Elites vs Masses: Expanding Entrepreneurial Finance through Equity Crowdfunding

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Abstract

Equity crowdfunding (CF) platforms that connect startups with a multitude of investors online are fast emerging as an important source of entrepreneurial finance. In this study, we examine how equity crowdfunded (CF) startups perform relative to startups funded by traditional venture capital(ists) (VC). Controlling for the selection of startups, we find that CF startups raise less money and are less likely to funded by more successful investors in the subsequent round. They are also less likely to strike a successful exit. Such inferior performance of crowdfunded startups is explained by the attributes of investors who participate on CF platforms. CF investors tend to be less experienced and less successful than an average VC. The performance of the crowdfunded startups is at least at par with those funded by VCs with less of a track record. In fact, relative to less experienced and less successful VC-funding, CF is more likely to be followed by investment from more successful investors. Our results indicate that CF investors while substituting for less experienced and less successful VCs and expanding the reach of more successful VCs, are less able to provide value-added services to startups relative to VCs with a better track record.

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1. Introduction

Technological advances, including the diffusion of social networks and online platforms, have yielded fundamental changes in entrepreneurial financing. Notable among these is the emergence of equity-based crowdfunding, whereby a startup raises relatively small amounts from a large number of investors in exchange for equity in its business. While equity crowdfunding is a relatively nascent phenomenon - legalized in the U.S. through the passage of the Jumpstart of Our Business Ventures (JOBS) Act only in April 2012 and estimated globally to be around USD 2.1 billion in 2015 compared to trillions of dollars in traditional equity funding[1] - it has been growing rapidly, roughly doubling every year between 2012 and 2015. Despite accelerated growth and increasing attention from regulators, funders, founders, and researchers, the investor dynamics in these markets and the performance of startups remain underinvestigated. Yet, an understanding of these issues is critical to the effective design of crowdfunding platforms and forms the central question of this study.

Crowdfunding markets differ from traditional venture financing in important ways. First, these online platforms leverage the geographic and social reach of the Internet to significantly expand market access on both the supply side (investors) and demand side (startups). Second, these platforms have properties that are purposefully designed to lower costs of transacting and overcome distance-related frictions. These include easier information search and acquisition, reduced need to monitor progress, lower costs of providing input, and information transparency on other market participants (Agrawal, Catalini, and Goldfarb, 2015). As a result, consistent with prior research that emphasizes how online settings allow people to overcome offline barriers to market transactions (Choi and Bell 2010, Brynjolfsson, Hu, and Rahman 2009, Goldfarb and Tucker 2010), crowdfunding platforms

[1]Rainey, Sagalongos, Tansey, and Srivatsan (2017) Retrieved from: https://static1.squarespace.com/static/598b47ff6a49631e85d75e53/t/5a20764cc8302566a3a23863/1512076878794/SauderS3i_Equity_Crowdfunding_FINAL.pdf

have facilitated the unbundling of resources and expertise, leading to greater democratization of funding (Kim and Viswanathan 2018).

Indeed, a rich body of work (e.g. Sorenson et al. 2016; Mollick and Robb, 2016) demonstrates that crowdfunding has the potential to relax many constraints posed by traditional venture capital and in turn, expand access to innovation finance to geographies, gender and races underserved by traditional venture financing. This is because venture capitalists (VCs) mitigate the risk of tacit and ambiguous signals of entrepreneurship quality by funding entrepreneurs with shared characteristics and direct and indirect ties to them.[2] They also tend to finance startups in the same geography since colocation provides opportunities for frequent interactions and encounters that help signal trustworthiness and demonstrate competences[3]. However, the properties of crowdfunding platforms have the potential to eliminate many of these distance-related costs, thereby, facilitating broader participation from projects and startups across diverse geographies and demographic strata, typically excluded from venture capital, and expanding the geographic reach of venture capital itself.

Much of the prior work has focused on the demand side of crowdfunding platforms, notably, demonstrating expanded access to entrepreneurial finance (Sorenson et al. 2016; Mollick and Robb, 2016), assessing its economic implications (Kitchens and Torrence 2012), and discerning signals of quality that help mitigate investor risks in these noisy, dispersed markets (Agrawal, Catalini, and Goldfarb 2015; Kim and Viswanathan 2018). However, the unbundling of resources and

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[2] For example, Shane and Stuart (2002) provide evidence on the role of network between VCs and entrepreneurs. Bengtsson and Hsu (2015) find that startups are more likely to get funded when there is shared ethnicity between VCs and entrepreneurs. See a comprehensive survey by Da-Rin, Hellmann, and Puri (2013) for a detailed discussion on match between VCs and startups. VCs are successful in their screening at least to some extent. Chemmanur, Krishnan, and Nandy (2011) find that VCs are more likely to finance firms with greater factor productivity, larger size, and higher number of plants operated. Puri and Zarutskie (2012) find that VCs select the firms to invest in based on their actual and potential employment and sales.

[3] Stuart and Stuart (2005) report that the average distance between lead VCs and their respective target firms is approximately 70 miles. Similarly, Sohl (1999) and Wong (2002) report that angel investors locate close to the entrepreneurs they finance (more than 50% are within half a day of travel).

expertise and ensuing democratization of participation also has important implications for the supply side. While on the one hand, unbundling may facilitate democratization of funding, on the other hand, participation from investors with resources but not the expertise to invest in and guide the startups may lead to adverse performance outcomes for crowdfunded startups, potentially impacting the viability of the platform. Emergent anecdotal evidence (e.g., Deustch, 2018) indeed suggests that crowdfunded startups might underperform VC-funded startups, but this evidence rests on a relatively small number of possibly unrepresentative firms and offers few insights into the mechanisms underlying the performance differential. Our study uses comprehensive data on the investment history of investors in 1,800 VC-funded and crowdfunded startups to present new statistical evidence of the performance of crowdfunding platforms relative to traditional VCs and the mechanisms underlying this performance differential. Specifically, we comment on investor types who select into crowdfunding platforms, and relative performance of these investor types. In this way, our results provide a critical understanding of the sustainability of this rapidly growing, alternative mode of entrepreneurial finance.

Financing a venture is a risky business. Even sophisticated investors like VCs are able to pick winners only with a small probability. If the pool of investors is expanded to crowds, one concern, as Chemmanur and Fulghieri (2014) point out, is that such relatively uninformed, small investors may lose large sums of money. Thus, understanding the relative performance of crowdfunded startups is important from the perspective of investors as well.

Any observed performance differences between crowdfunded startups and VC-funded startups may well be an outcome of systematic differences in the quality of startups that select into these two markets. However, given that the focus of our study is to understand investor differences between online and offline markets, we do not focus on the selection model for startups but rather, control for differences in startup quality in examining all outcomes. Specifically, we use Coarsened Exact Matching (CEM) to match the crowdfunded startups with VC-funded startups on age, geographic location, sector as well as the total amount raised by the startup.[4]

We begin with an assessment of performance differences between crowdfunded startups and VC-funded startups. We use three measures of startup performance: the amount of funding raised in the subsequent round, the probability of funding by more successful investors in the next round, and the probability of a successful exit. The underlying justification behind using outcomes in subsequent rounds of funding is that most investments in startups are "staged". The startups are periodically evaluated and receive follow-on funding only if their potential for success remains high (Gompers 1995, Hochberg et al. 2007). Indeed, the theoretical model in Dahiya and Ray (2012) shows that funders use staged financing as a screening device and find that more valuable ventures in the running to becoming successful raise greater amounts in the later stages. Sørensen (2007) and Bottazzi, Da Rin, and Hellmann (2008) find that experienced VCs positively impact the chances of success of a startup. So, the probability of getting funding by investors with a better track record of success is a useful performance milestone. Additionally, consistent with prior research (Gompers and Lerner 1998; Gompers and Lerner 2000; Brander et al. 2002; Sørensen 2007), we examine successful or failed exits as a measure of startup performance.

We find that the presence of equity crowdfunding is associated with inferior performance of the venture on all three dimensions relative to pure VC financing. CF startups raise less money in the next round, are less likely to receive funding from more successful investors and have a lower

[4] Many studies have used matching to control for startup quality. For example, Chemmanur, Krishnan, and Nandy (2011) compare efficiency gains of firms with and without VC financing using propensity score matching based on industry, size and total factor productivity. Puri and Zarutskie (2012) examine outcomes for VC-financed and non-VC-financed firms matched on age, industry, geographical region, and number of employees.

likelihood of eventual success. These observed performance differences between crowdfunded and VC-backed startups may be an outcome of a combination of (i) the preponderance of certain economic frictions in online markets and (ii) differences in the characteristics of investors between online and offline markets.

Prior research emphasizes that many but not all economic frictions are muted in online settings (Blum and Goldfarb 2006, Hortacsu, Martinez-Jerez, and Douglas 2009). Some other frictions are likely to get even stronger. Offline markets may provide certain informational advantages in monitoring and mentoring relative to the online platforms. For example, Agarwal et al. (2015) find that CF platforms may eliminate many economic frictions associated with offline early stage financing such as acquiring tangible information (e.g. prior experience and expertise), monitoring measurable progress, and providing concrete input. But they do not eliminate certain frictions associated with continuous, soft information about the entrepreneur (e.g. tendency to recover from revealed setbacks, grit) that is more likely to be embedded in personal social networks. Such continuous, soft information is a crucial input to effective mentoring and monitoring by the investors. As such, it is likely that the efficiency of interactions and transactions between VCs and entrepreneurs and the ability of the VC to effectively mentor the startup is somewhat diminished in the online setting.

VCs are also likely to increasingly suffer from limitations described above as the physical distance between them and the investee companies gets larger. Indeed, Bernstein, Giroud, and Townsend (2016) show that as it becomes easier for VCs to travel to the investee companies, the performance of those companies improves. If this is the friction that explains the performance differential between VC and CF-funded startups, we should find that CF funded startups perform similar to those funded by VCs that are located far from the startups. However, for all three outcomes we find that CF startups perform worse than even far-VC funded startups. Thus, a simple relative difficulty of face-to-face interaction between the investors and the startups does not explain the underperformance of CF startups.

Can differences in investor characteristics explain the performance differential? CF investors themselves are a heterogeneous group. While democratization undeniably facilitates broader participation from the crowd, investors on CF platforms can well be sophisticated members of the startup ecosystem (Abrams 2017). Therefore, we classify CF startups, in two categories: i) Funded by a pseudo crowd - this is the case if crowdfunding is syndicated and the lead of the syndicate is a VC or an individual associated with a VC firm; ii) Funded by a pure crowd - this is the case if the crowdfunding is not syndicated or an individual not associated with a VC leads the syndicate. We posit that if the observed performance differential between the online and offline markets is an outcome of fundamental differences in VC and crowd investors, then this differential should not persist for startups funded by the pseudo crowd that should demonstrate attainments similar to those funded by VCs. However, we find that the pseudo crowdfunded startups also perform poorly relative to the VC-funded startups. Further, their performance is no different from the startups funded by the pure crowd.

Next, we draw on the differences between CF and VC investors to discern mechanisms underlying the observed performance differential. Univariate comparisons suggest that investors who fund via the CF platform are, indeed, very different from traditional VCs. CF investors in our sample, on average, have fewer years of experience. They have participated in and led fewer number of investments. Therefore, observed persistent performance differences between CF and VC-funded ventures, after controlling for startup quality, may be attributable to systematic differences in investor quality between online and offline markets.

To further examine this hypothesis, we assess differences in performance between CF startups and those funded by different types of VCs. Prior research (Mason 1999, Sørensen 2007, Chemmanur, Krishnan, and Nandy 2011, Rindermann 2015) suggests that not all venture capital is created equal and there is significant heterogeneity in the experience and in turn, informational advantages presented by different types of VCs. VCs sit on boards, mentor founders, and professionalize hiring practices (see, for example, the survey by Da Rin, Hellmann, and Puri, 2013). They have a greater understanding of the commercialization process and firm milestones (Pahnke, Katila, and Eisenhardt 2015) compared to non-VC financiers, and therefore, play an important role in resource acquisitions and growth (Puri and Zarutskie, 2012; Chemmanur, Krishnan, and Nandy, 2011). Bottazzi, Da Rin, and Hellmann (2008), Bernstein, Giroud, and Townsend (2016), and Ewens and Marx (2018) provide evidence on the direct link between VC activism and performance of the startup. All these benefits are likely to be particularly salient to more experienced and successful VCs and help significantly with the financing and growth of the startup.

Therefore, we assess how crowdfunded startups perform relative to similar quality startups funded by more or less experienced as well as more or less successful VCs. We measure experience using the number of years, the number of investments or the fraction of lead investments. Track record of success is captured by their overall rate of successful exits. We find that crowdfunded startups fare worse than those funded by more experienced or more successful VCs but similar to those funded by less experienced or less successful VCs. On one dimension, however, CF startups generally do better than the those funded by less experienced or less successful VCs. A startup crowdfunded in the previous round is more likely to get funding from a more successful investor in the next round compared to a startup funded by a less experienced or less successful VC. This result attests to either fundamental benefits accorded by crowdfunding that are unobserved in this study or the superior credentialing effect of the crowd relative to less successful VCs.[5]

Our paper makes important contributions to the literature on crowdfunding as well as the broader field that studies the financing of new businesses. The research on crowdfunding is still largely focused on reward-based and lending-based crowdfunding (for example, see a survey of crowdfunding research by Short et al., 2017). However, it not clear that the insights from reward- and lending-based crowdfunding will translate to equity crowdfunding. As Agrawal, Catalini, and Goldfarb (2014) note, information asymmetry issues are likely to be critically different for nonequity and equity crowdfunding. Further, investors in reward-based crowdfunding may care about non-financial benefits from the success of the venture. Crowd lenders may worry more about default risk. Equity crowdfunding investors, like other equity investors, are likely to care more about the financial upside as well as the downside.

Research on equity crowdfunding is nascent but growing fast (see the survey by Mochkabadi and Volkmann, 2018). It is only beginning to investigate the performance of equity crowdfunded startups. Signori and Vismara (2018) examine success or failure post initial equity investment *within* a sample of equity crowdfunded startups. Di Pietro, Prencipe, and Majchrzak (2018) qualitatively examine around 60 equity crowdfunded startups to understand factors behind their subsequent performance. We contribute to the crowdfunding literature by examining the performance of crowdfunded startups relative to VC funded startups.

There is a large literature on equity financing of new businesses. Da Rin, Hellmann, and Puri (2013) conduct a comprehensive survey of the research on VCs. Drover et al. (2017) take stock

[5] Using an experimental setting, Drover, Wood, and Zacharakis (2017) examine the certification effects for angel investing and crowdfunding. They find that a VC is more likely to conduct a due diligence for a startup if the seed round is funded by more experienced angels or more reputed crowdfunding platform.

of the entrepreneurial equity financing research more broadly. Our paper adds to two strands of this literature. One strand compares different funding sources and the performance of the firms. Kerr, Lerner, and Schoar (2011) show that, after controlling for selection, ventures funded by angels have better outcomes. Goldfarb et al. (2013) find that, in a sample of ventures where VCs and angels compete, angel-financed ventures take a longer time to exit. The larger ventures are less likely to succeed when financed by angels. Berger and Schaeck (2011) examine how bank and VC financing substitute each other for small and medium enterprises. Puri and Zarutskie (2012) look at businesses with VC financing and those funded by other sources. Da Rin, Hellmann, and Puri (2013) conclude that "trade-offs between VC, banks and angel financing still remain poorly understood." More recently, Ryu, Kim, and Hahn (2018) find that subsequent funding outcomes for technology startups are similar for reward-based crowdfunding and angel financing. Our contribution to this literature is to provide evidence on how equity crowdfunding, a relatively new source of financing, fares compared to traditional VC financing.

The second strand of the literature examines the relationship between investor characteristics and outcomes of the investee firms. Sørensen (2007) shows, using a structural model, that more experienced VCs finance more successful ventures, a result of both selection as well as the influence of the VCs. Chemmanur, Krishnan, and Nandy (2011) find that firms backed by high-reputation VCs have faster sales growth and slower cost growth compared to those financed by low-reputation VCs. We add to this literature by showing that crowdfunding does at least as well as less successful VCs but worse than more successful VCs.

Our results emphasize that CF may offer distinctive benefits and substitute for less experienced or less successful VCs. Brown et al. (2017) report based on interviews, that crowds accord timely capital and autonomy to equity crowdfunded entrepreneurs. Di Pietro, Prencipe, and

Majchrzak (2018) find that equity crowdfunded startups benefit from inputs of the crowd into product design and development, access to networks of investors, and increased public awareness of the firm. Our results suggest that these benefits of CF trade off against the expertise, resources and credentialing provided by less experienced and less successful VC, and consistent with prior research (Sorenson et al. 2016), expands the reach of more experienced and successful VC. In contrast, the monitoring, mentoring and other valued added services provided by VCs with better track record trade off against the documented benefits of CF. We find that CF has a greater propensity to invest in early stages of the startup and thus is more likely to provide risk capital to fuel the entrepreneurial engine, as anticipated by the JOBS Act. Given that CF startups perform at least as well as those funded by the VCs with less of a track record, equity crowdfunding, similar to other modes of crowdfunding examined in prior research, expands access to entrepreneurial finance.

We describe our data and methodology next.

2. Data and Methodology

For our study, we combine data primarily from three sources on crowdfunded startups, VC-funded startups, and startup investors. This section describes the data and our methodology.

A. Crowdfunded Startups

We obtain data on crowdfunded ventures from AngelList (https://angel.co/), a dominant platform in the equity crowdfunding space. There are many equity crowdfunding platforms (AngelList, FundersClub, WeFunder, EquityNet, Crowdcube, CircleUp, OurCrowd, and SyndicateRoom, amongst others), which operate as two-sided markets that bring together investors and entrepreneurs. We focus on AngelList, which is a leading equity-based crowdfunding platform in the United States[6] and works with accredited investors under Regulation D of the Security and Exchange Commission (SEC). We collected data on crowdfunded ventures from AngelList's publicly accessible website, which lists ventures that raised online funding through the platform. Forms of investment in these ventures include: (a) individual investments, where one or more individuals invest directly in the venture, (b) syndicates, where the crowd invests along with a lead investor who can be an individual or a VC fund, and (c) online introductions to investors who then close the funding deal offline. For our analysis, we consider (a) and (b) but not (c) as crowdfunding. We focus our analysis to 402 crowdfunded startups headquartered in the U.S., which received the first round of funding during a period from 2011 to 2017. We performed a basic keyword analysis of the business descriptions of the crowdfunded startups to classify them into one of five industries - e-commerce, hardware, software, services, and non-internet.

B. Venture Capital Backed Startups

Our second data source comprises a comparison set of startups funded by traditional venture capital. We collected the data on these startups from Thomson Reuters' VentureXpert database, which collates information on venture capital-backed firms and has been used by a rich body of prior work.[7] We included firms from VentureXpert in our sample if they received their first round of financing during 2011 to 2017, were founded in or after 2007, and are in the same industries as those of the startups funded on AngelList.

The union of these two datasets comprises our final sample of 7,335 startups. For the startups that exist in both databases, we used the VentureXpert data to verify the funding information

[6] See Agrawal, Catalini, and Goldfarb (2016).
[7] For example, see Chemmanur, Krishnan, and Nandy (2011) and Bernstein, Giroud, and Townsend (2016) among many others. Survey by Da-Rin, Hellmann, and Puri (2013) lists VentureXpert as one of the primary commercial databases that has been used by many researchers.

obtained from AngelList. For each startup, data include age of the startup – proxied by years from the first round of investment, location of the headquarters, sector as mentioned above, the total number of rounds of funding, and amount of funding and timing for each of those rounds.

C. Descriptive Statistics

Table 1 presents the distribution of sample startups by funding source, type, stage, sector, and geography. Panel A of the table shows that about 6% of all the startups in the unmatched sample were crowdfunded at some stage in their lifecycle, while the remaining 94% received only VC funding.

Panel B presents the split in our sample of crowdfunded startups across different types of crowdfunding arrangements, notably syndicates and direct individual investments. In a syndicate, a well-informed lead investor selects and invests in a project and offers co-investment opportunities to the less-informed crowd. The lead investor is incentivized through retention of a fraction of the returns earned on capital invested by other members of the syndicate. We find that around 85% of all equity crowdfunding in our sample involves syndicates. This pattern is consistent with the dramatic rise of syndication in equity crowdfunding documented by Agrawal, Catalini, and Goldfarb (2016).

Panel C documents the relative split in crowdfunding and VC-funding between the early stage of the venture (seed funding) and later stages (other rounds). The proportion of crowdfunding in the early stages of a venture is significantly greater than the equivalent proportion of venture capital. About 76% of crowdfunding occurs in the early stage compared to only about 60% of VC funding.

Panels D and E provide the distribution of crowdfunded and the VC-funded startups across sectors and geographies, respectively. In Panel D we see some evidence that crowdfunding is much less concentrated across sectors. Top two sectors (software/technology and services) account for 83%

of the startups funded by VCs while they represent only about 58% of crowdfunded ventures. So, there is some evidence of democratization of access to capital via equity crowdfunding. However, this pattern is not present across geographies. From Panel E, we see that the top two geographies for startup locations, Silicon Valley and New York, host only 36% of VC-funded ventures but a significant 62% of crowdfunded ventures. Hence, crowdfunding in our sample is more geographically concentrated.

D. Matching

Given our goal of comparing the role of venture capital and crowdfunding on a startup's performance, we need to control for startup selection. To this end, we use Coarsened Exact Matching (CEM, Iacus, King, and Porro, 2011, 2012) to match startups based on their city, sector, age and the total amount of funding acquired by them. Nanda and Rhodes-Kropf (2017) theoretically show that in the presence of financing risks, the kind of ventures that are funded would vary by geography and industry. So, it is important to match on these characteristics to control for startup selection. Our matching approach is similar to that by Chemmanur, Krishnan, and Nandy (2011) who match VC-financed and non-VC-financed private firms using industry, size and total factor productivity; and that by Puri and Zarutskie (2012) who use age, industry, geographical region, and number of employees to match business with and without VC funding. We match on the total amount of funding raised by the startups with the objective to compare CF and VC startups of similar quality. Given that this matching procedure ensures balance based on the total amount of capital raised by a startup, our estimations rely on variation between rounds or the variation in the amount of capital raised by a startup in the seed stage relative to the subsequent stages. The matched sample has 248 startups that received some crowdfunding and 1,560 startups that are purely VC-funded.

E. Investor Characteristics and Startup Exits Data

Since neither of the two databases, AngelList or VentureXpert, tracks information on the exit details for the startups, we use CrunchBase for obtaining acquisition details, IPO details and current state – active or inactive – for each of the startups in the matched sample of startups. For each startup, CrunchBase provides information on whether the startup was acquired or publicly listed, the corresponding timelines for IPO or acquisition, and whether the startup is active or has gone out of business. Specifically, for the startups that were acquired, CrunchBase provides details on the acquisition value and whether the acquirer was a publicly-listed company or a financial sponsor. We use this data for classifying each of the exit events as a successful or an unsuccessful exit. We classify each exit through an IPO as a successful exit. For acquisitions, we classify the exit as successful if it satisfies one of the following conditions: (a) the acquisition value is higher than the total capital raised by the startup or (b) the startup is acquired by a publicly listed acquirer or a financial sponsor – a venture capital firm or a private equity firm – in case either the acquisition value or the total capital raised by the startup is unavailable. Finally, we have classified all the cases in which the startup has gone out of business, i.e., the startup status on CrunchBase is closed/inactive, but the startup has not been acquired or publicly listed, as failed exits. The exit-related data are available for 1,527 of the 1,560 VC-funded startups and all 248 of the CF startups.

Only 8% of the crowdfunded startups witnessed a successful exit whereas 15% of the VC-funded startups experienced a successful exit. On the other hand, while only 10% of the VC funded startups failed, the corresponding figure for crowdfunded startups is 15%. Both the crowdfunded and VC-funded startups witnessed similar exit rates - 23% for crowdfunded and 25% for VC-funded startups.

In addition to the exit data, we obtained investment details for all the investors – Crowd-funders as well as Venture Capital-funders – who made at least one investment in any of the 1,808 startups in the matched sample. For each investor, we obtained details for all the investments made. Using this data, we discerned the number of yearly investments, number of yearly lead investments, number of yearly seed investments, and the number of yearly exits, where the exit is defined for each investee startup of the investor. Using the criteria described above, we classify each exit by an investor as a success or a failure. We segregate the investors into more successful and less successful groups based on the median of the success rate, defined as the ratio of the total number of successful exits to the total number of unique portfolio investments.

A total of 1,456 investors invested in the matched sample of startups, out of which 8% participated in at least one crowdfunding round. Remaining 92% of the investors participated in only VC rounds. While 70% of the crowdfunders are less successful investors, only 48% of the VCs are less successful investors.

F. Characteristics of crowdfunded and VC-funded startups

Table 2 provides descriptive statistics for the key variables we use in our analysis for the matched sample of crowdfunded and VC-funded startups. We measure variables either for each startup-round level or for each startup.

Around 14% of the startups in the matched sample have received some equity crowdfunding in their lifetime. These are the crowdfunded startups (CF startups for short). We call those who have never received any equity crowdfunding as the VC-funded startups (VC startups). CF startups are slightly younger (by about three months) and have raised about the same amount of money overall as VC startups. They go through, on average, 0.2 higher funding rounds.

Looking at the round-level variables, around 5% of the rounds across all startups have been crowdfunded. We also look at amounts raised in a round and prior track record of the investors participating in a round. A round is said to be funded by more successful investors if the majority of the investors in that round are more successful. As described in the previous section, an investor is more successful if the success rate of her investee companies is above the median. In Table 2, we see that the amount raised in a crowdfunded round is statistically no different from that raised in a VC round. However, in the round following a crowdfunded round, money raised and the likelihood of funding by more successful investors are less. As we discussed in the introduction, amount raised and receiving funding by a more successful investor in the subsequent round are important intermediate milestones given the staged nature of investment in entrepreneurial ventures. Thus, there is some early indication that controlling for quality via matching, CF startups do worse than VC startups. Next, we compare the performance of CF and VC startups more rigorously.

3. Startup Performance

A. Comparing CF and VC funded startups

Table 3 compares the intermediate performance of CF and VC startups for the matched sample. Column (1) presents the OLS regression of log amount raised in a round. Column (2) shows the probit regression for the probability of funding by more successful investors. The specifications are:

$$logAmount_{ijs} = \beta_0 + \beta_1 PrevRoundCF_{ijs} + \beta_2 logTimePrevRound_{ijs} + X_s + R_j + \epsilon_{ijs} \quad (1)$$

$$Prob(SuccessfulInv_{ijs}) = \beta_0 + \beta_1 PrevRoundCF_{ijs} + \beta_2 logTimePrevRound_{ijs} + X_s + R_j + \epsilon_{ijs} \quad (2)$$

Subscript *i* denotes the startup and *j* the round of funding. *s* denotes the CEM strata within the matched sample to which is startup belongs. $logAmount_{ijs}$ is the log of the amount of capital raised in the round. $SuccessfulInv_{ij}$ is 1 if the majority of the investors in that round are more successful and 0 otherwise. $PrevRoundCF_{ijs}$ is an indicator variable which equals 1 if the startup was crowdfunded in the previous round (j-1). $logTimePrevRound_{ijs}$ the log of the number of years from the previous round of funding (j-1) to the current round. We include CEM strata fixed effects (X_s). Thus, the analysis gives within-matched-strata effects and hence controls for unobserved variation in the startup quality that is correlated with the matching variables. We also control for the stage of funding by including the round number fixed effects (R_j). The results suggest that compared to VC-funding, crowdfunding in the previous round is associated with a lower amount of funding and a lower probability of funding by more successful investors in the current round.

Table 4 presents the results for the multinomial logistic regression for the probability of success or failure, relative to neither success nor failure (base outcome) for the matched sample of crowdfunded and VC-funded startups.:

$$Prob(Success_{isy}/Failure_{isy}) = \beta_0 + \beta_1 EverCF_{is} + X_s + \epsilon_{isy} \tag{3}$$

The outcome is in year y for startup i belonging to the CEM-matched-strata s. The main explanatory variable here is an indicator *EverCFis* which is 1 if the startup ever received any equity crowdfunding. As before, X_s are the CEM strata fixed effects. We estimate a competing hazard model in which there are two absorbing states: success and failure, and one intermediate state: neither success nor failure. We use 8,837 observations, where the unit of observation is a startup-year, ranging from the year of the first round until the year of exit, or 2018, whichever is earlier. The results show that CF startups are less likely to succeed than their VC-funded counterparts, while there is no significant difference between rates of failure for the two categories of startups. So examining the final outcomes of the startups, we again find that CF startups perform relatively poorly.

Thus, the results so far have established that, after controlling for startup quality via matching, CF startups underperform VC funded ones. We turn to examining some possible mechanisms for this relative poor performance.

B. Is it distance?

While online platforms mitigate many disadvantages of lack of proximity, they may not be able to eliminate all (Blum and Goldfarb 2006, Hortacsu, Martinez-Jerez, and Douglas 2009). In particular, ongoing effectiveness of an entrepreneur-investor relationship is likely to be predicated on continuous flow of soft information, which comes out only in face-to-face interactions or via close social networks (Agarwal et al, 2015). VCs that are located far from their investee companies are also likely to face similar impediments to information acquisition. So to examine the possibility that relative underperformance of CF startups is due to relative difficulty in having regular interactions, we compare their performance of with startups located far from their VC investors. We estimate specifications similar to Specifications (1), (2) and (3), but bifurcate the VC-funding in the previous round by the distance of the VC from the startups.

For every startup-round purely funded by VCs, we calculate average distance between the city of the startup and the city of the VC headquarter, for all the investors. Then we define *PrevRoundFarVC* to be 1 if the average distance for the prior round is above the median distance for all the VC funded startup-rounds. Table 5 shows the results for the outcomes log round amount and probability of successful investors in the next round. We find that CF startups raise less money in the next round than that raised by startups funded by VCs located near as well as far from them. They are also less likely to funded by successful investors in the next round, although the difference between *PrevRoundCF* and *PrevRoundCF* is borderline insignificant.

To examine success or failure on exit based on distance from the VCs, we define a startup level indicator *FarVC*, which is 1 if the average distance of a startup from all VC investors over its life is above the median distance for all startups. Table 6 shows that CF startups are less likely to be successful compared to startups funded by both near as well as far VCs.

Since both intermediate and final outcomes of CF startups continue to be worse than even those startup with a distance disadvantage with reference to their investors, we conclude that frictions similar to those based on physical distance do not explain the underperformance of CF.

4. Investor Characteristics and Startup Performance

We next turn to investigate if inherent differences in investors could explain the performance differential.

A. Pseudo and pure crowds

Increasingly sophisticated members of the startup ecosystem invest via a crowdfunding platform (Abrams, 2017). Is the performance of the startups different if the crowdfunding is by sophisticated vs. naïve investors? We examine this possibility by looking at who leads the syndicated crowdfunded investments. If the lead investor in a syndicate for an equity crowdfunding round is a VC or an individual associated with a VC firm, we call such instances funding by a “pseudo” crowd. If a CF round is not syndicated or if the syndicate lead is an individual not associated with a VC firm, we call that funding by a “pure” crowd. Correspondingly, we define $PrevRoundPseudoCF_{ijs}$ and $PrevRoundPureCF_{ijs}$ indicator variables at the startup-round level and $EverPseudoCF_{is}$ and $EverPureCF_{is}$ at the startup level. Every startup receives crowdfunding in at most one round. So, the indicator variables at the startup level are mutually exclusive. A pure crowd funds 40% of the crowdfunded startups while the remaining 60% are funded by a pseudo crowd.

To compare the performance of pseudo and pure CF startups, we conduct the analysis similar to Specifications (1), (2) and (3) with the overall CF indicators replaced by the pseudo and pure crowd indicators. Table 7 presents the results for intermediate performance outcomes and Table 8 for final success or failure. The tables also test the hypothesis that the coefficients for pseudo and pure crowd indicators are the same. For all three specifications, we are unable to reject this hypothesis. Thus, the results clearly suggest that there are no differences in startup performance for the two categories of crowdfunding – pure crowd or pseudo crowd. This finding is consistent with Kim and Viswanathan (2018), who document that crowd appropriately puts weight on the involvement of the right kind of experts as early investors. The result that the underperformance of CF is not limited to "pure" crowd means that the differences between individuals and the VC firms do not explain the worse outcomes of CF startups.

B. Are CF and VC investors different?

So far we have established that, controlling for startup quality using a matched sample, CF startups perform poorly relative to VC startups. In this section, we investigate if CF and VC investors have similar characteristics and if not, whether the difference is related to the gap in outcomes for the startups.

A total of 1,456 investors invested in the matched sample of startups, out of which 8% participated in at least one crowdfunding round. Remaining 92% participated in only VC rounds. While 70% of the crowd funders are less successful investors, only 48% of the VCs are less successful investors. There are 285 investors in the matched sample of investors, with a 30% - 70% split between crowd funders and VC-funders. Also, 71% of the crowd funders and 80% of the VCs are less successful investors in the matched sample of investors.

Table 9 documents the descriptive statistics for the entire history of all the investors who have invested in our matched sample of startups, separately for CF and VC investors. The last column of the table reports the differences in means for CF and VC investors and the corresponding *t*-statistic. We see that over their investment career, VC investors make a significantly greater number of investments and a larger fraction of investments as lead investors compared to CF investors. VC investors also have been investing for a longer period and invest more per round. The portfolio companies of VC investors take longer to exit and are more likely to succeed eventually.

So, is the performance of CF startups is also similar to startups funded by the VCs with a worse track record?

C. Startup Performance: CF and more and less experienced VCs

In the previous subsection we saw that the CF investors, on an average, have less investment experience. They have made fewer investors, been around for fewer number of years and also are less likely to be lead investor compared to a typical VC in our sample. To better understand if this difference in experience is a factor for the relative underperformance of CF startups, we compare their performance of with that of the ones funded by less experienced VCs. Tables 10 and 11 present the regression results for the same outcome variables as those presented in Tables 3 and 4 respectively, i.e., Specifications (1), (2) and (3), but segregating the VC-funding by the experience of VC investors. Specifically, the indicator $PrevRoundLessEVC_{ijs}$ is 1 if the majority of the investors in the previous VC-funded round are less experienced. Similarly, the startup level indicator variable $LessEVC_{is}$ is equal to 1 if the majority of the investors over the life of a VC-startup are less experienced investors. We define an investor as less experienced if she has below-median experience, where experience is measured as either the number of investments made, the number of years as investor or the fraction of lead investments.

In Table 10, we see that the coefficient for *PrevRoundCF* is always negative and statistically significant, indicating that CF startup have worse intermediate outcomes than those for the startups funded by more experienced VCs. But the amount raised in the next round by the CF startups is statistically no different from that raised by startups funded by less experienced VCs. We see in the last two rows of the table which test the hypothesis that "*PrevRoundCF – PrevRoundLess EVC* = 0". In fact, CF startups seem to be more likely than startups of less experienced VCs to be funded by successful investors in the next round, for two out of three measures of experience.

Looking at Table 11, we see that compared to startups funded by more experienced VCs, CF startups are less likely to have a successful exit. But their success propensity is no different from that of the startups funded by less experienced VCs. Overall, in terms of starup performance CF does as well as or better than less experienced VCs.

D. Startup Performance: CF and more and less successful VCs

Tables 12 and 13 present the regression results by separating the VC-funding by the track record of success of investors. As described in Section 2.E, we define a more successful investor as one with an above-median success rate of portfolio companies. We set the indicator $PrevRoundLessSVC_{ijs}$ to 1 if the majority of the investors in the previous VC-funded round are less successful and 0 otherwise. Similarly, the startup level indicator variable $LessSVC_{is}$ is 1 if the over the life of the startup majority are less successful investors. 78% of the VC-funded startups were funded by majority more successful investors, while majority less successful investors funded the remaining 22%.

The results in Tables 12 and 13 are similar to those in Tables 10 and 11. Table 12 shows that the coefficient for $PrevRoundLessSVC_{ijs}$ in both the specifications – using log round amount as well as the probability of more successful investors in the next round – is negative and significant.

Thus, the startup-rounds funded by less successful VCs are followed by worse outcomes than those funded by more successful VCs. Further, the coefficient for *PrevRoundCF* is statistically the same (for round amount) or higher (for the probability of more successful investor) as that for *PrevRoundLessSVC.* Thus, CF funded startups perform as well as or better than those funded by less successful VCs.

Table 13 shows a similar pattern for the multinomial logit regression for the probability of success and failure. The rate of success for startups funded by less successful VCs is lower than the success rate for the ones funded by more successful VCs. But it is similar to the probability of success for CF startups.

Overall, differences in investor experience and expertise go a long way in explaining the performance differential between CF and VC startups. The fact that on some dimensions CF startups perform better than startups funded by less established VCs highlights the nuances in the trade-offs between the two platforms.

5. Conclusion

Using a comprehensive sample of 402 equity crowdfunded and nearly 7,000 VC-funded startups, we investigate the relative performance of ventures funded by these two sources. A primary reason for the performance differential is likely to be that the inherent quality of startups financed by the two sources is not the same. We control for startup quality via Coarsened Exact Matching on key startup characteristics – age, sector, location and the total amount raised by the startups. In the matched sample of more than 1,800 startups, we find that the CF startups underperform compared to VC startups. In the round following CF funding, they raise less money and are less likely to be funded by more successful investors. Their rates of successful exits are also lower. CF startups perform worse than even the startups funded by VCs located farther away from the startups. Thus, distance related frictions seem unlikely to explain the relative underperformance of CF. Further, the performance differential between VC and CF is not driven by the VC-vs-individuals distinction. We do not find any difference in the performance of CF startups that are funded on the platform by VCs and VC-affiliated individuals and the performance of those crowdfunded by unaffiliated individuals.

When we compare the CF investors to VCs, we find them less experienced and with worse track record of success. Both CF and startups funded by less experienced (successful) VCs perform worse that those funded by more experienced (successful) VCs. Further, the CF startups perform broadly at par with those financed by less experienced or less successful VCs, except on one dimension. CF startups are more likely to attract successful investors in the next round. Thus, CF platforms expand the reach of more successful investors.

Taken together our results indicate that the distinctive benefits that CF funding may offer – for example, timely capital, autonomy, input into product design, a better public profile for the startup – compare favorably to mentoring and monitoring that less successful VCs may provide. On the other hand, the value-added services by more successful VCs dominate the benefits of equity crowdfunding.

Our study contributes to the emerging field of equity crowdfunding research, the literature on how venture performance differs by funding source, and the research on how investor characteristics are related to startup outcomes. By highlighting the nuances in trade-offs between VC-funding and CF, it underscores the importance of understanding the mechanisms for the performance differential of the two types of startups.

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Table 1: Distribution of Sample Startups

This table shows the distribution of startups (all panels except Panel C) or startup-rounds (Panel C) by various characteristics. A startup that received any equity crowdfunding is classified as a crowd-funded started. A startup which is purely VC-funded and did not receive any crowdfunding is classified as VC-funded.

Panel A: Crowdfunded (CF) and VC-funded Startups

Funding type	CF	VC	Total
Fraction	0.055	0.945	1.000
Number of startups	402	6,933	7,335

Panel B: Syndication in Crowdfunding

	Syndicate	Individual	Total
Fraction	0.851	0.149	1.000
Number of startups	342	60	402

Panel C: Funding by stage

	Unit of observation	Early	Late
Crowdfunding	Startup-Round	0.756	0.244
VC-funding	Startup-Round	0.594	0.405

Panel D: Funding by sector (Fraction of startups)

Sector	Overall	CF	VC
Clean Technology	0.05	0.01	0.05
Internet	0.07	0.12	0.07
Hardware	0.01	0.06	0.00
Non-Internet Related	0.06	0.22	0.05
Services	0.31	0.22	0.32
Software/technology	0.50	0.36	0.51
Total	**1.00**	**1.00**	**1.00**

Panel E: Funding by location

City	Overall		Crowdfunded		VC-funded	
	No. of startups	Proportion	No. of startups	Proportion	No. of startups	Proportion
Silicon Valley	1,943	0.265	203	0.505	1,740	0.251
New York	776	0.106	47	0.117	729	0.105
Boston	214	0.029	28	0.070	186	0.027
Austin	161	0.022	5	0.012	156	0.023
Chicago	156	0.021	8	0.020	148	0.021
Seattle	134	0.018	8	0.020	126	0.018
Los Angeles	129	0.018	9	0.022	120	0.017
Philadelphia	104	0.014	0	0.000	104	0.015
Cambridge	102	0.014	0	0.000	101	0.015
Pittsburgh	100	0.014	0	0.000	99	0.014
Santa Monica	90	0.012	0	0.000	87	0.013
Atlanta	80	0.011	0	0.000	77	0.011
Portland	77	0.010	4	0.010	73	0.011
San Jose	77	0.010	0	0.000	77	0.011
Boulder	0	0.000	7	0.017	0	0.000
Oakland	0	0.000	5	0.012	0	0.000
Washington, DC	0	0.000	5	0.012	0	0.000
Berkeley	0	0.000	4	0.010	0	0.000
Denver	0	0.000	4	0.010	0	0.000
Others	3,192	0.435	65	0.162	3110	0.449
Total	**7,335**	**1.000**	**402**	**1.000**	**6,933**	**1.000**

Table 2: Summary Statistics - Matched Sample

This table shows the summary statistics of different variables of interest for the sample of matched startups. See Section 2.D for the details of the matching procedure. Column 3 shows the numbers for the overall matched sample, Column 4 for the crowdfunded startups or round, Column 5 for VC-funded startup or round. The last column shows the difference between the values for VC and CF startups or rounds, with t-statistics for the difference in parentheses.

Variable Name	Unit of Observation	All Startups / Rounds	CF Startups / Round	VC Startups / Round	Diff. (VC - CF)
Startup ever crowdfunded (0/1)	Startup	0.137	1.000	0.000	-1.000
Age (years)	Startup	3.385	3.173	3.419	0.245
					(2.497)
Total amount raised (USD in millions)	Startup	22.400	18.700	23.100	4.400
					(1.212)
Number of rounds	Startup	2.373	2.560	2.344	-0.217
					(2.059)
Round crowdfunded (0/1)	Startup-round	0.047	1.000	0.000	-1.000
Amount raised in the round (USD in millions)	Startup-round	9.275	6.693	9.410	2.717
					(1.001)
Amount raised in the subsequent round (USD in millions)	Startup-round	14.400	9.153	14.700	5.547
					(1.757)
Time till the subsequent round (years)	Startup-round	0.977	0.887	0.981	0.094
					(1.522)
Majority more successful investors in subsequent round (0/1)	Startup-round	0.741	0.589	0.747	0.158
					(3.363)

Table 3: Intermediate Performance of Startups

This table compares the intermediate performance of CF and VC startups in the matched sample. Column (1) presents the OLS regression of log amount raised in a round. Column (2) shows the probit regression for the probability of funding by more successful investors. *PrevRoundCF* is an indicator variable which equals 1 if the startup was crowdfunded in the previous round. *logTimePrevRound* is the log of the number of years from the previous round of funding to the current round. CEM strata fixed effects are for the stratas based on CEM matching. See Section 2.D. Robust t-statistics / z-statistics are in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% respectively.

	Log round amount	More successful investor participation in round
PrevRoundCF	-0.279**	-0.345**
	(-2.252)	(-2.154)
logTimePrevRound	0.948***	0.061
	(11.501)	(0.538)
CEM strata fixed effects	Yes	Yes
Round number fixed effects	Yes	Yes
Observations (Startup-round)	2,169	2,052
R-squared	0.370	

Table 4: Success and Failure

This table presents the results for the multinomial logistic regression for the probability of success or failure, relative to neither success nor failure (base outcome) for the matched sample of crowdfunded and VC-funded startups. We estimate a competing hazard model in which there are two absorbing states: success and failure, and one intermediate state: neither success nor failure. The unit of observation is a startup-year, ranging from the year of the first round until the year of exit, or 2018, whichever is earlier. *EverCF* is an indicator which is 1 if the startup ever received any equity crowdfunding, and 0 otherwise. CEM strata fixed effects are for the stratas based on Coarsened Exact Matching. See Section 2.D. Robust z-statistics are in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% respectively.

	Success	Failure
EverCF	-0.613**	0.161
	(-2.401)	(0.740)
CEM strata fixed effects	Yes	Yes
Observations (Startup-year)	8,837	8,837

Table 5: Intermediate Performance – Near and Far Investors

This table compares the intermediate performance of CF and VC startups in the matched sample. Column (1) presents the OLS regression of log amount raised in a round. Column (2) shows the probit regression for the probability of funding by more successful investors. *PrevRoundCF* is an indicator variable which equals 1 if the startup was crowdfunded in the previous round. *PrevRoundVCFar* is 1 if the average distance between the startup and the investors in the previous VC-funded round is above-median and 0 otherwise. *logTimePrevRound* is the log of the number of years from the previous round of funding to the current round. CEM strata fixed effects are for the stratas based on CEM matching. See Section 2.D. Robust t-statistics / z-statistics are in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% respectively. The last two rows test the hypothesis that the coefficients for *PrevRoundCF* and *PrevRoundVCFar* are equal.

	Log round amount	More successful investor participation in round
PrevRoundCF	-0.316**	-0.592***
	(-2.357)	(-3.447)
PrevRoundVCFar	0.004	-0.323***
	(0.060)	(-3.451)
logTimePrevRound	0.970***	0.081
	(10.177)	(0.641)
CEM strata fixed effects	Yes	Yes
Round number fixed effects	Yes	Yes
Observations (Startup-round)	1,760	1,664
R-squared	0.372	
PrevRoundCF - *PrevRoundVCFar*	-0.320**	-0.269
	(-2.399)	(-1.552)

Table 6: Success and Failure - Near and Far Investors

This table presents the results for the multinomial logistic regression for the probability of success or failure, relative to neither success nor failure (base outcome) for the matched sample of crowdfunded and VC-funded startups. We estimate a competing hazard model in which there are two absorbing states: success and failure, and one intermediate state: neither success nor failure. The unit of observation is a startup-year, ranging from the year of the first round until the year of exit, or 2018, whichever is earlier. *EverCF* is an indicator which is 1 if the startup ever received any equity crowdfunding, and 0 otherwise. *FarVC* is 1 if over the life of the startup the average distance between the VC investors and the startup is above median. CEM strata fixed effects are for the stratas based on Coarsened Exact Matching. See Section 2.D. Robust z-statistics are in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% respectively. The last two rows test the hypothesis that the coefficients for *EverCF* and *FarVC* are equal.

	Success	Failure
EverCF	-0.595**	0.037
	(-2.223)	(0.149)
FarVC	0.017	-0.248
	(0.106)	(-1.294)
CEM strata fixed effects	Yes	Yes
Observations	7,787	7,787
EverCF - FarVC	-0.612**	0.284
	(-2.255)	(1.128)

Table 7: Intermediate Performance - Pseudo and Pure Crowd

This table compares the intermediate performance of CF and VC startups in the matched sample. Column (1) presents the OLS regression of log amount raised in a round. Column (2) shows the probit regression for the probability of funding by more successful investors. *PrevRoundPseudoCF* is an indicator variable which equals 1 if the startup was crowdfunded by a pseudo crowd (crowdfunding syndicates led by VCs or individual associated with VCs). *PrevRoundPureCF* is an indicator variable which equals 1 if the startup was crowdfunded by a pure crowd (unsyndicated crowdfunding or syndicates led by individuals not-associated with VCs). *logTimePrevRound* is the log of the number of years from the previous round of funding to the current round. CEM strata fixed effects are for the stratas based on CEM matching. See Section 2.D. Robust t-statistics / z-statistics are in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% respectively. The last two rows test the hypothesis that the coefficients for *PrevRoundPseudoCF* and *PrevRoundPureCF* are equal.

	Log round amount	More successful investor participation in round
PrevRoundPseudoCF	-0.242	-0.476**
	(-1.580)	(-2.149)
PrevRoundPureCF	-0.314*	-0.224
	(-1.704)	(-0.979)
logTimePrevRound	0.947***	0.063
	(11.497)	(0.550)
CEM strata fixed effects	Yes	Yes
Round number fixed effects	Yes	Yes
Observations (Startup-round)	2,169	2,052
R-squared	0.370	
PrevRoundPseudoCF - *PrevRoundPureCF*	0.071	-0.252
	(0.306)	(-0.801)

Table 8: Success and Failure – Pseudo and Pure Crowd

This table presents the results for the multinomial logistic regression for the probability of success or failure, relative to neither success nor failure (base outcome) for the matched sample of crowdfunded and VC-funded startups. We estimate a competing hazard model in which there are two absorbing states: success and failure, and one intermediate state: neither success nor failure. The unit of observation is a startup-year, ranging from the year of the first round until the year of exit, or 2018, whichever is earlier. *EverPseudoCF* is an indicator which is 1 if the startup ever received any equity crowdfunding by a pseudo crowd (crowdfunding syndicates led by VCs or individual associated with VCs). *EverPureCF* is an indicator which is 1 if the startup ever received any crowdfunding by a pure crowd (unsyndicated crowdfunding or syndicates led by individuals not-associated with VCs). CEM strata fixed effects are for the stratas based on Coarsened Exact Matching. See Section 2.D. Robust z-statistics are in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% respectively. The last two rows test the hypothesis that the coefficients for *EverPseudoCF* and *EverPureCF* are equal.

	Success	Failure
EverPseudoCF	-0.582*	-0.067
	(-1.798)	(-0.234)
EverPureCF	-0.659*	0.428
	(-1.660)	(1.513)
CEM strata fixed effects	Yes	Yes
Observations (Startup-year)	8,837	8,837
EverPseudoCF - *EverPureCF*	0.077	-0.494
	(0.153)	(-1.34)

Table 9: Investor Characteristics – CF and VC Investors

This table shows the average of various characteristics for the entire history of all the investors who have invested in our matched sample of startups, separately for investors of CF and VC startups. The last column of the table reports the differences in means for CF and VC investors and the corresponding *t*-statistic in parentheses.

	Unit of observation	All Investors	CF	VC	VC - CF
Number of investments (startup-rounds)	Investor	73.552	47.712	75.684	27.972
					(2.042)
Total percentage of lead investments	Investor	22.728	9.019	23.860	14.841
					(7.291)
Total percentage of seed investments	Investor	30.909	69.420	27.730	-41.690
					(-14.845)
Total exits	Investor	15.917	8.730	16.510	7.780
					(2.380)
Successful exits as a % of number of investee startups	Investor	14.194	9.325	14.596	5.271
					(3.538)
Failed exits as a % of number of investee startups	Investor	12.952	14.597	12.816	-1.781
					(-1.263)
Average round amount (USD mm)	Investor	18.600	4.480	19.700	15.220
					(4.067)
Average years to exit	Investor	3.479	2.751	3.531	0.780
					(4.507)
Average years to successful exits	Investor	3.577	2.906	3.616	0.709
					(3.101)
Average years to failed exits	Investor	3.533	2.645	3.600	0.955
					(4.645)
Number of years as investor	Investor	10.257	6.559	10.562	4.004
					(6.794)
Yearly investments	Investor-year	8.474	9.215	8.439	-0.776
					(-1.314)
Yearly % of lead investments	Investor-year	23.120	6.665	23.899	17.233
					(14.152)
Yearly % of seed investments	Investor-year	22.767	64.537	20.790	-43.747
					(-32.332)
Yearly exits	Investor-year	1.614	1.413	1.623	0.210
					(1.589)
Yearly successful exits (% of yearly exits)	Investor-year	58.445	36.436	59.249	22.813
					(8.639)

Table 10: Intermediate Performance –More and Less Experienced Investors

This table compares the intermediate performance of CF and VC startups in the matched sample. Column (1) presents the OLS regression of log amount raised in a round. Column (2) shows the probit regression for the probability of funding by more successful investors. *PrevRoundCF* is an indicator variable which equals 1 if the startup was crowdfunded in the previous round. *PrevRoundLessEVC* is 1 if the majority of the investors in the previous VC-funded round are less experienced and 0 otherwise. A more experienced investor is one with an above-median experience. A less experienced investor has a below-median experience. Experience is measured as either number of investments, number of years as an investor or fraction of investments where the investor is a lead investor. *logTimePrevRound* is the log of the number of years from the previous round of funding to the current round. CEM strata fixed effects are for the stratas based on CEM matching. See Section 2.D. Robust t-statistics / z-statistics are in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% respectively. The last two rows test the hypothesis that the coefficients for *PrevRoundCF* and *PrevRoundLessEVC* are equal.

	Experience = No of investments		Experience = No of years		Experience = Fraction of Lead Investments	
	Log round amount	More successful investor participation in round	Log round amount	More successful investor participation in round	Log round amount	More successful investor participation in round
PrevRoundCF	-0.303**	-0.406**	-0.317**	-0.465***	-0.338***	-0.502***
	(-2.430)	(-2.544)	(-2.526)	(-2.848)	(-2.687)	(-3.098)
PrevRoundLessEVC	-0.320***	-0.779***	-0.254***	-0.869***	-0.220***	-0.561***
	(-3.083)	(-5.077)	(-3.322)	(-7.637)	(-3.581)	(-6.729)
logTimePrevRound	0.953***	0.049	0.945***	0.050	0.937***	0.038
	(11.651)	(0.435)	(11.545)	(0.437)	(11.392)	(0.328)
Observations (Startup-round)	2,169	2,052	2,169	2,052	2,169	2,052
R-squared	0.373		0.373		0.374	
CEM strata fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Round number fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
PrevRoundCF – *PrevRoundLessEVC*	0.017	0.373*	- 0.062	0.403**	-0.118	0.059
	(0.112)	(1.728)	(-0.461)	(2.137)	(-0.930)	(0.356)

Table 11: Success and Failure - More and Less Experienced Investors

This table presents the results for the multinomial logistic regression for the probability of success or failure, relative to neither success nor failure (base outcome) for the matched sample of crowdfunded and VC-funded startups. We estimate a competing hazard model in which there are two absorbing states: success and failure, and one intermediate state: neither success nor failure. The unit of observation is a startup-year, ranging from the year of the first round until the year of exit, or 2018, whichever is earlier. *EverCF* is an indicator which is 1 if the startup ever received any equity crowdfunding, and 0 otherwise. *LessEVC* is 1 if over the life of the startup majority investors are less experienced. A more experienced investor is one with an above-median experience. A less experienced investor has a below-median experience. Experience is measured as either number of investments, number of years as an investor or fraction of investments where the investor was a lead investor. CEM strata fixed effects are for the stratas based on Coarsened Exact Matching. See Section 2.D. Robust z-statistics are in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% respectively. The last two rows test the hypothesis that the coefficients for *EverCF* and *LessSVC* are equal.

	Experience = No of investments		Experience = No of years		Experience = Fraction of Lead Investments	
	Success	Failure	Success	Failure	Success	Failure
EverCF	-0.663***	0.105	-0.672***	0.091	-0.670***	0.228
	(-2.589)	(0.479)	(-2.631)	(0.412)	(-2.594)	(1.016)
LessEVC	-0.731**	-0.520	-0.795**	-0.577*	-0.415	0.324
	(-1.986)	(-1.543)	(-2.336)	(-1.783)	(-1.504)	(1.315)
CEM strata fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,837	8,837	8,837	8,837	8,837	8,837
EverCF - LessEVC	0.068	0.626*	0.122	0.668*	-0.255	-0.097
	(0.157)	(1.664)	(0.299)	(1.844)	(-0.725)	(-0.332)

Table 12: Intermediate Performance – More and Less Successful Investors

This table compares the intermediate performance of CF and VC startups in the matched sample. Column (1) presents the OLS regression of log amount raised in a round. Column (2) shows the probit regression for the probability of funding by more successful investors. *PrevRoundCF* is an indicator variable which equals 1 if the startup was crowdfunded in the previous round. *PrevRoundLessSVC* is 1 if the majority of the investors in the previous VC-funded round are less successful and 0 otherwise. A more successful investor is one with an above-median success rate of portfolio companies. A less successful investor has a below-median success rate. See Section 2.E for details. *logTimePrevRound* is the log of the number of years from the previous round of funding to the current round. CEM strata fixed effects are for the stratas based on CEM matching. See Section 2.D. Robust t-statistics / z-statistics are in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% respectively. The last two rows test the hypothesis that the coefficients for *PrevRoundCF* and *PrevRoundLessSVC* are equal.

	Log round amount	More successful investor participation in round
PrevRoundCF	-0.378***	-0.770***
	(-2.975)	(-4.650)
PrevRoundLessSVC	-0.356***	-1.644***
	(-4.684)	(-15.924)
logTimePrevRound	0.998***	0.015
	(11.178)	(0.118)
CEM strata fixed effects	Yes	Yes
Round number fixed effects	Yes	Yes
Observations (Startup-round)	1,937	1,841
R-squared	0.377	
PrevRoundCF – PrevRoundLessSVC	-0.023	0.874***
	(-0.167)	(4.819)

Table 13: Success and Failure - More and Less Successful Investors

This table presents the results for the multinomial logistic regression for the probability of success or failure, relative to neither success nor failure (base outcome) for the matched sample of crowdfunded and VC-funded startups. We estimate a competing hazard model in which there are two absorbing states: success and failure, and one intermediate state: neither success nor failure. The unit of observation is a startup-year, ranging from the year of the first round until the year of exit, or 2018, whichever is earlier. *EverCF* is an indicator which is 1 if the startup ever received any equity crowdfunding, and 0 otherwise. *LessSVC* is 1 if over the life of the startup majority investors are less successful. A more successful investor is one with an above-median success rate of portfolio companies. A less successful investor has a below-median success rate. See Section 2.E for details. CEM strata fixed effects are for the stratas based on Coarsened Exact Matching. See Section 2.D. Robust z-statistics are in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% respectively. The last two rows test the hypothesis that the coefficients for *EverCF* and *LessSVC* are equal.

	Success	Failure
EverCF	-0.931***	0.119
	(-3.393)	(0.529)
LessSVC	-1.182***	-0.174
	(-4.271)	(-0.760)
CEM strata fixed effects	Yes	Yes
Observations (Startup-year)	8,647	8,647
EverCF - LessSVC	0.251	0.294
	(0.698)	(1.039)