effects (μ_t) in all specifications. We estimate the regression on the entire sample in Panel A. In Panel B, we divide our sample into two categories based on whether the angels' *Degree Centrality* is below ("Low network capital") or above ("High network capital") the sample median during the year. We then estimate the regression in Panel A separately on these two groups in Panel B. The last row in Panel B reports the $p-$value of the χ^2-test to reject the null hypothesis that $\sum_{\tau=1}^{\tau=3} \gamma_\tau$ for the group with low network capital is not statistically different from the corresponding sum for group with high network capital.
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: Full sample

	$\Delta(Eigenvector\ Centrality\ Decile)_{i,t}$		
	$Success_{i,t}$ (1)	$Seed\ Success_{i,t}$ (2)	$Successful\ Exit_{i,t}$ (3)
$PreSuccess_{-3}$	-0.017	-0.016	-0.009
	(0.014)	(0.014)	(0.014)
$PreSuccess_{-2}$	0.020	0.019	0.005
	(0.014)	(0.016)	(0.016)
$PreSuccess_{-1}$	0.024	0.022	0.025
	(0.016)	(0.013)	(0.015)
$PostSuccess_{+1}$	0.130***	0.078***	0.077**
	(0.015)	(0.019)	(0.035)
$PostSuccess_{+2}$	0.128***	0.069***	0.022
	(0.016)	(0.020)	(0.039)
$PostSuccess_{+3}$	0.092***	0.091***	0.088**
	(0.016)	(0.019)	(0.036)
Observations	21964	19934	21197
Adj. R^2	0.082	0.039	0.019
Investor & Year F.E.	Yes	Yes	Yes

Panel B: Low vs. High network capital angels

	$\Delta(Eigenvector\ Centrality\ Decile)_{i,t}$					
	Low network capital angels			High network capital angels		
	$Success_{i,t}$	$Seed\ Success_{i,t}$	$Successful\ Exit_{i,t}$	$Success_{i,t}$	$Seed\ Success_{i,t}$	$Successful\ Exit_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$PreSuccess_{-3}$	0.012	0.016	-0.006	-0.052	-0.058	-0.026
	(0.015)	(0.013)	(0.014)	(0.036)	(0.038)	(0.037)
$PreSuccess_{-2}$	0.022	0.021	0.026	-0.032	-0.029	-0.047
	(0.014)	(0.014)	(0.016)	(0.035)	(0.036)	(0.037)
$PreSuccess_{-1}$	0.028	0.030	0.041	0.040	0.046	0.044
	(0.020)	(0.019)	(0.025)	(0.031)	(0.031)	(0.033)
$PostSuccess_{+1}$	0.113***	0.060***	0.076**	0.049	0.071	0.083
	(0.015)	(0.018)	(0.038)	(0.040)	(0.057)	(0.067)
$PostSuccess_{+2}$	0.120***	0.068***	0.060	0.131***	0.120**	0.001
	(0.016)	(0.019)	(0.043)	(0.041)	(0.057)	(0.070)
$PostSuccess_{+3}$	0.111***	0.061***	0.087**	0.021	0.035	0.097
	(0.015)	(0.018)	(0.039)	(0.043)	(0.060)	(0.068)
Observations	11001	9867	10913	10963	10067	10284
Adj. R^2	0.127	0.073	0.049	0.027	0.020	0.021
Investor & Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
$\sum_{\tau=1}^{\tau=3} \gamma_{\tau,Low} = \sum_{\tau=1}^{\tau=3} \gamma_{\tau,High} : p-value$	0.068	0.019	0.000			

Table 7 Effect of Success on New Investment Opportunities

This table reports the results of regressions investigating the effect of successful performance on angels' ability to generate new investment opportunities, both as a lead investor and as a participant. The measure of successful performance is *Success* in columns (1) and (4), *Seed Success* in columns (2) and (5), and *Successful Exit* in columns (3) and (6) . For each measure of success, we use the nearest neighbor matching procedure to match each successful angel-year observation (the "treated" group) with at least three unsuccessful angels during the same year that are similar in terms of *Degree Centrality*, *Rounds Invested*, and *Experience* (the "control" group). For each treated angel-year observation and its corresponding control group, the dummy variables $PostSuccess_\tau$ identify the year $\tau \in \{1, 2, 3\}$ *after* the success year, whereas the dummy variables $PreSuccess_\tau$ identify the year $\tau \in \{-3, -2, -1\}$ *before* the success year. We then estimate the following difference-in-differences regression on all the angel-year observations in the treated and control groups.

$$Ln(1 + y_{i,t}) = \alpha + \sum_{\tau=-3}^{\tau=-1} \beta_\tau \times \text{PreSuccess}_\tau + \sum_{\tau=1}^{\tau=3} \gamma_\tau \times \text{PostSuccess}_\tau + \mu_i + \mu_t + \epsilon_{i,t}$$

The variable y is *New Investments* in columns (1) to (3), and *New Lead Investments* in columns (4) through (6). We include angel fixed effects (μ_i) and year fixed effects (μ_t) in all specifications. We estimate the regression on the entire sample in Panel A. In Panels B and C, we divide our sample into two categories based on whether the angels' *Degree Centrality* is below ("Low network capital") or above ("High network capital") the sample median during the year. We then estimate the regression with $Ln(1 + \textit{New Investments}_{i,t})$ as the dependent variable separately on these two groups in Panel B, and the regression with $Ln(1 + \textit{New Lead Investments}_{i,t})$ as the dependent variable separately on these two groups in Panel C. The last rows in Panels B and C reports the $p-$value of the χ^2-test to reject the null hypothesis that $\sum_{\tau=1}^{\tau=3} \gamma_\tau$ for the group with low network capital is not statistically different from the corresponding sum for group with high network capital.
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: Full sample

	$Ln(1 + New\ Investments_{i,t})$			$Ln(1 + New\ Lead\ Investments_{i,t})$		
	$Success_{i,t}$ (1)	$Seed\ Success_{i,t}$ (2)	$Successful\ Exit_{i,t}$ (3)	$Success_{i,t}$ (4)	$Seed\ Success_{i,t}$ (5)	$Successful\ Exit_{i,t}$ (6)
$PreSuccess_{-3}$	-0.026	-0.023	-0.033	-0.031	-0.022	-0.030
	(0.024)	(0.022)	(0.023)	(0.021)	(0.019)	(0.020)
$PreSuccess_{-2}$	-0.034	-0.035	-0.036	-0.021	-0.016	0.038*
	(0.024)	(0.024)	(0.026)	(0.020)	(0.020)	(0.022)
$PreSuccess_{-1}$	0.039	0.019	0.038	0.032	0.024	0.022
	(0.024)	(0.022)	(0.024)	(0.022)	(0.018)	(0.020)
$PostSuccess_{+1}$	0.209***	0.244***	0.155***	0.137***	0.221***	0.127***
	(0.026)	(0.031)	(0.057)	(0.022)	(0.026)	(0.048)
$PostSuccess_{+2}$	0.219***	0.210***	0.368***	0.168***	0.191***	0.358***
	(0.027)	(0.033)	(0.063)	(0.023)	(0.028)	(0.054)
$PostSuccess_{+3}$	0.098***	0.139***	0.135**	0.109***	0.126***	0.165***
	(0.026)	(0.032)	(0.059)	(0.022)	(0.027)	(0.050)
Observations	23936	20102	23198	23936	20102	23198
Adj. R^2	0.195	0.188	0.165	0.143	0.151	0.121
Investor & Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Effect of success on new investments

	$Ln(1 + New\ Investments_{i,t})$					
	Low network capital angels			High network capital angels		
	$Success_{i,t}$	$Seed\ Success_{i,t}$	$Successful\ Exit_{i,t}$	$Success_{i,t}$	$Seed\ Success_{i,t}$	$Successful\ Exit_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$PreSuccess_{-3}$	-0.032	-0.031	-0.034	-0.066	-0.063	-0.054
	(0.031)	(0.028)	(0.029)	(0.046)	(0.048)	(0.046)
$PreSuccess_{-2}$	-0.019	-0.018	-0.026	-0.063	-0.069	-0.059
	(0.031)	(0.029)	(0.033)	(0.045)	(0.046)	(0.046)
$PreSuccess_{-1}$	0.045	0.053*	-0.008	0.061	0.062	-0.055
	(0.028)	(0.028)	(0.032)	(0.039)	(0.040)	(0.040)
$PostSuccess_{+1}$	0.233***	0.234***	0.149*	0.026	0.118	0.132
	(0.033)	(0.037)	(0.079)	(0.051)	(0.072)	(0.082)
$PostSuccess_{+2}$	0.233***	0.239***	0.264***	0.147***	0.05	0.495***
	(0.035)	(0.039)	(0.089)	(0.053)	(0.073)	(0.086)
$PostSuccess_{+3}$	0.079**	0.117***	0.027	0.091*	0.098	0.307***
	(0.032)	(0.037)	(0.082)	(0.055)	(0.077)	(0.083)
Observations	11988	9950	11943	11948	10152	11255
Adj. R^2	0.216	0.219	0.189	0.106	0.085	0.158
Investor & Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
$\sum_{\tau=1}^{\tau=3} \gamma_{\tau,Low} = \sum_{\tau=1}^{\tau=3} \gamma_{\tau,High} : p - value$	0.000	0.000	0.001			

Panel C: Effect of success on new lead investments

	$Ln(1 + New\ Lead\ Investments_{i,t})$					
	Low network capital angels			High network capital angels		
	$Success_{i,t}$	$Seed\ Success_{i,t}$	$Successful\ Exit_{i,t}$	$Success_{i,t}$	$Seed\ Success_{i,t}$	$Successful\ Exit_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$PreSuccess_{-3}$	-0.041	-0.039	-0.042	-0.062	-0.050	-0.061
	(0.027)	(0.024)	(0.025)	(0.038)	(0.040)	(0.038)
$PreSuccess_{-2}$	-0.016	-0.006	-0.045	-0.042	-0.052	-0.027
	(0.027)	(0.025)	(0.028)	(0.037)	(0.038)	(0.038)
$PreSuccess_{-1}$	0.039	0.040	0	-0.003	-0.007	-0.050
	(0.025)	(0.024)	(0.027)	(0.032)	(0.033)	(0.033)
$PostSuccess_{+1}$	0.151***	0.228***	0.127*	0.027	0.105*	0.081
	(0.029)	(0.031)	(0.068)	(0.042)	(0.060)	(0.067)
$PostSuccess_{+2}$	0.177***	0.208***	0.244***	0.068	0.008	0.527***
	(0.030)	(0.034)	(0.077)	(0.043)	(0.060)	(0.071)
$PostSuccess_{+3}$	0.091***	0.112***	-0.050	0.135***	0.131**	0.345***
	(0.028)	(0.032)	(0.071)	(0.045)	(0.064)	(0.068)
Observations	11988	9950	11943	11948	10152	11255
Adj. R^2	0.159	0.178	0.139	0.063	0.049	0.133
Investor & Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
$\sum_{\tau=1}^{\tau=3} \gamma_{\tau,Low} = \sum_{\tau=1}^{\tau=3} \gamma_{\tau,High} : p-value$	0.000	0.000	0.005			

Table 8 Effect of Success on Angel's Other Portfolio Companies

This table reports the results of regressions investigating the effect of successful performance on the performance of angels' other portfolio companies. The measure of successful performance is *Success* in columns (1) and (4), *Seed Success* in columns (2) and (5), and *Successful Exit* in columns (3) and (6). For each measure of success, we use the nearest neighbor matching procedure to match each successful angel-year observation (the "treated" group) with at least three unsuccessful angels during the same year that are similar in terms of *Degree Centrality*, *Rounds Invested*, and *Experience* (the "control" group). For each treated angel-year observation and its corresponding control group, the dummy variables $PostSuccess_\tau$ identify the year $\tau \in \{1, 2, 3\}$ *after* the success year, whereas the dummy variables $PreSuccess_\tau$ identify the year $\tau \in \{-3, -2, -1\}$ *before* the success year. We then estimate the following difference-in-differences regression on all the angel-year observations in the treated and control groups.

$$y_{i,t} = \alpha + \sum_{\tau=-3}^{\tau=-1} \beta_\tau \times \text{PreSuccess}_\tau + \sum_{\tau=1}^{\tau=3} \gamma_\tau \times \text{PostSuccess}_\tau + \mu_i + \mu_t + \epsilon_{i,t}$$

The variable y is *Other Seed Success* in columns (1) to (3), and *VC Financing* in columns (4) to (6). We include angel fixed effects (μ_i) and year fixed effects (μ_t) in all specifications. We estimate the regression on the entire sample in Panel A. In Panels B and C, we divide our sample into two categories based on whether the angels' *Degree Centrality* is below ("Low network capital") or above ("High network capital") the sample median during the year. We then estimate the regression with $\textit{Other Seed Success}_{i,t}$ as the dependent variable separately on these two groups in Panel B, and the regression with $\textit{VC Financing}_{i,t}$ as the dependent variable separately on these two groups in Panel C. The last rows in Panels B and C reports the $p-$value of the χ^2-test to reject the null hypothesis that $\sum_{\tau=1}^{\tau=3} \gamma_\tau$ for the group with low network capital is not statistically different from the corresponding sum for group with high network capital.
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: Full sample

	Other Seed Success$_{i,t}$			*VC Financing*$_{i,t}$		
	$Success_{i,t}$	$Seed\ Success_{i,t}$	$Successful\ Exit_{i,t}$	$Success_{i,t}$	$Seed\ Success_{i,t}$	$Successful\ Exit_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$PreSuccess_{-3}$	0.007	0.012	0.004	-0.004	-0.003	-0.003
	(0.005)	(0.008)	(0.004)	(0.003)	(0.003)	(0.002)
$PreSuccess_{-2}$	0.001	0.003	0.008	0.000	0.003	0.008
	(0.005)	(0.007)	(0.005)	(0.002)	(0.003)	(0.006)
$PreSuccess_{-1}$	0.005	-0.002	0.004	0.003	0.004	0.033***
	(0.004)	(0.007)	(0.004)	(0.002)	(0.003)	(0.004)
$PostSuccess_{+1}$	0.045***	0.095***	0.024***	0.071***	0.080***	0.127***
	(0.005)	(0.007)	(0.004)	(0.003)	(0.004)	(0.004)
$PostSuccess_{+2}$	0.049***	0.100***	0.036***	0.206***	0.184***	0.154***
	(0.005)	(0.007)	(0.006)	(0.005)	(0.005)	(0.007)
$PostSuccess_{+3}$	0.036***	0.061***	0.060***	0.112***	0.094***	0.356***
	(0.004)	(0.007)	(0.007)	(0.005)	(0.007)	(0.015)
Observations	23936	20102	23198	23936	20102	23198
Adj. R^2	0.275	0.291	0.294	0.275	0.243	0.212
Investor & Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Effect of Success an angel's other seed-stage portfolio firms

	$Other\ Seed\ Success_{i,t}$					
	Low network capital angels			High network capital angels		
	$Success_{i,t}$ (1)	$Seed\ Success_{i,t}$ (2)	$Successful\ Exit_{i,t}$ (3)	$Success_{i,t}$ (4)	$Seed\ Success_{i,t}$ (5)	$Successful\ Exit_{i,t}$ (6)
$PreSuccess_{-3}$	-0.007	-0.011	-0.010	-0.007	-0.012	-0.008*
	(0.008)	(0.012)	(0.006)	(0.006)	(0.010)	(0.005)
$PreSuccess_{-2}$	-0.004	-0.012	0.010	-0.000	-0.012	-0.002
	(0.008)	(0.011)	(0.007)	(0.006)	(0.010)	(0.007)
$PreSuccess_{-1}$	0.009	-0.006	0.009	-0.008	-0.015	0.005
	(0.007)	(0.009)	(0.006)	(0.006)	(0.009)	(0.005)
$PostSuccess_{+1}$	0.024***	0.059***	0.010	0.034***	0.079***	0.013**
	(0.006)	(0.010)	(0.009)	(0.006)	(0.010)	(0.005)
$PostSuccess_{+2}$	0.011*	0.061***	0.005	0.061***	0.109***	0.020***
	(0.006)	(0.011)	(0.014)	(0.006)	(0.010)	(0.006)
$PostSuccess_{+3}$	0.015**	0.047***	0.038*	0.031***	0.061***	0.041***
	(0.007)	(0.011)	(0.020)	(0.005)	(0.009)	(0.007)
Observations	11988	9950	11943	11948	10152	11255
$Adj.\ R^2$	0.346	0.351	0.386	0.245	0.258	0.267
Investor & Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
$\sum_{\tau=1}^{\tau=3} \gamma_{\tau,Low} = \sum_{\tau=1}^{\tau=3} \gamma_{\tau,High} : p-value$	0.002	0.000	0.069			

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

	$VC\ Financing_{i,t}$					
	Low network capital angels			High network capital angels		
	$Success_{i,t}$ (1)	$Seed\ Success_{i,t}$ (2)	$Successful\ Exit_{i,t}$ (3)	$Success_{i,t}$ (4)	$Seed\ Success_{i,t}$ (5)	$Successful\ Exit_{i,t}$ (6)
$PreSuccess_{-3}$	0.000	0.001	-0.000	-0.004	-0.021***	-0.007*
	(0.001)	(0.000)	(0.000)	(0.005)	(0.008)	(0.004)
$PreSuccess_{-2}$	-0.000	-0.001	-0.000	0.006	0.012	-0.005
	(0.001)	(0.001)	(0.000)	(0.004)	(0.007)	(0.005)
$PreSuccess_{-1}$	0.000	0.000	0.001	0.008	0.010	0.097***
	(0.001)	(0.000)	(0.001)	(0.005)	(0.006)	(0.007)
$PostSuccess_{+1}$	0.000	0.000	0.000	0.106***	0.139***	0.149***
	(0.000)	(0.000)	(0.000)	(0.006)	(0.008)	(0.007)
$PostSuccess_{+2}$	0.000	0.000	0.000	0.279***	0.291***	0.096***
	(0.000)	(0.000)	(0.000)	(0.007)	(0.009)	(0.010)
$PostSuccess_{+3}$	0.000	0.001***	0.002***	0.100***	0.111***	0.315***
	(0.000)	(0.000)	(0.000)	(0.008)	(0.012)	(0.019)
Observations	11988	9950	11943	11948	10152	11255
$Adj.\ R^2$	0.198	0.228	0.251	0.298	0.272	0.259
Investor & Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
$\sum_{\tau=1}^{\tau=3} \gamma_{\tau,Low} = \sum_{\tau=1}^{\tau=3} \gamma_{\tau,High} : p-value$	0.000	0.000	0.000			

Table 9 Effect of Success on Angel's Future Career Path

This table reports the results of regressions investigating the effect of successful performance on angels' future career path, in terms of their propensity to form angel groups or join venture capital firms. The measure of successful performance is *Success* in column (1), *Seed Success* in column (2), and *Successful Exit* in column (3). For each measure of success, we use the nearest neighbor matching procedure to match each successful angel-year observation (the "treated" group) with at least three unsuccessful angels during the same year that are similar in terms of *Degree Centrality*, *Rounds Invested*, and *Experience* (the "control" group). For each treated angel-year observation and its corresponding control group, the dummy variables $\textit{PostSuccess}_\tau$ identify the year $\tau \in \{1, 2, 3\}$ *after* the success year, whereas the dummy variables $\textit{PreSuccess}_\tau$ identify the year $\tau \in \{-3, -2, -1\}$ *before* the success year. We then estimate the following difference-in-differences regression on all the angel-year observations in the treated and control groups.

$$y_{i,t} = \alpha + \sum_{\tau=-3}^{\tau=-1} \beta_\tau \times \text{PreSuccess}_\tau + \sum_{\tau=1}^{\tau=3} \gamma_\tau \times \text{PostSuccess}_\tau + \mu_i + \mu_t + \epsilon_{i,t}$$

The variable y is *Formed Angel Group* in columns (1) to (3), and *Joined VC* in columns (4) to (6). We include angel fixed effects (μ_i) and year fixed effects (μ_t) in all specifications. We estimate the regression on the entire sample in Panel A. In Panels B and C, we divide our sample into two categories based on whether the angels' *Degree Centrality* is below ("Low network capital") or above ("High network capital") the sample median during the year. We then estimate the regression with $\textit{Formed Angel Group}_{i,t}$ as the dependent variable separately on these two groups in Panel B, and the regression with $\textit{Joined VC}_{i,t}$ as the dependent variable separately on these two groups in Panel C. The last rows in Panels B and C reports the $p-$value of the χ^2-test to reject the null hypothesis that $\sum_{\tau=1}^{\tau=3} \gamma_\tau$ for the group with low network capital is not statistically different from the corresponding sum for group with high network capital.
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.

	$Formed\ Angel\ Group_{i,t}$			$Joined\ VC_{i,t}$		
	$Success_{i,t}$ (1)	$Seed\ Success_{i,t}$ (2)	$Successful\ Exit_{i,t}$ (3)	$Success_{i,t}$ (4)	$Seed\ Success_{i,t}$ (5)	$Successful\ Exit_{i,t}$ (6)
$PreSuccess_{-3}$	-0.004	-0.004	0.002	0.001	-0.004	0.001
	(0.005)	(0.009)	(0.003)	(0.003)	(0.003)	(0.002)
$PreSuccess_{-2}$	0.005	0.011	-0.001	-0.003	0.005	-0.001
	(0.005)	(0.007)	(0.003)	(0.003)	(0.004)	(0.002)
$PreSuccess_{-1}$	0.018***	0.014**	-0.001	0.003	0.004	0.003
	(0.004)	(0.006)	(0.003)	(0.002)	(0.003)	(0.002)
$PostSuccess_{+1}$	0.011***	0.016***	0.005	0.000	0.000	0.003
	(0.003)	(0.005)	(0.003)	(0.002)	(0.003)	(0.002)
$PostSuccess_{+2}$	0.005	0.006	0.007*	0.002	0.003	0.001
	(0.003)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)
$PostSuccess_{+3}$	0.016***	0.016***	0.008	0.001	0.001	0.003
	(0.003)	(0.005)	(0.005)	(0.002)	(0.003)	(0.003)
Observations	23936	20102	23198	23936	20102	23198
$Adj.\ R^2$	0.132	0.120	0.144	0.304	0.296	0.320
Investor & Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Table 10 Effect of Success on Angels' "Follower" Networks

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 *Success* in columns (1) and (4), *Seed Success* in columns (2) and (5), and *Successful Exit* in columns (3) and (6). For each measure of success, we use the nearest neighbor matching procedure to match each successful angel-year observation (the "treated" group) with at least three unsuccessful angels during the same year that are similar in terms of *Degree Centrality*, *Rounds Invested*, and *Experience* (the "control" group). For each treated angel-year observation and its corresponding control group, the dummy variables $PostSuccess_{+1}$ and $PreSuccess_{-1}$ identify the year after and before the success year, respectively.
In columns (1) through (3), we estimate the following difference-in-differences regression on all the angel-year observations in the treated and control groups, where $Followers_{i,t}$ is the number of followers for angel i in year t on the AngelList platform.

$$Ln(1 + Followers_{i,t}) = \alpha + \beta \times \text{PreSuccess}_{-1} + \gamma \times \text{PostSuccess}_{+1} + \mu_i + \mu_t + \epsilon_{i,t}$$

In columns (4) through (6), we study the likelihood of an angel's follower becoming a co-investor after a success event. The sample for these regressions 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.

$$\begin{aligned} y_{ij,t} = {} & \alpha + \beta \times \text{PreSuccess}_{-1} + \gamma \times \text{PostSuccess}_{+1} + \delta Followed_{ij,t} \\ & + \zeta \times \text{PreSuccess}_{-1} \times Followed_{ij,t} + \eta \times \text{PostSuccess}_{+1} \times Followed_{ij,t} \\ & + \mu_i + \mu_t + \epsilon_{ij,t} \end{aligned}$$

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.

	$Ln(1 + Followers_{i,t})$			$Co-invest_{ij,t}$		
	$Success_{i,t}$	$Seed\ Success_{i,t}$	$Successful\ Exit_{i,t}$	$Success_{i,t}$	$Seed\ Success_{i,t}$	$Successful\ Exit_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$Followed_{ij,t}$				0.007	0.009	0.006
				(0.007)	(0.008)	(0.004)
$PreSuccess_{-1}$	-0.020	-0.017	0.025	-0.015	-0.012	-0.007
	(0.008)	(0.021)	(0.015)	(0.014)	(0.014)	(0.008)
$PostSuccess_{+1}$	0.035**	0.058***	0.048***	0.029**	-0.004	0.025**
	(0.016)	(0.021)	(0.014)	(0.012)	(0.016)	(0.011)
$PreSuccess_{-1} \times Followed_{ij,t}$				0.025	0.010	0.020
				(0.018)	(0.017)	(0.015)
$PostSuccess_{+1} \times Followed_{ij,t}$				0.028*	0.033**	0.019**
				(0.015)	(0.016)	(0.009)
Observations	2957	2957	2957	3390786	2992342	3130198
$Adj.\ R^2$	0.411	0.393	0.402	0.064	0.065	0.066
Investor & Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Appendix: Variable Definitions

Start-up Financing Stages:

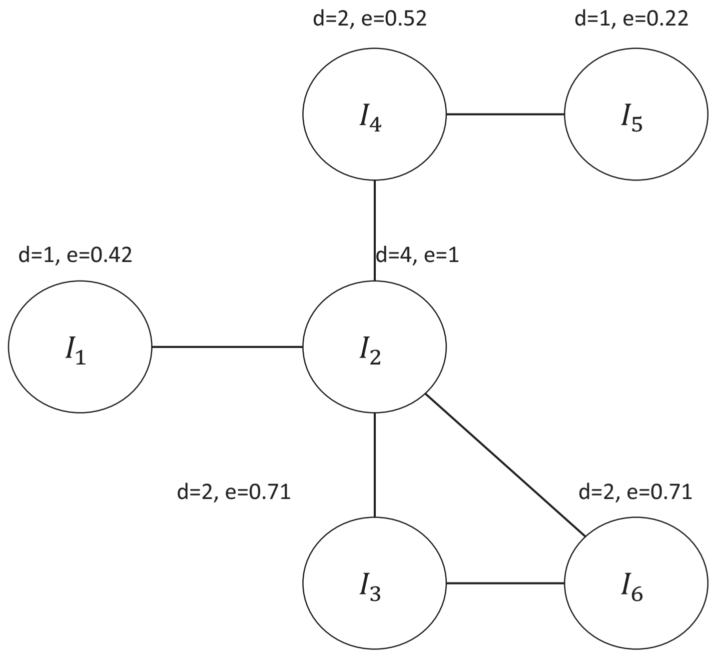
Start-ups raise funds at various stages of their life cycle. Industry participants classify these financing stages as *Seed*, *Series A*, *Series B*, *Series C*, and so on. The academic literature (e.g., see Gompers (1995)) sometimes refers to series A as "early stage," series B as "expansion stage," and series C and beyond as "late stage." The informal definitions of the these stages are as follows:[19]

- *Seed stage:* The purpose of the series seed is for the startup to figure out the product it is building, the market it is in, and the user base. Typically, a seed round helps the company scale to a few employees past the founders and to build and launch an early product.
- *Series A:* Startups that get to this stage have figured out their product and user base, and are trying to establish a viable business model and scale up their operations.
- *Series B:* This stage is all about scaling. Startups that get to this stage have an established product and business model, and are trying to scale up their business model and user base.
- *Series C:* This stage is used by startups to accelerate their growth beyond the Series B stage; e.g., by going international or by making acquisitions. Firms requiring more funds raise them in stages Series D, E, etc.

The startups disclose the financing stage when they raise funds, and this information is reported by CrunchBase and AngelList. Each financing stage may itself involve multiple funding rounds.

[19]See `http://blog.eladgil.com/2011/03/how-funding-rounds-differ-seed-series.html` for a more detailed description of these funding stages.

Network Measures:



Co-investment networks may be viewed as a set of nodes and edges. For example, in the network of 6 investors shown above, the nodes are investors and the edges represent co-investment connections between investors. In order to compute centrality measures, networks are represented in the form of $N \times N$ "adjacency" matrices, where N is the total number of investors in the network. The figure below shows the adjacency matrix for the network represented above, where a '1' denotes the presence of a co-investment connection between the two investors (e.g., investors I_1 and I_2), whereas a '0' denotes the lack of a connection (e.g., between investors I_1 and I_3).

Investor	I_1	I_2	I_3	I_4	I_5	I_6
I_1	-	1	0	0	0	0
I_2	1	-	1	1	0	1
I_3	0	1	-	0	0	1
I_4	0	1	0	-	1	0
I_5	0	1	0	1	-	0
I_6	0	1	1	0	0	-

The network measures are defined as follows:

- *Degree Centrality*$_t$ denotes the total number of co-investment connections that an investor has as of year t. It is obtained by summing the investor's row (or column) vector in the adjacency matrix. For example, in the network above, investor I_1 has a degree centrality of 1 ('d' in the network figure shows degree centrality of each investor).

- *Eigenvector Centrality* 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. It is the positive eigenvector of the network's undirected adjacency matrix. Mathematically, eigenvector of investor 'i' (ev_i) is given by $ev_i = \sum_j p_{ij}.ev_j$, where p_{ij} takes a value 1 if there is a relationship between investors i and j. We use power iteration method (100 iterations) recommended by Bonacich (1987) to calculate eigenvector centrality of each investor.

- *Eigenvector Centrality Decile*$_t$ represents the decile to which the individual angel belongs in year t when all individual angels are ranked based on their eigenvector centrality.

- $\Delta(Eigenvector\,Centrality\,Decile)_t$ represents change in *Eigenvector Centrality Decile* from year $t-1$ to t.

- *New Connections*$_t$ is the number of new 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:

- *Success*$_{it}$ is a dummy variable that identifies if any portfolio firm, for which angel i acted as lead investor, successfully progressed to the next financing stage during year t; e.g., from the seed stage to series A stage, or from series A stage to series B stage, and so on. *No. of Successes*$_{it}$ is the number of such successes for angel i in year t.

- *Seed Success*$_{it}$ is a dummy variable that identifies if any seed-stage portfolio firm, for which angel i acted as lead investor, successfully progressed to Series A stage during year t. *No. of Seed Successes*$_{it}$ is the number of such seed successes experienced by angel i in year t.

- *Successful exit*$_{it}$ is a dummy variable that identifies if any portfolio firm, for which angel i acted as lead investor, underwent an IPO or was acquired during year t. *No. of Successful Exits*$_{it}$ is the number of successful exits for angel i in year t.

- *PreSuccess*$_\tau$ for $\tau \in \{-3, -2, -1\}$ are dummy variables that identify the year τ *before* the success year. We create these dummy variables separately for each of the three success measures above.

- *PostSuccess*$_\tau$ for $\tau \in \{1, 2, 3\}$ are dummy variables that identify the year τ *after* the success year. We create these dummy variables separately for each of the three success measures above.

Angel Characteristics:

- *Start-ups invested*$_{it}$ 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*$_{it}$ is the number of new start-ups in which angel i invested for the first time in year t, either as a lead investor or as a participant.

- *New Lead Investments*$_{it}$ is the number of new start-ups in which angel i invested for the first time as a lead investor in year t.

- *Rounds invested*$_{it}$ is the number of funding rounds in which angel i invested in year t, either as a lead investor or as a participant.

- *Rounds lead*$_{it}$ is the number of funding rounds for which angel i acted as lead investor in year t. 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.

- *Experience*$_{it}$ is the difference (in years) between year t and the first year in which angel i made an investment reported on CrunchBase or AngelList.

- *Other Seed Success*$_i t$ 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*$_{it}$ 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.

- *Formed Angel Group*$_{it}$ is a dummy variable that identifies whether angel i forms an angel group in year t.

- *Joined VC*$_{it}$ is a dummy variable that identifies whether angel i joins a VC firm in year t.

- *No. of Competing Firms Funded*$_{i,t}$ is the number of start-ups that raised funding in the angel's product market category in year t. In cases where the angel has invested in more than one product market category, we take the average across all categories he has invested in as of year t. The product market categories are from Crunchbase.

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.

Internet Appendix: Additional Tests

Table IA.1 Effect of Seed Success on Angel's Network Growth and Deal Outcomes: Instrumental Variables Estimation

This table reports the results of instrumental variable regressions investigating the effect of angels' first *Seed Success* on future network capital and deal flow. We use *No. of Competing Firms Funded* in an angel's product market category as an instrument for his *Seed Success*. We estimate the following two stage model on all angel-year observations in our panel dataset.

$$1^{st} Stage: \quad Seed\,Success_{i,t-1} = \alpha_0 + \alpha_1 Ln(1 + No.\,of\,Competing\,Firms\,Funded)_{i,t-1} + \alpha_X X_{i,t-1} + \mu_i + \mu_t + \epsilon_{i,t}$$
$$2^{nd} Stage: \quad y_{i,t} = \beta_0 + \beta_1 Seed\,\widehat{Success}_{i,t-1} + \beta_X X_{i,t-1} + \mu_i + \mu_t + u_{i,t}$$

The first six columns report the second stage results and the last column reports the first stage regression where *Seed Success* is the dependent variable. We include angel fixed effects (μ_i) and year fixed effects (μ_t) in all specifications. All variables are defined in the Appendix. Standard errors reported in parentheses are robust to heteroskedasticity. We use ***, **, and * to denote statistical significance at 1%, 5% and 10% levels, respectively.

	$Ln(1+New\,Connections_{i,t})$	$\Delta(Eigenvector\,Centrality\,Decile)_{i,t}$	$Ln(1+New\,Investments_{i,t})$	$Ln(1+New\,Lead\,Investments_{i,t})$	$Other\,Seed\,Success_{i,t}$	$VC\,Financing_{i,t}$	$Seed\,Success_{i,t-1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Seed\,\widehat{Success}_{i,t-1}$	0.178***	0.064	0.443***	0.191***	0.106***	0.074***	
	(0.034)	(0.068)	(0.019)	(0.017)	(0.023)	(0.027)	
$Ln(Degree)_{i,t-1}$	-0.723***	-1.642***	-0.255***	-0.121***	0.069***	-0.257***	0.142***
	(0.021)	(0.041)	(0.010)	(0.008)	(0.010)	(0.012)	(0.054)
$Ln(Experience)_{i,t-1}$	0.205***	-0.690***	0.988***	0.409***	0.065	0.352***	11.860***
	(0.042)	(0.144)	(0.024)	(0.022)	(0.048)	(0.063)	(0.228)
$Ln(Rounds\,invested)_{i,t-1}$	1.837***	1.936***	1.008***	0.593***	0.435***	0.499***	1.505***
	(0.039)	(0.070)	(0.017)	(0.021)	(0.019)	(0.024)	(0.091)
$Ln(Market\,funds\,inflow)_{t-1}$	-0.427***	-0.037***	-0.549***	-0.222***	0.017***	0.004***	-0.051***
	(0.027)	(0.003)	(0.014)	(0.012)	(0.001)	(0.001)	(0.006)
$Ln(\#Competing\,firms\,funded)_{i,t-1}$							-9.056***
							(0.569)
Observations	24290	23617	24290	24290	24290	24290	24290
Adj./Pesudo R^2	0.674	0.358	0.695	0.597	0.521	0.605	0.671
Investor & Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.2 Falsification Test

This table reports results of falsification tests that investigate the effect of placebo success on future network capital and deal flow of angels. We use the nearest neighbor matching procedure to match each angel that has experienced *Seed Success* (the "treated" group) with at least three unsuccessful angels during the same year that are similar in terms of *Degree Centrality*, *Rounds Invested*, and *Experience* (the "control" group). For each angel that experienced a seed success, we randomly assign *PlaceboSuccess*= 1 for one of the angels in the control group and set *PlaceboSuccess*=0 for the successful angel and all other angels in the control group. For each angel-year observation, the dummy variables *Post-PlaceboSuccess*$_\tau$ identify the year $\tau \in \{1,2,3\}$ *after* the placebo success year, whereas the dummy variables *Pre-PlaceboSuccess*$_\tau$ identify the year $\tau \in \{-3,-2,-1\}$ *before* the placebo success year. We then estimate the following difference-in-differences regression on all the angel-year observations in the treated and control groups.

$$y_{i,t} = \alpha + \sum_{\tau=-3}^{\tau=-1} \beta_\tau \times \text{Pre-PlaceboSuccess}_\tau + \sum_{\tau=1}^{\tau=3} \gamma_\tau \times \text{Post-PlaceboSuccess}_\tau + \mu_i + \mu_t + \epsilon_{i,t}$$

We include angel fixed effects (μ_i) and year fixed effects (μ_t) in all specifications. 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.

	$Ln(1+New\ Connections_{i,t})$ (1)	$\Delta(Eigenvector\ Centrality\ Decile)_{i,t}$ (2)	$Ln(1+New\ Investments_{i,t})$ (3)	$Ln(1+New\ Lead\ Investments_{i,t})$ (4)	$Other\ Seed\ Success_{i,t}$ (5)	$VCFinancing_{i,t}$ (6)
$PrePlaceboSuccess_{-3}$	0.044	0.001	0.027	0.025	-0.011	0.011
	(0.028)	(0.002)	(0.019)	(0.016)	(0.011)	(0.020)
$PrePlaceboSuccess_{-2}$	0.070**	0.002	0.025	-0.001	0.009	0.013
	(0.029)	(0.002)	(0.019)	(0.016)	(0.011)	(0.020)
$PrePlaceboSuccess_{-1}$	0.008	-0.001	0.003	-0.008	-0.027**	0.015
	(0.029)	(0.002)	(0.019)	(0.016)	(0.011)	(0.020)
$PostPlaceboSuccess_{+1}$	-0.031	-0.002	-0.013	-0.014	-0.012	-0.039*
	(0.029)	(0.002)	(0.019)	(0.016)	(0.011)	(0.020)
$PostPlaceboSuccess_{+2}$	0.013	-0.001	0.009	0.004	0.004	0.026
	(0.029)	(0.002)	(0.019)	(0.016)	(0.011)	(0.020)
$PostPlaceboSuccess_{+3}$	-0.028	-0.001	-0.009	0.013	0.005	0.003
	(0.029)	(0.002)	(0.019)	(0.016)	(0.011)	(0.020)
Observations	20102	19934	20102	20102	20102	20102
Adj. R^2	0.113	0.031	0.101	0.101	0.113	0.113
Investor & Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.3 Effect of First Seed Success on Angel's Network Growth and Deal Outcomes

This table reports the results of regressions investigating the effect of angels' first *Seed Success* on future network capital and deal flow. We use the nearest neighbor matching procedure to match each angel that has experienced his first *Seed Success* (the "treated" group) with at least three unsuccessful angels during the same year that are similar in terms of *Degree Centrality*, *Rounds Invested*, and *Experience* (the "control" group). For each treated angel-year observation and its corresponding control group, the dummy variables $PostSuccess_{\tau}$ identify the year $\tau \in \{1, 2, 3\}$ *after* the success year, whereas the dummy variables $PreSuccess_{\tau}$ identify the year $\tau \in \{-3, -2, -1\}$ *before* the success year. We then estimate the following difference-in-differences regression on all the angel-year observations in the treated and control groups.

$$y_{i,t} = \alpha + \sum_{\tau=-3}^{\tau=-1} \beta_{\tau} \times \text{PreSuccess}_{\tau} + \sum_{\tau=1}^{\tau=3} \gamma_{\tau} \times \text{PostSuccess}_{\tau} + \mu_i + \mu_t + \epsilon_{i,t}$$

We include angel fixed effects (μ_i) and year fixed effects (μ_t) in all specifications. 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.

	$Ln(1 + New\ Connections_{i,t})$ (1)	$\Delta(Eigenvector\ Centrality\ Decile)_{i,t}$ (2)	$Ln(1 + New\ Investments_{i,t})$ (3)	$Ln(1 + New\ Lead\ Investments_{i,t})$ (4)	$Other\ Seed\ Success_{i,t}$ (5)	$VC\ Financing_{i,t}$ (6)
$PreSuccess_{-3}$	-0.021	-0.036	-0.017	-0.009	-0.005	-0.004
	(0.018)	(0.026)	(0.011)	(0.010)	(0.006)	(0.003)
$PreSuccess_{-2}$	-0.011	-0.032	-0.001	0.011	-0.004	-0.000
	(0.016)	(0.025)	(0.009)	(0.008)	(0.006)	(0.002)
$PreSuccess_{-1}$	0.022	-0.033	0.015	0.011	0.008	0.004*
	(0.015)	(0.022)	(0.009)	(0.007)	(0.005)	(0.002)
$PostSuccess_{+1}$	0.144***	0.053**	0.187***	0.114***	0.066***	0.089***
	(0.016)	(0.025)	(0.010)	(0.008)	(0.006)	(0.003)
$PostSuccess_{+2}$	0.048***	0.045*	0.207***	0.104***	0.065***	0.189***
	(0.014)	(0.027)	(0.010)	(0.007)	(0.005)	(0.005)
$PostSuccess_{+3}$	0.043***	0.063**	0.014	0.011	0.034***	0.084***
	(0.015)	(0.029)	(0.010)	(0.007)	(0.005)	(0.006)
Observations	20102	20018	20102	20102	20102	20102
Adj. R^2	0.220	0.067	0.260	0.247	0.211	0.288
Investor & Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.4 Effect of Seed Success on Angel Outcomes: Condensed Panel

This table investigates the effect of angels' *Seed Success* on future network capital and deal flow using an alternative difference-in-differences regression framework that addresses the Bertrand et al. (2004) critique. We use the nearest neighbor matching procedure to match each angel that has experienced *Seed Success* (the "treated" group) with at least three unsuccessful angels during the same year that are similar in terms of *Degree Centrality*, *Rounds Invested*, and *Experience* (the "control" group). For each angel in the treated group and the corresponding angels in their control group, we condense all observations prior to treatment into a single observation and all observations after treatment into a single observation by taking the time-series averages of all variables. The dummy variable *Treated* identifies the angels in the treated group, whereas the dummy variable *Post* identifies the period after treatment for the treated angels as well as angels in the control group. We then estimate the following difference-in-differences regression:

$$y_{i,t} = \alpha + \beta \times \text{Treated} + \psi \times \text{Post} + \gamma \times (\text{Post} \times \text{Treated}) + \mu_i + \mu_t + \epsilon_{i,t}$$

We include angel fixed effects (μ_i) and year fixed effects (μ_t) in all specifications. 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.

	$Ln(1 + New\ Connections_{i,t})$ (1)	$\Delta(Eigenvector\ Centrality\ Decile)_{i,t}$ (2)	$Ln(1 + New\ Investments_{i,t})$ (3)	$Ln(1 + New\ Lead\ Investments_{i,t})$ (4)	$Other\ Seed\ Success_{i,t}$ (5)	$VC\ Financing_{i,t}$ (6)
Treated	-0.061	-0.045	0.030	0.004	0.013	-0.035**
	(0.037)	(0.042)	(0.022)	(0.016)	(0.016)	(0.016)
Post	-0.048	0.069**	-0.016	-0.010	-0.005	0.041***
	(0.032)	(0.034)	(0.020)	(0.016)	(0.015)	(0.015)
Treated × Post	0.030**	0.110***	0.151***	0.103***	0.132***	0.130***
	(0.012)	(0.017)	(0.020)	(0.017)	(0.016)	(0.015)
Observations	4562	4562	4562	4562	4562	4562
Adj. R^2	0.631	0.686	0.668	0.660	0.526	0.684
Investor & Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.5 Effect of Seed Success on Angel Outcomes: Including angels who have invested in fewer than 3 startups

This table reports the results of regressions investigating the effect of *Seed Success* on future network capital and deal flow of angels. For these tests we relax the sample selection criterion that an angel should have invested in at least 3 startups. Thus the sample used here is an unbalanced panel of 12,147 angels. We use the nearest neighbor matching procedure to match each angel that has experienced *Seed Success* (the "treated" group) with at least three unsuccessful angels during the same year that are similar in terms of *Degree Centrality*, *Rounds Invested*, and *Experience* (the "control" group). For each treated angel-year observation and its corresponding control group, the dummy variables $PostSuccess_\tau$ identify the year $\tau \in \{1, 2, 3\}$ *after* the success year, whereas the dummy variables $PreSuccess_\tau$ identify the year $\tau \in \{-3, -2, -1\}$ *before* the success year. We then estimate the following difference-in-differences regression on all the angel-year observations in the treated and control groups.

$$y_{i,t} = \alpha + \sum_{\tau=-3}^{\tau=-1} \beta_\tau \times \text{PreSuccess}_\tau + \sum_{\tau=1}^{\tau=3} \gamma_\tau \times \text{PostSuccess}_\tau + \mu_i + \mu_t + \epsilon_{i,t}$$

We include angel fixed effects (μ_i) and year fixed effects (μ_t) in all specifications. 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.

	$Ln(1 + New\ Connections_{i,t})$ (1)	$\Delta(Eigenvector\ Centrality\ Decile)_{i,t}$ (2)	$Ln(1 + New\ Investments_{i,t})$ (3)	$Ln(1 + New\ Lead\ Investments_{i,t})$ (4)	$Other\ Seed\ Success_{i,t}$ (5)	$VC\ Financing_{i,t}$ (6)
$PreSuccess_{-3}$	-0.002	0.009	-0.004	0.006	-0.046	-0.018
	(0.033)	(0.028)	(0.019)	(0.017)	(0.037)	(0.016)
$PreSuccess_{-2}$	0.003	0.014	0.003	0.016	0.023	0.001
	(0.032)	(0.026)	(0.019)	(0.016)	(0.046)	(0.015)
$PreSuccess_{-1}$	0.024	0.002	-0.012	0.025*	0.036	-0.005
	(0.027)	(0.022)	(0.016)	(0.014)	(0.022)	(0.013)
$PostSuccess_{+1}$	0.141***	0.006	0.099***	0.029**	0.093***	0.012
	(0.042)	(0.018)	(0.023)	(0.011)	(0.009)	(0.011)
$PostSuccess_{+2}$	0.049**	0.096***	0.040***	0.040***	0.038***	0.027***
	(0.020)	(0.017)	(0.012)	(0.010)	(0.009)	(0.010)
$PostSuccess_{+3}$	0.028**	0.046***	0.019***	0.017***	-0.043***	0.022***
	(0.011)	(0.009)	(0.007)	(0.006)	(0.005)	(0.005)
Observations	39543	36899	39543	39543	39543	39543
$Adj.\ R^2$	0.078	0.062	0.111	0.157	0.285	0.098
Investor & Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes