On the signaling effect of reward-based crowdfunding: (When) do later stage venture capitalists rely more on the crowd than their peers?

Abstract

Venture capitalists (VCs) make only a small number of investments and are more likely to invest in ventures where other VCs have invested previously. As such, valuable opportunities may be forgone if they are not funded by VCs in the first place. We demonstrate how crowdfunding (CF) can remedy this concern. Using a sample of new technology-based ventures, we reveal that ventures initially funded through reward-based CF can be even more likely than those initially backed by VCs in attracting follow-up funds from VCs. This happens when ventures originally funded via reward-based CF complement the certification they derive from CF with patents and a founding team with a track record of success. In those cases, VCs rely on the crowd more than their peers. Overall, the results suggest that signal complementarity can at least equalize the effectiveness of an *a priori* inferior and an *a priori* superior signal.

Keywords: reward-based crowdfunding, venture capital, signal, new ventures, certification effect.

1. Introduction

Crowdfunding (CF) is a relatively new means to finance early stage entrepreneurial firms complementing traditional sources of entrepreneurial finance such as business angels and venture capitalists (VCs). Indeed, CF has allowed numerous new ventures to secure early stage funding mostly from non-professional investors and the academic literature on CF has grown considerably to match its increasing relevance (Short et al., 2017). For instance, a number of contributions have explained, among others, what makes a CF campaign successful highlighting the role of project, campaign, and entrepreneur characteristics (e.g., Ahlers et al., 2015; Allison et al., 2017; Anglin et al., 2018; Chan and Parhankangas, 2017; Colombo et al., 2015; Courtney et al., 2017; Crosetto and Regner, 2018; Davis et al., 2017; Mollick, 2014; Vismara, 2018). More recently, also in response to calls highlighting the need to compare different types of initial funding sources (Drover, Busenitz, et al., 2017; Dutta and Folta, 2016; McKenny et al., 2017), an emerging strand of the CF literature has started to provide insights about the relationship of CF with traditional forms of entrepreneurial finance, including angel and venture capital investments. The main conclusion of these works is that, as a channel for early-stage funding, CF can offer a certification of unobserved quality that attracts later-stage traditional investors (Drover, Wood, et al., 2017; Roma et al., 2017; Colombo and Shafi, 2019; Wang et al., 2019).

What we know less about is how the attraction of CF for follow up investments *compares* to the attraction realized when the first infusion of funds originates from professional investors such as early-stage VCs. Are ventures initially funded through CF less likely to raise later stage funds from VCs compared to ventures initially funded by VCs? If so, why and (how) can this change? These are the questions we are asking.

Promising entrepreneurial ventures may be forgone/not scale up if they are not funded by VCs in the first place as VCs make only limited investments and often in firms where other VCs have invested previously (Franke et al., 2008; Guerini and Quas, 2016; Mäkelä and Maula, 2008; Powell et al., 2002; Ragozzino and Reuer, 2011; Zider, 1998). It is therefore important to understand whether, and if so how, CF can allow ventures not funded initially by VCs to attract later stage funds from VCs.

As we elaborate below, we expect initial funding from CF to offer a weaker signal compared to having initial funding from VCs. We then make progress on theory. We ground on signal interplay and propose that this initial disadvantage may shrink or even be overcome if the venture in question transmits additional signals that complement the unobserved information transmitted when initial funding comes from CF. Further, we delineate that different signals and their interactions (with, per Howell (2017), certification from third parties being one of the most common forms of a signal) work towards reducing both Knightian uncertainty and information asymmetries (Foss et al., 2020; Packard et al., 2017; Townsend et al., 2018). They reduce Knightian uncertainty during the very early stages of firm growth, i.e., during the first infusion of capital, either by venture capitalists or by the crowd. They reduce information asymmetries at later stages, i.e., past the first infusion of capital.

Our template is reward-based CF, under which entrepreneurs solicit individuals to fund their projects in exchange for rewards (typically the product that they intend to develop and commercialize). We build our arguments upon the different unobserved information that different sources of initial funding may transmit to subsequent VCs. Before the initial infusion of capital the firm is surrounded by all sorts of unknown factors, including market performance and technical adequacy. In the presence of such unknowns, even the entrepreneur is likely unsure about her project; let alone the finance providers. A first infusion of capital, either by VCs or by CF, can reduce such Knightian uncertainty via certification as the reduction originates from a third party endorsement and not directly from the firm (Megginson and Weiss, 1991). Indeed, we follow Howell (2017) in considering certification from a third party as the most common form of a signal, with a signal defined as any costly action meant to transmit unobserved information of the sender to the receiver (Spence, 1973). Such consideration is consistent with both Megginson and Weiss' (1991) definition of certification and Spence's (1973) conceptualization of a signal.[1] But, we expect the certification from CF to be weaker than the certification from VCs.

The main informational benefit of reward-based CF is that it serves as a test market, thus providing information regarding the market potential of a new venture (Drover, Wood, et al., 2017; Roma et al., 2017; Strausz, 2017; Viotto da Cruz, 2018). However, we argue that, in the eyes of subsequent VCs, this benefit is *per se* insufficient to compensate the "stamp of approval" provided by VCs who have previously funded the new venture. This is in large part because funding from peers is the result of a more comprehensive selection process that goes well beyond estimation of market demand extending to screening human, social and intellectual capital. As a result, we expect that, *ceteris paribus*, new ventures initially funded via CF will have a lower likelihood of receiving subsequent VC funding than similar firms initially funded by (different) early-stage VCs.

Once Knightian uncertainty has been reduced, unknowns remain but then, we expect, a probability function of future performance can be drawn. Accordingly, when seeking supplemental funds from subsequent VCs, any efforts the firm is engaging in to eliminate those unknowns are efforts to reduce information asymmetries. Given that VCs typically scan investment targets also on intellectual, human and social capital, these efforts often manifest in signals meant to convey information on those forms of capital. Prompted by evidence that intellectual, human and social capital matter *per se* in new venture financing, we capture them with patents, entrepreneurial team past record in securing funding, and affiliation with prestigious partners, respectively (Audretsch et al., 2012; Conti, Thursby and Thursby, 2013;

[1] Indeed, most signals involve, either directly or indirectly a third party. For example, patents go through the patent office and education, per Spence's (1973) original intuition, goes through an academic institution.

Haeussler et al., 2014; Hoenen et al., 2014; Hsu, 2007; Hsu and Ziedonis, 2013; Inkpen and Tsang, 2005; Kolympiris et al., 2018; McFadyen and Cannella Jr, 2004; Reagans and McEvily, 2003; Shane and Cable, 2002; Stuart et al., 1999). As long as such signals complement the potential market information transmitted by being originally funded by CF, we expect originally CF-backed ventures to reduce, and even overcome, their gap with similar ventures originally funded by VCs. This is because, we advance, the different characteristics of crowd investors and VCs make the certification provided by the former type of investors more complementary to signals of intellectual, human and social capital.

To test our arguments, we construct a new dataset that combines data from different sources. We identify ventures that have used CF as the initial resource infusion via Kickstarter (e.g., Allison et al., 2017; Courtney et al., 2017). We identify similar ventures, founded in the same period, that never launched a CF campaign, and received their first infusion of capital from VCs via CrunchbasePro (e.g., Ko and McKelvie, 2018; Nuscheler et al., 2019). The combined sample includes 625 new ventures in the Hardware industry (electronics, computer hardware, 3D printers, Internet of Things devices, drones, smart sensors, robotics, medical devices, and space applications). We focus on hardware ventures because, irrespective of their source of initial funding (i.e., CF or VC), such ventures require follow up funding to scale and this feature makes them a suitable template for our study. For each of the 625 hardware ventures we gather data on funding, patents granted for the given new product idea, the past experience of the entrepreneurial team in securing funding from professional investors and/or successfully exiting from previously founded ventures, prestigious affiliations, as well as a number of additional factors that describe the firms comprehensively.

Because being initially funded through CF or by early-stage VCs is not a random outcome, empirical concerns may still arise in our setting including endogeneity and comparing firms inherently different or at least on different paths (Walthoff-Borm et al., 2018).

Conceptually, we are looking at early stage firms within the same industry during the same period. In other words, these firms are roughly at the prototype/early-concept stage. At this stage, financing needs are typically rather limited. This indicates that they could be covered by a CF campaign or by a VC investing in early stage ventures. Therefore, the main distinguishing feature, and likely a make or break outcome at least in the short run, is whether they can raise enough funds. The origin of the funds (VC or CF) is of course relevant but the first order of business for this cohort of firms is survival. The firms we analyze, in both cohorts, have passed this hurdle. They have attracted funds – some from VCs; others from CF. We are not arguing they are on the exact level playfield and, as we detail next, this is corroborated by the analysis as without additional complementary signals initially CF-backed ventures are at a disadvantage. But, they are not miles apart either. They are in the same industry, in the same period, they have raised similar amounts allowing them to seek more funds and for both cohorts the next step is VC, as CF is not a viable option for scaling up.

Differences may indeed remain. This is why we are careful in using different methods including matching procedures to find originally VC-backed and originally CF-backed ventures that resemble each other in many respects, including what VCs consider in their financing decisions: information on human, social and intellectual capital.

The estimates from the empirical analysis are largely consistent with our theoretical expectations. While initially crowdfunded ventures are less likely to receive subsequent funding from VCs when compared to similar firms that received initial funding from (other) VCs, this relationship can even reverse if initially crowdfunded ventures transmit signals that complement the information conveyed by having a successful CF campaign. Across the board, we reveal that when initially crowdfunded ventures have patents and a strong founding team, they can become even more likely to raise follow up capital from (other) VCs when compared with their similar

VC-backed counterparts. In those cases, subsequent VCs rely on the crowd more than their peers.

We make three main contributions. One, we add to the literature on CF by bringing to light the novel finding that CF has a certification effect that, under contingencies we reveal, can allow entrepreneurial ventures *without* initial funding from VCs to compete with those *with* initial funding from VCs in attracting later stage funds from VCs. In this respect, we also add to the general entrepreneurship literature on new venture financing by comparing the certification effect of new and traditional forms of early-stage funding. In spite of the increasing number of funding alternatives and their interconnectedness, the explicit comparison of different types of initial funding sources is still very limited (Drover, Busenitz, et al., 2017; Dutta and Folta, 2016; McKenny et al., 2017). For example, McKenny et al. (2017) note that with the emergence of new funding channels such as CF, a comparison between CF and traditional sources of funding is worth future examination. This is what we do. Two, we contribute to the growing discussion on signal interplay in new venture financing (Bapna, 2019; Colombo et al., 2019; Plummer et al., 2016; Scheaf et al., 2019; Stern et al., 2014; Vanacker et al., 2020) by revealing the nontrivial result that signals that are stand-alone weaker (reward-based CF certification, in our application) can equalize, and even become more effective than stand-alone stronger ones (certification from VCs), when combined with complementary third signals. Three, we also contribute to the literature on the role of patents and founding team characteristics as a way to reduce information asymmetries between funders and founders (e.g., Audretsch et al., 2012; Conti, Thursby and Thursby, 2013; Haeussler et al., 2014; Hoenen et al., 2014; Hsu and Ziedonis, 2013; Kolympiris et al., 2018; Shane and Cable, 2002; Stuart et al., 1999). We do so by demonstrating that patents and founding team characteristics do not matter only *per se* as a signal valued by investors; they also matter as a device that boosts the effectiveness of other means of certification such as CF.

Our work has direct managerial implications as well. Crowdfunding is not without costs (Agrawal et al., 2014) and despite the significant benefits associated with it some entrepreneurs may still be hesitant to engage in CF campaigns. Our estimates improve the cost-benefit analysis of such founders not only in terms of the relevance of CF in addressing the early stage dearth of funds but also, and perhaps more importantly, in assisting attracting necessary funds for growth especially for cases where the initial funds did not originate from early-stage VCs.

2. Literature background and hypotheses

2.1 The certification effect: reward-based CF versus funding from VCs

VCs identify promising new ventures but the inherent uncertainty surrounding such ventures makes scanning a thorny task (Zacharakis and Meyer, 2000). These ventures are often prone to what previous works have described as Knightian uncertainty referring to cases where a probability distribution of future performance cannot be drawn (Foss et al., 2020; Packard et al., 2017; Townsend et al., 2018). Indeed, because true quality of new ventures is usually difficult to discern, VCs turn to accessible information related to ventures' observable attributes "thought to co-vary with their underlying but unknown quality" (Stuart et al., 1999) in order to mitigate the uncertainty at hand. Such attributes include industry features, founding team characteristics, the business model, potential target market as well signs of technological competency and high human and social capital (Bernstein et al., 2017; Hsu, 2007; Kolympiris et al., 2018; MacMillan et al., 1985; Shane and Cable, 2002; Zider, 1998).

Along these lines, VCs evaluate positively previous initial funding received by a new venture as, coming from a third party, it offers a certification of largely unobserved quality (Conti, Thursby and Thursby, 2013; Drover, Wood, et al., 2017; Guerini and Quas, 2016; Kerr et al., 2014; Lerner, 2002; Megginson and Weiss, 1991; Roma et al., 2017). But, are there differences in the strength of the certification effect in the eyes of subsequent VCs between different sources of initial funding? Using reward-based CF as our template we argue that there are. This is so in large part because different sources of initial funding certify different attributes of a given venture. For instance, as we detail below, reward-based CF can be particularly effective in conveying the presence of market demand but conveys little about technical merits.

We posit that subsequent VCs should evaluate ventures initially backed by early-stage VCs and ventures initially backed by CF differently in terms of attractiveness for funding. We expect such divergence in evaluation to stem from two main sources. First, the funding motives and screening strategies between different funders differ. Second, the degree of involvement in the venture past investment differs across funders. In turn, these differences influence the value of "stamp of approval" that different sources of initial funding convey to subsequent potential VCs.

2.1.1 Differences in the motives for funding and screening strategies

VCs and crowds have divergent objectives, assessment capabilities, and consequently follow different funding decision-making processes (Drover, Busenitz, et al., 2017). As introduced above, VCs are experts that spend considerable time and effort into screening their potential target firms (Amit et al., 1990; Hall and Hofer, 1993; Kaplan and Stromberg, 2001; Kolympiris et al., 2011). They tend to focus on specific industries and/or geographic locations, thus developing context-specific screening capabilities that enable them to conduct extensive due diligence and discover the most promising new ventures (Amit et al., 1998; Colombo and Grilli, 2010; Sorenson and Stuart, 2001). In this respect, they are often viewed as scouts of business opportunities (Baum and Silverman, 2004). When making funding decisions, VCs rely on a broad set of venture characteristics as evaluation criteria. Besides estimating the market potential of the new venture and the potential financial returns of their investment, VCs typically consider three types of attributes, namely intellectual, human, and social capital (Ahlers et al., 2015; Baum and Silverman, 2004; Petty and Gruber, 2011). For instance, VCs often consider the presence of patents granted for the product idea to infer the entrepreneurial team' innovative capabilities as well as value appropriability and technological viability (Baum and Silverman, 2004; Conti, Thursby and Thursby, 2013; Hoenen et al., 2014; Hsu and Ziedonis, 2013). They also carefully scrutinize the characteristics of the startup team, e.g., education, experience and past successes of founders, which represent the new venture's human capital (Franke et al., 2008; Hsu, 2007; Kolympiris et al., 2018; Zacharakis and Meyer, 2000). When it comes to social capital, VCs value ties to third parties such as suppliers and partners that are critical to the success of the new venture and serve as external endorsements (Baum and Silverman, 2004; Chang, 2004; Inkpen and Tsang, 2005; McFadyen and Cannella Jr, 2004; Reagans and McEvily, 2003). The endorsement from trusted third parties is particularly relevant especially when it comes from other VCs. Having received previous funds from VCs may a) carry a reputation effect (Stuart et al., 1999) and b) allow the potential funder to better assess information about the venture under consideration that would be difficult to obtain otherwise (Alexy et al., 2012; Shane and Cable, 2002). Indeed, in their seminal contribution Megginson and Weiss (1991) explain how previous funding from VCs is a strong certification for follow up investors.

On the other hand, reward-based CF campaigns are distinct from VC funding. These campaigns involve a large number of (non-professional) unsophisticated investors, referred to as backers, who provide relatively small contributions and typically do not possess adequate competences to assess entrepreneurial ventures comprehensively, thus often disregarding factors such as the technological viability of the project, among others (Agrawal et al., 2014; Ahlers et al., 2015; McKenny et al., 2017). This holds in part because backers are not always motivated by pursuing financial returns (Gerber et al., 2012). Instead, they are regularly guided by passion or participate to pursue social causes (Colombo et al., 2015; Galak et al., 2011; Gerber et al., 2012). Importantly, funding decisions in reward-based CF are also often driven by the interest for the reward offered by the projects seeking funding (e.g., the product the new venture aims to commercialize). In such cases, backers are essentially consumers who commit to invest funds to buy (at some risk) products yet to be produced (Agrawal et al., 2014; Allison et al., 2017; Cholakova and Clarysse, 2015; Roma et al., 2017; Yang et al., 2020). For this reason, the main benefit of reward-based CF is that it can provide entrepreneurs with direct information on consumers' preferences and thus on the market potential of the new entrepreneurial project (Agrawal et al., 2014; Drover, Wood, et al., 2017; Roma et al., 2018; Roma et al., 2017). The ability of working as a direct test market is a peculiar benefit of reward-based CF, which is often not available to ventures funded through traditional funding channels. Similarly, running a CF campaign can lead to an additional benefit in that backers can post on the campaign page important feedback for the entrepreneurs allowing them to improve their initial ideas in order to commercialize a product that better matches consumers' preferences, and thus is more likely to succeed in the market (Gleasure et al., 2019; Stanko and Henard, 2017).

Therefore, a successful CF campaign can act as a certification of market demand for follow up VC investors as the three main requirements for the certification to be credible are met (Megginson and Weiss, 1991). One, reputation is at stake. From the side of the CF platform, if mostly poor quality projects are funded, in the long run there will be no longer interest in projects proposed on the platform. As such, CF platforms have strong incentives to maintain sufficiently high project quality and they do so by implementing mechanisms that help screen project proponents based on their quality (e.g., a number of requirements for launching the campaign such as the existence of a real prototype for hardware projects). Moreover, although we cannot properly refer to reputational capital for backers, there is money at stake for them as they face a clear risk of losing (at least part of) their money without any product in reward if investing in projects that turn out to be unsuccessful. Thus, if a plethora of backers commit their money to receive a product early in advance at a risk, then this should be a serious and credible signal of market demand. Two, the reputation loss is higher than any possible transfer of money to make the third party certify falsely. The reward-based CF mechanism itself is based on a call for funding that involves a multitude of small and geographically dispersed individuals that are simply interested in the product. Therefore, it is unlikely that all individuals will coordinate to behave improperly. Indeed, we are not aware of any evidence suggesting otherwise. Three, it is costly for the new venture to acquire the services of the certifying party (i.e., the crowd and the platform). Besides the fees for platforms that any campaign accrues, CF requires significant effort before, during and after the campaign (Mollick, 2014). On top of perfecting working prototypes, videos need to be prepared, coordination with backers is required, addressing comments and requests is paramount and if successful, ensuring that promises are met is another core task.

In sum, both initial VC funding and initial CF funding can reduce Knightian uncertainty occurring in new venture's early stages via certification. VC funding is the outcome of a sophisticated and comprehensive process whereas initial CF funding is not. But, only initial reward-based CF provides an early direct test of the presence of a market. The above stark differences in the screening strategies and funding motives between backers and VCs lead us to propose that having received funding from early-stage VCs should be a stronger certification for subsequent VCs when compared to having received initial funds from a CF campaign. VCs are more qualified to screen new ventures' potential and share more similar financial goals and assessment criteria among each other, which increases the chances of reciprocal recognition and trust.

2.1.2 Differences in the ex-post involvement

The second reason we expect to drive differences in the certification effect between early-stage VCs and the crowd is differences in their degree of involvement in the target ventures. VCs are shareholders and active investors who coach entrepreneurs, aid and guide in order for the firm's potential to realize (Bertoni et al., 2011; Croce et al., 2013; Gompers and Lerner, 2001;

Hellmann, 2000). Indeed, VCs not only contribute to the managerial professionalization of new ventures by providing them with management skills and governance (Colombo and Grilli, 2010; Hellmann and Puri, 2002) but also use their own social capital to facilitate new ventures' access to external resources, competencies and, ultimately, to further funding (Alexy et al., 2012; Bottazzi et al., 2008; Hsu, 2007). Besides such substantive benefits, the coaching and networking functions of early-stage VCs can also have a certification effect in the eyes of subsequent VCs. Observing the involvement of previous VCs, subsequent VCs can acknowledge that the new venture has been trained to receive advice, exhibits better entrepreneurial skills, and enjoys a larger network to access strategic resources (Jääskeläinen and Maula, 2014).

On the other side, in light of their limited business competencies, crowds do not typically offer coaching and networking.

Combining the differences in funding motives and screening strategies on the one hand and those in *ex-post* involvement on the other hand, we formulate our first hypothesis as follows:

H1. The likelihood of receiving subsequent funding from VCs is, ceteris paribus, lower for ventures initially funded through reward-based crowdfunding than for those initially funded by early-stage VCs.

2.2 Signal interaction

So far, we have argued that initial funding, either from the crowd or from VCs, certifies unobserved quality for follow up VC investors and in doing so it reduces Knightian uncertainty. We have also argued that the certification from CF original funding will be inferior compared to the certification provided by VC original funding.

The next question we examine is whether this gap in certification can shrink or even disappear, thus reducing the comparative disadvantage of crowdfunded ventures in terms of attractiveness in the eyes of subsequent VCs. Our main tenet is that this is possible as long as the focal venture transmits quality signals on aspects that the reward-based CF certification is silent about. On the other side, when quality signals are transmitted by originally VC-backed firms, we expect them to have a comparatively smaller impact on reducing information asymmetries between entrepreneurs and potential subsequent investors. This holds because, as compared with being originally funded through reward-based CF, being originally backed by VCs offers a comprehensive certification already, and as such any additional signals tend to convey less complementary information.

We anchor our discussion on the literature on signal interplay, which, in a nutshell, analyzes the relative effectiveness of different signals conditional on other signals (Colombo et al., 2019; Plummer et al., 2016; Stern et al., 2014; Vanacker et al., 2020). Specifically for CF, Scheaf et al. (2018) examine how signals (e.g., media coverage and patents ownership) and visual cues interact to determine CF campaign performance, whereas Courtney et al. (2017) analyze how, in CF, signals obtained from multiple information sources enhance or diminish one another's effects. Bapna (2019) shows how signals informing about product characteristics are more effective when combined with signals informing about market characteristics or investment-related characteristics. Our argument is similar in spirit to Bapna (2019). Indeed, we expand it as a) we analyze different signals from those in Bapna (2019) and more importantly, b) we zoom in on how signal complementarity has the potential to enhance or even equalize the effectiveness of an *a priori* inferior signal (i.e., the certification from reward-based CF in our application) to the effectiveness of an *a priori* superior one (i.e., the certification from VCs). In other words, while in Bapna (2019), all potential signals start from the same base, in our case we have a signal that is *a priori* inferior.

What can then shrink or even eliminate the certification gap between originally VC-backed and originally CF-backed ventures? In our application, we posit, signals that convey what a successful reward-based CF campaign does not and subsequent VCs care about: information on intellectual, human and social capital. We identify such signals, i.e., patents, founding team characteristics and prestigious affiliations respectively, based on a) the evidence that *per se* they shape the funding decisions of VCs and b) they certify new venture's features that reward-based CF does not (Audretsch et al., 2012; Conti, Thursby and Thursby, 2013; Haeussler et al., 2014; Hoenen et al., 2014; Hsu, 2007; Hsu and Ziedonis, 2013; Inkpen and Tsang, 2005; Kolympiris et al., 2018; McFadyen and Cannella Jr, 2004; Reagans and McEvily, 2003; Shane and Cable, 2002; Stuart et al., 1999). In essence, we argue that these additional signals show a higher degree of complementarity with the certification offered by CF than with the certification offered by initial VCs because they inform about types of information asymmetries that CF is silent about, but prior funding from VCs is not.

Patents, as a proxy for intellectual capital, should be indeed more beneficial to initially crowdfunded new ventures than to similar new ventures originally funded by VCs. The presence of patents increases the odds of access to funding from professional investors as it informs them about the new venture's capability to develop technological solutions that are novel and capable of industrial application, provides indications of learning and professionalism, and it reveals that the new venture may benefit from an exclusive protection over certain markets, thus reducing this type of information asymmetries surrounding the new venture (Audretsch et al., 2012; Conti, Thursby and Rothaermel, 2013; Haeussler et al., 2014; Hoenen et al., 2014; Lee et al., 2001; Mann and Sager, 2007). In other words, patents help certify the technological viability of the project and its relative value appropriation (Graham and Sichelman, 2008; Helmers and Rogers, 2011; Hoenig and Henkel, 2015; Hsu and Ziedonis, 2013; Lee et al., 2001). This is precisely the sort of certification not offered by CF! It follows that compared to similar ventures initially backed by VCs, a CF-backed new venture should gain larger benefits from these positive effects of patents. This is so because a successful reward-based CF campaign provides indications of the market potential of the entrepreneurial project, but it is silent on whether the new venture is technologically capable to turn the new product idea into a final product.

On the other hand, previous funding from VCs speaks to appropriability and technological competencies (i.e., intellectual capital) already because the due diligence of the first instance of financing from early-stage VCs has signed off on those. Patents should then transmit somewhat more redundant information and hence be less informative in terms of intellectual capital for initially VC-backed ventures. Hence, we posit that:

H2. Having patents reduces the negative gap in terms of likelihood of securing subsequent funding from VCs between initially crowdfunded ventures and similar ventures initially funded by early-stage VCs.

With regards to human capital, initially CF-backed ventures can mitigate their certification disadvantage if the entrepreneurial team has a positive track record in securing venture capital funding for (or successfully exiting from) previously-founded ventures (Hsu, 2007). Compared to novice entrepreneurs, entrepreneurs with prior successful experience have developed better entrepreneurial and managerial skills, have been coached already and overall they have been through the process of running a company (Shane and Cable, 2002; Zhang, 2011). In fact, in their previous experience, entrepreneurs have likely overcome obstacles, which are likely to face again, have received training in spotting opportunities, and they have acquired know-how primarily via learning curves (Baron and Ensley, 2006). As well, a significant record of previous venture capital funding received (or a successful exit) for previously founded new ventures can increase the trust of subsequent potential investors in the current venture's capabilities (Hsu, 2007; Gompers et al., 2010; Ko and McKelvie, 2018). For these reasons, previous successful entrepreneurial experience leads to higher chances of raising capital (Gompers et al., 2010; Mueller et al., 2012).

Similar to the case of patents, we propose that a crowdfunded new venture derives greater benefits than similar ventures initially funded by VCs when it is founded by an entrepreneurial team with a positive track record. As noted above, information revealed via a successful CF campaign is largely confined to indicating market prospects of the entrepreneurial project. Such information is hardly enough for subsequent VCs who assess potential target firms more comprehensively. But, a strong founding team can complement the marketability indications that a CF campaign offers and thus be of value to VCs considering investing in previously crowdfunded new ventures. On the contrary, we expect the added value of a strong founding team to be of smaller relevance for ventures initially funded by VCs. In this case, the indications of firm-specific unobserved human capital offered by such team are already assessed by the early funders. This, in turn, decreases the necessity for subsequent VCs to look deeply into the past experience of the entrepreneurial team. Accordingly:

H3. Past successful experience of the entrepreneurial team in securing venture capital or exiting from previously founded ventures reduces the negative gap existing in the likelihood of securing subsequent funding from VCs between initially crowdfunded ventures and similar ventures initially funded by early-stage VCs.

Social capital is the third form of capital that VCs are looking for when making investment decisions. This is not surprising. Social capital is key in any (entrepreneurial) venture as, among others, it allows for a better identification of opportunities, provides enhanced access to resources and information, and generates alternative ways of tackling problems (Burt, 2004; Granovetter, 1973; Putnam, 2000; Shane and Cable, 2002). It follows that new ventures need to signal they have it. A common way to do that is via affiliations with prestigious partners. Such prestigious affiliations signal the ability of the managerial team to establish strategic ties, which ultimately can help them in accessing other resources and knowledge critical to their performance (Baum et al., 2000; Baum and Silverman, 2004; Colombo et al., 2019; Stuart et al., 1999). Because prestigious organizations do not ally with low-quality new ventures to preserve their high reputation, potential investors tend to consider new ventures affiliated to prominent partners as more legitimate compared to those not having such prestigious ties, and hence perceive such affiliation as strong signals (Baum and Silverman, 2004; Bonardo et al., 2011; Colombo et al., 2019; Deeds et al., 2004; Gulati and Higgins, 2003; Inkpen and Tsang, 2005).

Tailored to our context, we argue that having prestigious affiliations will be more valuable for initially CF-backed ventures than initially VC-backed ventures. Being initially backed by VC implies that the adequacy of social capital for the focal venture has been examined and signed off by the previous VCs' due diligence. As such, having prestigious affiliations, we argue, should bring little additional information to the table. On the other side, being initially backed by CF indicates some degree of social capital as a connection with the crowd is built but it says little with regards to the ability to build social ties with relevant professionals, such as resource providers and organizations that can augment the venture's knowledge depository and hence allow it to better address obstacles which are yet to come. In essence, a prestigious affiliation signal could complement more effectively the information transmitted by being originally backed by CF than that provided by being originally VC-backed, and thus reduce information asymmetries between the focal venture and follow up investors to a greater extent for crowdfunded ventures. Given the above, we formulate our last hypothesis:

H4. Being affiliated with a prestigious partner reduces the negative gap in terms of likelihood of securing subsequent funding from VCs between initially crowdfunded ventures and similar ventures initially funded by early-stage VCs.

3. Data and methods

3.1 Sample construction

To test the above hypotheses, we construct a new cross sectional dataset that combines two samples. As we elaborate below, we compare two groups. For the first group, the first infusion of funds has come from CF. For the second group, the first infusion of funds has come from VCs. Our outcome variable is the second infusion of funds from (other) VCs. This would be Round 1 VC funding for initially crowdfunded ventures and Round 2 VC funding for initially VC-backed ventures.

The first sample includes early stage technology ventures that have been founded between 2005 and 2014 and have secured funds for the first time from successful CF campaigns launched in the category Hardware of the most popular reward-based CF platform, i.e., Kickstarter, starting from its inception in 2009 to the end of 2014.[2] The second sample includes early stage technology ventures, which never launched any CF campaign, have been founded in the same period as their crowdfunded counterparts, have secured (at least) a first round of funding from early-stage VCs, and fall in the category Hardware of CrunchbasePro[3], i.e., the online tech company database that includes data about the startup ecosystem consisting of companies, investors, incubators, key people, funding rounds and events.

Aligned with our hypotheses, the two samples above include only ventures that have received an initial round of funding: the former sample through reward-based CF and the latter sample through early-stage VCs. We focus on technology-based ventures as such ventures need follow-up funds to scale irrespective of the source of initial funding. The Hardware categories on Kickstarter and CrunchbasePro address this point as they include applications such as consumer electronics, computer hardware, robotics, 3D printing, etc., which clearly necessitate large investments for setting up of prototypes, engineering and manufacturing processes, and the like (Roma et al., 2017; Colombo and Shafi, 2019; Thies et al., 2019). More broadly, Hardware includes entrepreneurial projects where the technological component and the amount

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[2] In cases where CF project creators did not explicitly provide reference to their venture, not even founders' names, on their campaign pages we extensively searched on the web for any possible reference of the project/campaign name (e.g., magazine articles, social media, etc.). Though laborious and very time-consuming, this process allowed us to source the information we were seeking for the vast majority of cases.

[3] CrunchbasePro is one of the most complete and timely updated databases available encompassing data about startups and their investors, as reflected in its increasing use in new venture financing research (e.g., Ko and McKelvie, 2018; Nuscheler et al., 2019). To increase the reliability and consistency of our data, we also checked other databases providing information on new ventures and their funding rounds, such as ThomsonOne – VentureXpert, Angel.co, and, when available, the press section on the website of each new venture. Further, because Kickstarter and CrunchbasePro categories may not be comparable, we carefully picked hardware ventures within the Technology category on Kickstarter to make sure that they were related to technology and were comparable to those retrieved from the tech hardware category of CrunchbasePro. Specifically, we did not consider any hardware product that was outside the Technology category, and thus did not have any technological aspect. Finally, we sometimes noticed that some CF campaigns clearly related to software products were erroneously classified as hardware campaigns. We removed them from the sample to maintain consistency between the two sources. Overall, both subsamples (i.e., initially crowdfunded ventures and initially VC-backed ones) include exclusively technology hardware companies, so that they are comparable in terms of macro-category.

of funds required to support growth are expected to be relevant for both crowdfunded and initially VC-backed ventures, thus representing potentially attractive investment opportunities for subsequent VCs (PwC, 2014).

It follows that focusing on Hardware significantly decreases the risk of including in the sample entrepreneurial projects not seeking additional capital after their initial funding, which may in principle occur for crowdfunded ventures. Still, we make additional restrictions to further reduce this risk. Among crowdfunded new ventures we select only those collecting a sufficiently high amount of funds in the campaign to exclude small recreational projects (Colombo and Shafi, 2019; Mollick and Nanda, 2016), and thus further reduce the odds of considering projects unlikely to engage in a process of growth that may call for subsequent funding from VCs. Indeed, our interest is not to collect a set of successful campaigns that are representative of all successful Kickstarter campaigns *per se*. Rather, our interest is to source data, via Kickstarter, on crowdfunded new ventures likely seeking funding to scale up. This is why we considered only crowdfunded projects that have raised at least $5,000. We specify $5,000 as the cutoff point for consistency: a) in CrunchbasePro we observed similar minimum amount also for new ventures funded by early-stage VCs, for instance through seed capital, and b) similar amounts have been used in prior CF research (e.g., Mollick and Nanda, 2016). In Section 5, we show robustness of our results by using higher levels of the amount raised in CF as selection thresholds.[4]

In addition to the above restrictions, we excluded projects related to non-profit organizations. We also eliminated new entrepreneurial ventures that were no longer active at

[4] We also demonstrate the robustness of our conclusions when instead of using a threshold level of the raised amount as a criterion to include projects in the sample, we use a threshold level of the campaign *goal*, i.e., the money targeted in the campaign. We opt to use the amount raised for the baseline estimates because Kickstarter utilizes an all-or-nothing mechanism where the funds are transferred only if the goal is met. This feature may prompt risk adverse entrepreneurs to lower the goal to levels below what is actually required for the project. When that happens, the goal is an inaccurate measure of the size of the project and this could bias our sample by omitting relevant ventures (Roma et al., 2017).

the end of our period of observation (December 2017) irrespective of their initial funding source. We did so to rule out survival as a possible cause of subsequent funding from VCs. Keeping ventures who went bankrupt during our period of observation could introduce bias in our results because those ventures would naturally be less exposed to subsequent funding.

More importantly, we excluded, among initially VC-backed ventures, those having at least one VC in common between initial and subsequent funding rounds, to avoid that follow up investments were due to reasons clearly unrelated to certification.[5] After removing also projects for which full information was not available, the final sample includes 625 new hardware ventures, of which 325 were initially funded via CF and 300 initially funded by early-stage VCs. Finally, note that all the variables explaining follow up investments by VCs are measured before subsequent funding took place (or the equivalent period for ventures that did not receive subsequent funds, as explained below).

Overall, we expect that our samples of crowdfunded and initially VC-backed new ventures are representative of their respective populations of new ventures likely to engage in a process of growth that may call for subsequent funding from VCs.[6] Indeed, new ventures' characteristics in our sample are similar to those in other related studies in terms of granted patents, entrepreneurial team with past successful funding experience, industry experience, and

[5] If we had not removed such ventures from the sample, an alternative explanation to certification could be that VCs rely on their own judgments rather than on their peers. In the same vein, VCs in the initial round may syndicate with other investors in later rounds and share information about the new venture from prior involvement, thus making syndication another alternative explanation. Therefore, the exclusion of ventures having at least one investor in common in the initial and subsequent funding rounds helps to rule out such explanations. At any rate, we do not expect syndication to drive the estimates because, by definition, syndication cannot take place for initially CF-backed ventures. If syndication is the mechanism behind the estimates, we should observe a higher likelihood of follow up funds for originally VCs-backed ventures when compared to *similar* originally CF-backed ventures, even in presence of signals of intellectual, human and social capital that complement the initial funding certification. This is not what we observe.

[6] For the entire duration of observation of the sample at hand, crowdfunded ventures in our sample did not launch multiple CF campaigns, which reassures us that these ventures do not use CF as the only funding channel. In turn, this suggests that, at least in terms of their interest in subsequent funding from VCs, they share a level of "exposure" similar to that of ventures initially funded by early-stage VCs (recall that we focus on projects requiring large amount of capital to favor growth), thus further increasing the suitability of our sample to test the hypotheses.

education background (Ahlers et al., 2015; Conti, Thursby and Thursby, 2013; Conti, Thursby and Rothaermel, 2013; Haeussler et al., 2014; Helmers and Rogers, 2011; Hsu, 2007; Kolympiris et al., 2018; Lee et al., 2001; Piva and Rossi-Lamastra, 2018; Roma et al., 2017).

3.2 Variables

Dependent Variable

Our dependent variable is a dummy (*Subsequent Funding from VCs*) indicating whether a new venture has received subsequent funding from VCs (until the end of our period of observation, December 2017) after its initial funding provided either via CF or by early-stage VCs (the variable takes the value of 1, 0 otherwise).[7]

Independent variables

The main variable of interest is a dichotomous variable (*Crowdfunding*) taking value of 1 if the given new venture has received initial funds via reward-based CF, and 0 if it has been initially funded by early-stage VCs. To test *H2*, we interact *Crowdfunding* and a dummy variable (*Patents*), equal to 1 if, irrespective of the first type of funding source, the new venture had been already granted at least one patent related to the new product idea before (possibly) receiving a subsequent funding from VCs, 0 otherwise.[8] For new ventures that received subsequent funding we measure the presence of patents before subsequent funding took place. For new ventures that did not attract subsequent funds within our sample period, we measure the presence of patents within a 2-year window since the initial inflow of funds. We opt for a 2-year horizon because this is the average time elapsed between initial funding and follow up funding for

[7] We consider the likelihood of receiving subsequent funding from VCs as our dependent variable, rather than the amount of funding they provide, mainly because numerous new ventures in our full sample (81.2% among crowdfunded new ventures and 40.7% among new ventures funded by early-stage VCs) did not receive any subsequent funding from VCs, which suggests that the primary question to ask is whether these entrepreneurial ventures are able to secure funding after their initial funding or not. It is also noteworthy that when we consider business angel investments as part of the dependent variable the results do not change.

[8] We follow previous studies on CF to model patent activity with a dummy variable (Ahlers et al., 2015; Roma et al., 2017). This empirical choice is consistent with the patent distribution of the sample firms for which, due to their early stages of growth, having more than one patent is rare.

sample firms that attracted subsequent funds. By specifying the same time window for both cohorts of firms we place neither ventures that raised follow up funds nor those that did not, at a disadvantage when modeling odds of follow up funding conditional on having a patent.[9] We retrieved data from the USPTO database to measure patent activity because the vast majority of entrepreneurial ventures in our sample were geographically located in the United States.

Before discussing the interaction term used to test our hypothesis *H3*, it is important to note that numerous new ventures are founded and managed by a team of individuals, rather than a single entrepreneur. We use the term entrepreneurial team to indicate the founder(s) and top management figures of the given new venture, such as the CEO and the President (in the case they do not coincide with the founders). For instance, in our sample, the size of the entrepreneurial team varies from one to six. In the presence of more than one leading person we gathered data about each member of the entrepreneurial team. Similar to the case of patents, for firms that did not receive subsequent funding we relate time-varying team characteristics to subsequent funding odds within a 2-year window since the initial inflow of funds.

To test *H3*, we interact *Crowdfunding* with a dummy variable (*Entrepreneur Past Successful Funding Experience*), equal to 1 if, irrespective of the first type of funding source, at least one team member of the new venture has received funding from professional investors such as VCs and business angels for previously founded new ventures and/or such previous new ventures have been successfully sold to established firms, 0 otherwise. This variable captures the history of the entrepreneurial teams and, specifically, their ability to secure funding from professional investors or successfully sell ventures founded (and managed) in the past. To construct the variable we sourced and combined data from CrunchbasePro (and the other aforementioned databases) and from LinkedIn profiles of each member of the team.

[9] Our findings are robust even if we consider the presence of patents (and other time-varying variables) at the end of our period of observation.

To test *H4* we interact the *Crowdfunding* variable with the variable *Affiliation with a Prestigious Partner* that takes the value of 1 if the focal venture is affiliated or has partnered with a prestigious organization before the second infusion of capital, if any, 0 otherwise (the same procedure used in the case of patents applies here as well for ventures that did not receive subsequent funding from VCs). As a measure of social capital, we consider affiliations or partnerships with top universities, prestigious governmental or non-governmental organizations, and with companies. For top universities we considered only those universities that have clear worldwide prestige, and thus are best positioned to signal affiliated ventures' quality to VCs. As such, consistent with prior literature, we considered as prestigious only ties with top 100 universities (e.g., Bai et al., 2020; Reese et al., 2020) using the Times Higher Education ranking (Tartari et al., 2014; Tartari and Salter, 2015).[10] For companies, in line with prior studies (e.g., Alexy and Reitzig, 2013; Crossland and Hambrick, 2011), we considered top Forbes 2000 global companies list, which has the advantage (over other lists, such as S&P500) of listing also non-US companies. For governmental or non-governmental institutions we considered only nation-level organizations in OECD countries (Higgins and Gulati, 2003; Tartari et al., 2014; Tartari and Salter, 2015). Some examples of prestigious partnerships of affiliations in our sample include MIT, Cambridge University, Harvard University, University of California at Berkeley, National Science Foundation, Canada's Research Council, Microsoft, and Philips. We sourced such information via extensive search on firm prospectuses, LinkedIn pages and the like.

Control variables

In addition to the variables that test the hypotheses, we control for other factors that may affect the likelihood of securing subsequent funding from VCs. We control for relevant quality aspects

[10] The results are robust to using alternative rankings (e.g., ARWU) and expanding the list to top 1000.

of the new venture by including the set of characteristics utilized by VCs to assess technology startup quality, namely intellectual, social, and human capital (Conti, Thursby and Thursby, 2013; Conti, Thursby and Rothaermel, 2013; Hsu, 2007; Hsu and Ziedonis, 2013; Kolympiris et al., 2018; Pollack et al., 2012). First, we control for the entrepreneur human capital built before the subsequent funding from VCs was (possibly) received through a set of variables. Specifically, we control for the entrepreneurial team's educational background using two variables, i.e., whether at least one member of the entrepreneurial team has received an MBA (*MBA*) and whether at least one member of the entrepreneurial team has received a Ph.D. (*PhD*), (Hall and Hofer, 1993; Kolympiris et al., 2018). In line with the previous studies (e.g., Conti, Thursby and Thursby, 2013; Conti, Thursby and Rothaermel, 2013), we also control for the average industry experience of the entrepreneurial team (*Average Industry Experience*) and for whether at least one team member has founded and/or managed previous new ventures in the past (*Previous New Ventures*). The variable *Size of the Entrepreneurial Team* is also introduced to broadly capture the amount of human capital (Ahlers et al., 2015). Finally, in addition to introducing its interaction with the variable *Crowdfunding*, we control for the direct effect of the variable *Entrepreneur Past Successful Funding Experience* by including the variable in its level form. This variable informs VCs on whether the entrepreneurial story of the team has been successful in the past, thus providing again a valuable quality indication on the entrepreneurial ability, also with regard to the current project (Hsu, 2007; Hsu and Ziedonis, 2013).

Besides its moderating effect, we control for the direct effect of the entrepreneur social capital by introducing the variable *Affiliation with a Prestigious Partner* also in its level form (Hsu, 2007). The variable *Size of the Entrepreneurial Team* is useful to control for social capital as well. Indeed, as argued by Baum and Silverman (2004), larger management teams are not only likely to possess higher human capital, but at the same time, they may have more social capital as the number of social connections tends to increase with the number of team members

(Ahlers et al., 2015). In addition to introducing its interaction with the variable *Crowdfunding*, we also control for the direct effect of the presence of patents granted for the given product idea (*Patents*), which captures the intellectual capital of the new venture (Ahlers et al., 2015).

Further, the empirical specifications include a number of controls related to remaining new venture attributes. Similar to Conti, Thursby and Thursby (2013) and Mollick (2014), we recognize that new ventures located in different entrepreneurial ecosystems may face a different probability of receiving subsequent funding from VCs because venture capital is not equally accessible for startups, but its availability varies across different geographical regions (Cumming and Dai, 2010; Kolympiris et al., 2011; Tian, 2011). As such, we introduce a dummy variable (*Top Startup Ecosystems*) indicating whether the new venture is located in the metropolitan area of one of the top 20 ecosystems worldwide for establishing and nurturing a startup, according to the Startup Genome Report (Marmer et al., 2012). We control for the year of new venture establishment by introducing ten dummies (*Year of Establishment 200x*), which help control for the different stages of new ventures' lifecycle and other time factors. Finally, in spite of the fact we have already restricted to the Hardware categories on Kickstarter and CrunchbasePro databases, we further take into account the heterogeneity related to the project nature. Specifically, taking advantage of the sub-categorization provided by Kickstarter as well as carefully analyzing the descriptions of each entrepreneurial project in our sample, we are able to introduce four dummies better indicating the type of product/applications related to each venture, namely *Consumer Electronics & Hardware*, *3D Printing & Robotics, Medical Devices,* and *Aerospace Applications*.[11]

---Table 1 about here---

[11] Recall that the crowdfunded projects were launched on Kickstarter in the period 2009-2014. In that period, projects in the Technology section of Kickstarter were simply divided in Hardware and Software (Mollick, 2014). The category Hardware included numerous projects, which are currently categorized in more specific sub-categories (e.g., 3D Printing, Robots, DIY Electronics, etc.). We use the current sub-categories (ex-post) as well as the detailed description of all entrepreneurial projects in our sample to group them in a reasonably accurate and manageable manner.

Table 1 presents the descriptive statistics of the sample. Compared to crowdfunded new ventures, new ventures initially funded by VCs are over three times more likely to receive subsequent funding from VCs (59% versus 19%). Compared to initially crowdfunded new ventures, new ventures initially funded by VCs are more likely to be granted a patent (12% versus 4%), have been founded and managed by an entrepreneurial team with larger industry experience (13 versus 7 years), with a better education background (23% versus 10% for the variable *MBA* and 23% versus 11% for the variable *PhD*), more prestigious affiliations (10% versus 8%) and have secured more funding for previously founded ventures (18% versus 9%). Similarities are instead observed regarding the location of new ventures, the size of the entrepreneurial team, and the presence of new ventures previously founded and managed by the entrepreneurial team. While these descriptive statistics may provide some initial insights on the certification effect of reward-based CF compared with funding received from early-stage VCs, they also intuitively highlight the fact that new ventures are not randomly assigned to the initial type of funding. This implies that some new ventures' characteristics may affect both the type of initial funding secured and the probability of receiving a subsequent funding from VCs, thus potentially introducing endogeneity bias to the analysis. To mitigate this concern, as discussed in the next section, we use a matching procedure as well as treatment effect regression models.[12]

The correlation matrix (included as Appendix Table 1) does not suggest a considerable degree of correlation, except for the case of two control variables.[13]

[12] Note that the variables testing H2 to H4 are somewhat skewed. While non-skeweness is not required for the regressions we perform (Greene, 2003; Wooldridge, 2010), the only potential problem, in principle, could be that if a binary independent variable was highly skewed, it would have many 0s or 1s. Therefore, with such low variability it would be difficult to find statistically significant relationships for the variables of our interest, even if they existed. As shown in Tables 3 and 4 (as well as in all our analyses), this is not the case.

[13] The Variance Inflation Factor (VIF) never exceeds the value of 10 for all our analyses, also reassuring us on the absence of multicollinearity.

4. Empirical results

The main challenge in our study is that whether a new venture is initially funded through reward-based CF or by early-stage VCs is not a random outcome. Consistent with the descriptive statistics in Table 1, the case might be that subsequent VCs prefer financing new ventures initially funded by their peers because these ventures are intrinsically of higher quality compared to crowdfunded ventures. If that holds, initially VC-backed ventures would be more likely to receive the subsequent round of funding irrespective of the source of initial funding. This form of potential endogeneity poses two concerns. One, it could plague our estimates. Two, and perhaps more importantly, it casts doubts on whether the mechanism behind the results is the differences in certification different initial funding sources offer. To address these concerns, we conduct two exercises that can allow us to better estimate the baseline coefficients and shed light on the driver of the estimates. In the first one we analyze a sample in which for each crowdfunded new venture we find a new venture initially funded by VCs of similar quality. In the second, we run treatment effect regression models that explicitly account for the drivers of initial funding.

4.1 Matching

To conduct the first exercise, we follow previous contributions (e.g., Croce et al., 2013; Guerini and Quas, 2016), employing a Propensity Score Matching (PSM) algorithm (Rosenbaum and Rubin, 1984). This procedure finds a non-treated unit (in our applications, a new venture initially funded by VCs) that is similar to a treated unit (in our application, a crowdfunded new venture) across several dimensions, by constructing a propensity score. To compute the propensity score and match crowdfunded and non-crowdfunded ventures, we used all the right-hand side variables available (except for the variable *Crowdfunding*).[14] We applied

[14] In our main matching procedure we do not include the amount raised as first fund infusion because it is undisclosed for a considerable number of sample ventures, and thus would significantly reduce the size of the matched sample. In principle, disregarding this variable for matching may be a concern as the

the one-to-one PSM procedure using the caliper option (caliper equal to 0.05) with no replacement. In a nutshell, we match initially crowdfunded ventures with initially VC-backed ventures based on key observable characteristics including those related to intellectual, human and social capital. Therefore, in our matched samples crowdfunded ventures with and without patents, previous successful experience in securing funding, and affiliation with a prestigious partner are similar to their counterparts initially funded by VCs.

The underlying assumption of matching procedures is that matching over observed characteristics allows matching also for unobserved characteristics, isolating the treatment as the only remaining difference between treated and non-treated units (Kolympiris et al., 2019; Marx et al., 2015). We expect this assumption to hold in our setting as we control for a comprehensive set of variables encompassing the most relevant characteristics utilized by VCs to assess technology startup quality (Ahlers et al., 2015; Baum and Silverman, 2004). In other words, at least from the perspective of the factors considered by VCs, new venture's unobserved characteristics should be highly correlated to the observed characteristics. If that holds, when matching for the observed characteristics, not only potential differences in these characteristics, but also those in the unobserved characteristics between crowdfunded and initially VC-backed new ventures should be significantly reduced, if not eliminated. This also helps identify crowdfunded ventures that are similar to VC-backed ventures also in terms of the tendency to seek subsequent VC funding.

Table 2 reports selected descriptive statistics of the matched sample, which consists of 312 new ventures equally divided between crowdfunded and VC-backed ventures. For each variable used in the matching procedure we report its mean for initially CF-backed and VC-

attractiveness of crowdfunded and VCs-backed ventures in the eyes of subsequent VCs can differ due to reasons unrelated to certification if these two samples of ventures significantly differ in the funding amounts they raise in the first infusion (for instance, a venture with higher amount raised in the first infusion can more easily scale up and thus become more attractive). In Section 5, we show robustness of our results even when the matching procedure includes this variable.

backed ventures, respectively. We find no statistically significant differences between the means, which further reassures on the goodness of matching.

---Tables 2 and 3 about here---

Table 3 presents the analysis using the matched sample. In the first column, we introduce the dummy variable *Crowdfunding* together with the control variables. The sign of the variable is negative and the coefficient is statistically significant, suggesting that, compared to ventures that received initial funding from VCs, crowdfunded new ventures are less likely to receive subsequent funding from VCs. The coefficients of the control variables display mostly the expected sign and significance. The odds of receiving subsequent funding from VCs are higher for new ventures holding patents, founded and managed by a larger entrepreneurial team possessing better education background, having lower number of years of industry experience, but, at the same time having been able to obtain funding and/or ensure successful exit for previously founded ventures. The variable indicating affiliation with prestigious partners is instead statistically insignificant.

In columns 2 to 5 we introduce the interaction terms testing *H2*, *H3*, and *H4* in a stepwise fashion. The results are consistent across specifications and hence we discuss only the full specification in column 5. *Crowdfunding* remains negative and significant, whereas the coefficients of the first two interaction terms, which measure the moderating effects of *Patents* (β=1.966) and *Entrepreneur Past Successful Funding Experience* (β=1.168), respectively, are positive and significant. In contrast, the third interaction, which measures the moderating effect of *Affiliation with a Prestigious Partner*, is insignificant. Therefore, these results support the first three hypotheses, but not the fourth one: when coupled with patents and a strong founding team, the certification effect disadvantage of crowdfunded ventures compared to ventures initially funded by early-stage VCs is significantly reduced.

The insignificant moderating effect of the variable *Affiliation with a Prestigious Partner* may be due to two main reasons. One, because one of the main resources that VCs offer to target firms is access to their social capital and networks, they may weigh less existing social capital of potential target firms (Alexy et al., 2012; Bottazzi et al., 2008; Hsu, 2007). Two, perhaps due to the early stage nature of the new ventures, they affiliate mostly with prestigious upstream organizations, such as providers of knowledge and technologies (e.g., top universities or national research organizations), rather than downstream partners that favor commercialization. But, alliances with upstream organizations do not always bring significantly benefits in terms of funding attraction (Baum and Silverman, 2004).

4.2 Treatment effect models

For the second exercise to address endogeneity, we use treatment effect regression models, which take into account the possibility that the treatment (in our application, the source of initial funding) and its interactions with other variables (in our application, the variables *Patents*, *Entrepreneur Past Successful Funding Experience*, and *Affiliation with a Prestigious Partner*) are endogenous, by means of two-stage regressions (Wooldridge, 2010). Table 4 presents estimates of this model under the full sample. In the first stage the probability of being initially funded through reward-based CF or by VCs is regressed against a number of factors expected to affect the likelihood of selection between CF and funding from early-stage VCs as initial funding source. The second stage regression is the specification of our interest but it is now corrected to consider that new ventures might have different probability of being exposed to different types of initial funding. To apply the treatment effect regression models, the exclusion restriction must be met: the first stage regression must include at least one additional predictor that is not correlated with the outcome of the second-stage regression and thus it is not included in the second-stage specification. For this predictor we use a variable, namely *B2B*, equal to 1 if the market of the new venture is mainly business-to-business, 0 if it is mainly business-to-consumers (B2C). Because of the reward mechanism, reward-based CF is mostly suitable for consumer products. Therefore, we expect most of the CF-backed ventures in our sample to focus on the B2C market. In fact, Table 1 indicates that approximately 74.2% of the "kickstarted" new ventures in our sample focus on the B2C market, whereas approximately half (52.7%) of the entrepreneurial ventures not engaging in CF operate in the B2C market. It follows that while the type of market clearly influences the likelihood to select reward-based CF as initial funding source (as shown by the negative and strongly significant coefficient of *B2B* in the first-stage regressions of the treatment effect models in Table 4), there is no strong theoretical argument that it should directly influence the likelihood of receiving subsequent financing from VCs, who generally invest in both types of market. This increases our confidence that the dummy *B2B* satisfies the exclusion restriction of the treatment effect regression models. In addition to this variable, the first stage regression includes all the variables also utilized in the second stage regression, but in this case, when necessary, these are computed right before the time of the first funding to capture their influence on the decision to use CF. The estimates, again, support our first three hypotheses but not the fourth one, and indicate that potential endogeneity does not impact our analysis in any meaningful way.

---Table 4 about here---

4.3 Marginal effects

The above conclusions rely on interpreting the coefficients of level and interaction terms in probit regression models. However, the interpretation of the interaction terms in non-linear models, such as the probit model, is not straightforward (Zelner, 2009). In response, to further test the reliability of our results, we followed the approach suggested in Zelner (2009): we tested the statistical significance of the marginal change in the likelihood of securing subsequent funding from VCs when switching from being a VC-backed venture to being a CF-backed venture (moving the variable *Crowdfunding* from zero to one), at different values of the variables *Patents*, *Entrepreneur Past Successful Funding Experience*, and *Affiliation with a Prestigious Partner*, while setting the remaining variables equal to zero if binary (except baseline year and industry dummies), or to the sample mean if continuous or integer.

As such, Figure 1 reflecting estimates obtained using the matched sample (see last column of Table 3) presents eight scenarios where the three moderators take values of 0 or 1 and then the values of the vertical axis measure the change in the probability of attracting follow up funds from VCs when switching the *Crowdfunding* variable from 0 to 1. To illustrate, when all three moderators are equal to zero or only the variable *Affiliation with a Prestigious Partner* is equal to 1 (left parts of Figures 1a and 1c, respectively), the switch from no CF to CF reduces the odds of receiving subsequent funds from VCs, as suggested by our hypothesis *H1*. On the other hand, when there is at least one patent and the variable *Entrepreneur Past Successful Funding Experience* is equal to 0, irrespective of whether the variable *Affiliation with a Prestigious Partner* is equal to 0 or 1 (right parts of Figures 1a and 1c, respectively) the switch from no CF to CF has no effect on the probability of raising follow up funds as the confidence interval (i.e., the vertical bar) includes 0. This is a relevant finding in that it implies that as long as there is a patent, whether initial funds originate from VCs or CF makes no difference in the eyes of subsequent VCs. Similarly, as shown in Figures 1b and 1d (left parts), as long as there is successful funding experience of the entrepreneurial team and there is no patent, irrespective of whether the variable *Affiliation with Prestigious a Partner* is equal to 0 or 1, later stage VCs are equally likely to fund ventures having received initial funds either from VCs or from CF (technically, the confidence intervals in left parts of Figures 1b and 1d include 0). More surprisingly, Figures 1b and 1d (right parts) show that, in the presence of both patents and past successful funding experience of the entrepreneurial team and irrespective of the presence of an affiliation with prestigious partners, crowdfunded ventures display higher likelihood of attracting subsequent funding from VCs than their VC-backed counterparts (the marginal effect in this case is positive and significant).

Overall, the marginal effects analysis strengthens our findings as it shows that initially CF-backed ventures not only reduce the certification gap, but also they become even more likely to attract later stage funds from VCs compared to ventures originally backed by VCs. This holds when the former cohort of firms complement the CF certification with patents and a strong entrepreneurial team. In this case, due to the higher degree of complementarity with these signals, the certification effect of reward-based CF can increase to the point that it can be even *superior* to that of prior funding from early-stage VCs. Indeed, when other signals compensate the informative deficiencies of reward-based CF, its feature of working as a direct test market provides crowdfunded ventures with a unique advantage hardly available to their VC-backed counterparts.

---Figures 1 about here---

5. Robustness checks

In this section, we test the sensitivity of our estimates to modeling choices that shape the sample we analyze.

---Tables 5 to 14 about here---

First, we test whether our conclusions are sensitive to the way we specify ventures at risk of receiving follow up funding. Specifically, in line with previous CF studies (e.g., Mollick and Nanda, 2016) we replace the \$5,000 threshold on the raised amount with a \$5,000 threshold on the campaign goal (see discussion in footnote 4) and conduct both empirical exercises of Section 4. Our conclusions, based on the new estimates of Tables 5 and 6, remain intact.

Second, to further reduce the risk of considering crowdfunded projects not interested in seeking funding, in Tables 7 and 8 we present estimates, using only matched samples for brevity, where the selection threshold on the raised amount is increased to \$10,000 and \$20,000, respectively. Again, our conclusions remain intact.

Third, we perform our analysis considering only exceptionally successful campaigns among crowdfunded new ventures to better appreciate the boundary conditions of the relationships we propose and document. In particular, we limit the analysis to CF campaigns with the minimum amount raised equal to \$100,000. We consider those as the very successful ones because only 1% of all campaigns on Kickstarter are able to reach such an amount (Montgomery, 2020; Pecota, 2018). Our main conclusions remain intact, as shown in Tables 9 and 10 (for matched and treatment effect models, respectively). The only noticeable difference is that under the treatment effect model (but not in the matched regressions) the *Crowdfunding* variable is no longer statistically significant. This suggests that in such rare cases of extreme success, the disadvantage of initially crowdfunded ventures hypothesized in our *H1* disappears.

Fourth, we include in the matching criteria also the amount raised for the first infusion of finance under the premise that ventures that have raised similar amounts either from early-stage VCs or from CF may be at similar odds of attracting follow up funds. Table 11 presents the analysis under the sample created using also the initial amount raised as a matching criterion. Our conclusions do not change.

Fifth, because it is possible that lower-priced products are more likely to appear on CF platforms we control for the price of the product. Retrieving price information about the products that crowdfunded ventures intended to commercialize was straightforward and indeed we were able to do so for all 325 ventures. Retrieving the same information for originally VC-backed ventures proved challenging. We had to perform an extensive online search, also contacting in some circumstances the companies to retrieve at least an indication of the product price and double-check the correctness of the product price information. At the end, we were able to retrieve product price indications for 283 out of 300 initially VC-backed ventures. Then, we re-ran the main models under both matching procedures and treatment effect models by including this product price information, as reported in Tables 12 and 13, respectively. The results are fully consistent with those in the main models of Tables 3 and 4.

Sixth, to test the robustness of our conclusions to the matching technique we employ (PSM), we follow recent examples in innovation and entrepreneurship (e.g., Kolympiris et al., 2019; Marx et al., 2015), to implement Coarsened Exact Matching (CEM) as CEM can overcome PSM's potential shortcomings (Blackwell et al., 2009). As shown in Table 14, estimates originating from samples out of CEM matching are qualitatively identical to estimates of samples originating from PSM matching.

6. Discussion and conclusion

We reveal contingencies that prompt VCs to rely more on the crowd and less on other VCs when making investment decisions. While initially crowdfunded ventures are less likely to receive subsequent funding from VCs when compared to similar firms that received initial funding from (other) VCs, this relationship can even reverse when initially crowdfunded ventures transmit signals that complement the information conveyed by having a successful CF campaign. In those cases, follow up VCs rely more on the crowd than their peers! This finding, which comes out of a series of empirical exercises including using matching estimators carefully, is consistent with our argument that signals reducing Knightian uncertainty (during the very early stages of firm growth) or information asymmetries (during later stages) are more useful for ventures originally backed by reward-based CF.

We contribute to the broader literature on entrepreneurial finance in three main ways. First, by grounding our discussion on works on signal interactions we advance arguments explaining how an *a priori* inferior signal can become at least as effective as an *a priori* superior one (Bapna, 2019; Colombo et al., 2019; Plummer et al., 2016; Stern et al., 2014; Vanacker et al., 2020). Our main contribution here is to propose that signal complementarity can not only generate a superior signal *per se* (as a limited number of previous works have done), but can even boost the effectiveness of an *a priori* inferior signal (CF certification in our application) to the degree that it can even surpass the effectiveness of an *a priori* superior signal (VC certification). This, we posit, is a particularly relevant theoretical addition to the literature in part because the core of the arguments can extend well beyond entrepreneurial finance to areas such as the job market and employee mobility. For instance, while graduating from a low status university can put a fresh graduate at a disadvantage in the job market when compared to a graduate of a high status university, the former graduate could overcome this handicap by transmitting signals that complement the information conveyed by the type of education one receives.

Second, we add to the CF literature by bringing to light the novel finding that CF has a certification effect that can allow entrepreneurial ventures *without* initial funding from VCs to compete with those *with* initial funding from VCs in attracting later stage funds from VCs. This literature has remained mostly confined to the study of crowdfunded new ventures alone, even when the relationship of CF with traditional forms of new venture financing has been investigated (Colombo and Shafi, 2019; Drover, Wood, et al., 2017; Roma et al., 2017). By explicitly comparing the certification effectiveness of crowdfunded and VC-backed new ventures, our study advances understanding on "how [different] earlier-stage funding mechanisms communicate positive signals to other prospective investors and stakeholders" (Drover, Busenitz, et al., 2017).

Third, we add to the literature on signals transmitted by entrepreneurial firms (e.g., Audretsch et al., 2012; Hoenen et al., 2014; Hsu and Ziedonis, 2013; Kolympiris et al., 2018; Shane and Cable, 2002; Stuart et al., 1999). We do so by demonstrating that two of the most common signals, patents and founding team characteristics, do not matter only *per se* as signals valued by investors; they also matter as a device that boosts the effectiveness of weaker signals (CF certification in our application), possibly turning them into superior ones.

From a practical perspective, our study is informative for technology entrepreneurs seeking to scale up their ventures in part by attracting later stage funds. The direct implication of our conclusions is that such entrepreneurs should pay attention to the choice of their initial funding sources, and specifically on whether to use a reward-based CF channel (when it is not a last resort), as this choice may strongly affect the chance of raising subsequent capital from VCs. However, considering the emerging role of CF in financing early stage entrepreneurial ventures, an important guideline to entrepreneurs engaging in successful reward-based CF is that they should endeavor to complement a successful CF performance with other positive attributes. When this happens, their chances of securing subsequent funding for their current ventures may become equivalent or even superior to those of VC-backed entrepreneurs.

For entrepreneurs that have already raised capital from VCs, our estimates imply that engaging in transmitting costly signals as a means to attract follow up capital may not be the best strategy (*vis-à-vis* crowdfunded ventures) if these additional signals convey (more) overlapping information to what is already transmitted by having received VC investments in the first place.

A worthwhile extension of our work would be to examine the effects of different forms of CF, such as equity CF. Largely because of the more complex legal issues involved, equity CF tends to attract professional and accredited investors such as angel investors or VCs. Therefore, in this case, the funding providers of the initial infusion of capital would be mostly the same with or without CF with differences mainly in terms of the geographical origin of investors and their size. As a result, differently from reward-based CF, consumers are less likely involved in funding new ventures under equity CF. This should reduce the ability of CF to work as a consumer preference eliciting mechanism and thus serve as a signal that significantly mitigates market uncertainty. As well, the fact that only accredited investors tend to operate in equity CF platforms should make securing funding in this channel more similar to securing funding from VCs in traditional channels, in the eyes of potential follow-up VCs. Due to the enhanced perceived similarity between equity crowdfunded and initially VC-backed ventures, we would expect to see a diminished initial disadvantage of the former ones as well as diminished role of the additional signals as means to boost the signal generated from equity CF.

A boundary condition of our work is the focus on hardware new ventures. While, as explained before, hardware is a fertile template to test our hypotheses, industry-specific idiosyncrasies call for follow up works to analyze new ventures outside hardware. As well, our research considers new ventures crowdfunded through a single platform, i.e., Kickstarter. Such platform differs from the other reward-based CF platforms (e.g., IndieGoGo) because of the (all-or-nothing) funding mechanism. Therefore, it would be worthwhile to check the robustness of our results also considering different reward-based CF platforms.

References

Agrawal, A., Catalini, C., Goldfarb, A., 2014. Some simple economics of crowdfunding. Innovation Policy and the Economy 14, 63-97.

Ahlers, G.K., Cumming, D., Günther, C., Schweizer, D., 2015. Signaling in equity crowdfunding. Entrepreneurship Theory and Practice 39, 955-980.

Alexy, O., Reitzig, M., 2013. Private–collective innovation, competition, and firms' counterintuitive appropriation strategies. Research Policy 42, 895-913.

Alexy, O.T., Block, J.H., Sandner, P., Ter Wal, A.L., 2012. Social capital of venture capitalists and start-up funding. Small Business Economics 39, 835-851.

Allison, T.H., Davis, B.C., Webb, J.W., Short, J.C., 2017. Persuasion in crowdfunding: An elaboration likelihood model of crowdfunding performance. Journal of Business Venturing 32, 707-725.

Amit, R., Brander, J., Zott, C., 1998. Why do venture capital firms exist? Theory and Canadian evidence. Journal of Business Venturing 13, 441-466.

Amit, R., Glosten, L., Muller, E., 1990. Entrepreneurial ability, venture investments, and risk sharing. Management Science 36, 1233-1246.

Anglin, A.H., Short, J.C., Drover, W., Stevenson, R.M., McKenny, A.F., Allison, T.H., 2018. The power of positivity? The influence of positive psychological capital language on crowdfunding performance. Journal of Business Venturing 33, 470-492.

Audretsch, D.B., Bönte, W., Mahagaonkar, P., 2012. Financial signaling by innovative nascent ventures: The relevance of patents and prototypes. Research Policy 41, 1407-1421.

Bai, X., Tsang, E.W., Xia, W., 2020. Domestic versus foreign listing: Does a CEO's educational experience matter? Journal of Business Venturing 35, 105906.

Bapna, S., 2019. Complementarity of signals in early-stage equity investment decisions: Evidence from a randomized field experiment. Management Science 65, 933-952.

Baron, R.A., Ensley, M.D., 2006. Opportunity recognition as the detection of meaningful patterns: Evidence from comparisons of novice and experienced entrepreneurs. Management Science 52, 1331-1344.

Baum, J.A., Calabrese, T., Silverman, B.S., 2000. Don't go it alone: Alliance network composition and startups' performance in Canadian biotechnology. Strategic Management Journal 21, 267-294.

Baum, J.A., Silverman, B.S., 2004. Picking winners or building them? Alliance, intellectual, and human capital as selection criteria in venture financing and performance of biotechnology startups. Journal of Business Venturing 19, 411-436.

Bernstein, S., Korteweg, A., Laws, K., 2017. Attracting early‐stage investors: Evidence from a randomized field experiment. The Journal of Finance 72, 509-538.

Bertoni, F., Colombo, M.G., Grilli, L., 2011. Venture capital financing and the growth of high-tech start-ups: Disentangling treatment from selection effects. Research Policy 40, 1028-1043.

Blackwell, M., Iacus, S., King, G., Porro, G., 2009. cem: Coarsened exact matching in Stata. The Stata Journal 9, 524-546.

Bonardo, D., Paleari, S., Vismara, S., 2011. Valuing university–based firms: The effects of academic affiliation on IPO performance. Entrepreneurship Theory and Practice 35, 755-776.

Bottazzi, L., Da Rin, M., Hellmann, T., 2008. Who are the active investors? Evidence from venture capital. Journal of Financial Economics 89, 488-512.

Burt, R.S., 2004. Structural holes and good ideas. American Journal of Sociology 110, 349-399.

Chan, R., Parhankangas, A., 2017. Crowdfunding innovative ideas: How incremental and radical innovativeness influence funding outcomes. Entrepreneurship Theory and Practice 41, 237-263.

Chang, S.J., 2004. Venture capital financing, strategic alliances, and the initial public offerings of Internet startups. Journal of Business Venturing 19, 721-741.

Cholakova, M., Clarysse, B., 2015. Does the possibility to make equity investments in crowdfunding projects crowd out reward–based investments? Entrepreneurship Theory and Practice 39, 145-172.

Colombo, M.G., Franzoni, C., Rossi-Lamastra, C., 2015. Internal social capital and the attraction of early contributions in crowdfunding. Entrepreneurship: Theory and Practice 39, 75-100.

Colombo, M.G., Grilli, L., 2010. On growth drivers of high-tech start-ups: Exploring the role of founders' human capital and venture capital. Journal of Business Venturing 25, 610-626.

Colombo, M.G., Meoli, M., Vismara, S., 2019. Signaling in science-based IPOs: The combined effect of affiliation with prestigious universities, underwriters, and venture capitalists. Journal of Business Venturing 34, 141-177.
Colombo, M.G., Shafi, K., 2019. Receiving external equity following successfully crowdfunded technological projects: an informational mechanism. Small Business Economics, 1-23.
Conti, A., Thursby, J., Thursby, M., 2013. Patents as signals for startup financing. Journal of Industrial Economics 61, 592-622.
Conti, A., Thursby, M., Rothaermel, F.T., 2013. Show me the right stuff: Signals for high-tech startups. Journal of Economics and Management Strategy 22, 341-364.
Courtney, C., Dutta, S., Li, Y., 2017. Resolving information asymmetry: Signaling, endorsement, and crowdfunding success. Entrepreneurship Theory and Practice 41, 265-290.
Croce, A., Martí, J., Murtinu, S., 2013. The impact of venture capital on the productivity growth of European entrepreneurial firms: 'Screening' or 'value added' effect? Journal of Business Venturing 28, 489-510.
Crosetto, P., Regner, T., 2018. It's never too late: Funding dynamics and self pledges in reward-based crowdfunding. Research Policy 47, 1463-1477.
Crossland, C., Hambrick, D.C., 2011. Differences in managerial discretion across countries: how nation-level institutions affect the degree to which CEOs matter. Strategic Management Journal 32, 797-819.
Cumming, D., Dai, N., 2010. Local bias in venture capital investments. Journal of Empirical Finance 17, 362-380.
Davis, B.C., Hmieleski, K.M., Webb, J.W., Coombs, J.E., 2017. Funders' positive affective reactions to entrepreneurs' crowdfunding pitches: The influence of perceived product creativity and entrepreneurial passion. Journal of Business Venturing 32, 90-106.
Deeds, D.L., Mang, P.Y., Frandsen, M.L., 2004. The influence of firms’ and industries’ legitimacy on the flow of capital into high-technology ventures. Strategic Organization 2, 9-34.
Drover, W., Busenitz, L., Matusik, S., Townsend, D., Anglin, A., Dushnitsky, G., 2017. A review and road map of entrepreneurial equity financing research: Venture capital, corporate venture capital, angel investment, crowdfunding, and accelerators. Journal of Management 43, 1820-1853.
Drover, W., Wood, M.S., Zacharakis, A., 2017. Attributes of angel and crowdfunded investments as determinants of VC screening decisions. Entrepreneurship Theory and Practice 41, 323-347.
Dutta, S., Folta, T.B., 2016. A comparison of the effect of angels and venture capitalists on innovation and value creation. Journal of Business Venturing 31, 39-54.
Foss, N., Klein, P.G., Murtinu, S., 2020. Entrepreneurial finance under Knightian uncertainty: Pathways for achieving cognitive overlap. Working paper, Baylor University.
Franke, N., Gruber, M., Harhoff, D., Henkel, J., 2008. Venture capitalists' evaluations of start-up teams: Trade-offs, knock-out criteria, and the impact of VC experience. Entrepreneurship Theory and Practice 32, 459-483.
Galak, J., Small, D., Stephen, A.T., 2011. Microfinance decision making: A field study of prosocial lending. Journal of Marketing Research 48, S130-S137.
Gerber, E.M., Hui, J.S., Kuo, P.-Y., 2012. Crowdfunding: Why people are motivated to post and fund projects on crowdfunding platforms, Proceedings of the International Workshop on Design, Influence, and Social Technologies: Techniques, Impacts and Ethics. Northwestern University Evanston, IL, p. 10.
Gleasure, R., Conboy, K., Morgan, L., 2019. Talking up a storm: How backers use public discourse to exert control in crowdfunded systems development projects. Information Systems Research 30, 447-465.
Gompers, P., Kovner, A., Lerner, J., Scharfstein, D., 2010. Performance persistence in entrepreneurship. Journal of Financial Economics 96, 18-32.
Gompers, P., Lerner, J., 2001. The venture capital revolution. Journal of Economic Perspectives 15, 145-168.
Graham, S.J., Sichelman, T., 2008. Why do start-ups patent. Berkeley Tech. LJ 23, 1063.
Granovetter, M.S., 1973. The strength of weak ties. American Journal of Sociology 78, 1360-1380.
Greene, W.H., 2003. Econometric analysis. Pearson Education India.

Guerini, M., Quas, A., 2016. Governmental venture capital in Europe: Screening and certification. Journal of Business Venturing 31, 175-195.
Gulati, R., Higgins, M.C., 2003. Which ties matter when? The contingent effects of interorganizational partnerships on IPO success. Strategic Management Journal 24, 127-144.
Haeussler, C., Harhoff, D., Mueller, E., 2014. How patenting informs VC investors - The case of biotechnology. Research Policy 43, 1286-1298.
Hall, J., Hofer, C.W., 1993. Venture capitalists' decision criteria in new venture evaluation. Journal of Business Venturing 8, 25-42.
Hellmann, T., 2000. Venture capitalists: the coaches of Silicon Valley. The Silicon Valley Edge 113, 276-294.
Hellmann, T., Puri, M., 2002. Venture capital and the professionalization of start-up firms: Empirical evidence. Journal of Finance 57, 169-197.
Helmers, C., Rogers, M., 2011. Does patenting help high-tech start-ups? Research Policy 40, 1016-1027.
Higgins, M.C., Gulati, R., 2006. Stacking the deck: The effects of top management backgrounds on investor decisions. Strategic Management Journal 27, 1-25.
Hoenen, S., Kolympiris, C., Schoenmakers, W., Kalaitzandonakes, N., 2014. The diminishing signaling value of patents between early rounds of venture capital financing. Research Policy 43, 956-989.
Hoenig, D., Henkel, J., 2015. Quality signals? The role of patents, alliances, and team experience in venture capital financing. Research Policy 44, 1049-1064.
Howell, S.T., 2017. Financing innovation: Evidence from R&D grants. American Economic Review 107, 1136-1164.
Hsu, D.H., 2007. Experienced entrepreneurial founders, organizational capital, and venture capital funding. Research Policy 36, 722-741.
Hsu, D.H., Ziedonis, R.H., 2013. Resources as dual sources of advantage: Implications for valuing entrepreneurial‐firm patents. Strategic Management Journal 34, 761-781.
Inkpen, A.C., Tsang, E.W., 2005. Social capital, networks, and knowledge transfer. Academy of Management Review 30, 146-165.
Jääskeläinen, M., Maula, M., 2014. Do networks of financial intermediaries help reduce local bias? Evidence from cross-border venture capital exits. Journal of Business Venturing 29, 704-721.
Kaplan, S.N., Stromberg, P., 2001. Venture capitals as principals: contracting, screening, and monitoring. American Economic Review 91, 426-430.
Kerr, W.R., Lerner, J., Schoar, A., 2014. The consequences of entrepreneurial finance: Evidence from angel financings. Review of Financial Studies 27, 20-55.
Ko, E.J., McKelvie, A., 2018. Signaling for more money: The roles of founders' human capital and investor prominence in resource acquisition across different stages of firm development. Journal of Business Venturing 33, 438-454.
Kolympiris, C., Hoenen, S., Kalaitzandonakes, N., 2018. Geographic distance between venture capitalists and target firms and the value of quality signals. Industrial and Corporate Change 27, 189-220.
Kolympiris, C., Hoenen, S., Klein, P.G., 2019. Learning by seconding: evidence from national science foundation rotators. Organization Science 30, 528-551.
Kolympiris, C., Kalaitzandonakes, N., Miller, D., 2011. Spatial collocation and venture capital in the US biotechnology industry. Research Policy 40, 1188-1199.
Lee, C., Lee, K., Pennings, J.M., 2001. Internal capabilities, external networks, and performance: A study on technology-based ventures. Strategic Management Journal 22, 615-640.
Lerner, J., 2002. When bureaucrats meet entrepreneurs: The design of effective 'public venture capital' programmes. Economic Journal 112, F73-F84.
MacMillan, I.C., Siegel, R., Narasimha, P.S., 1985. Criteria used by venture capitalists to evaluate new venture proposals. Journal of Business Venturing 1, 119-128.
Mäkelä, M.M., Maula, M.V.J., 2008. Attracting cross-border venture capital: the role of a local investor. Entrepreneurship & Regional Development 20, 237-257.
Mann, R.J., Sager, T.W., 2007. Patents, venture capital, and software start-ups. Research Policy 36, 193-208.
Marmer, M., Herrmann, B.L., Dogrultan, E., Berman, R., 2012. Startup Genome Report.

Marx, M., Singh, J., Fleming, L., 2015. Regional disadvantage? Employee non-compete agreements and brain drain. Research Policy 44, 394-404.
McFadyen, A., Cannella Jr, A.A., 2004. Social capital and knowledge creation: Diminishing returns of the number and strength of exchange relationships. Academy of Management Journal 47, 735-746.
McKenny, A.F., Allison, T.H., Ketchen, D.J., Short, J.C., Ireland, R.D., 2017. How should crowdfunding research evolve? A survey of the Entrepreneurship Theory and Practice editorial board. Entrepreneurship Theory and Practice 41, 291-304.
Megginson, W.L., Weiss, K.A., 1991. Venture capitalist certification in initial public offerings. The Journal of Finance 46, 879-903.
Mollick, E., 2014. The dynamics of crowdfunding: An exploratory study. Journal of Business Venturing 29, 1-16.
Mollick, E., Nanda, R., 2016. Wisdom or madness? Comparing crowds with expert evaluation in funding the arts. Management Science 62, 1533-1553.
Montgomery, J., 2020. The ultimate question: How much money should your Kickstarter video raise?. https://www.funded.today/blog/the-ultimate-question-how-much-money-should-your-kickstarter-video-raise.
Mueller, C., Westhead, P., Wright, M., 2012. Formal venture capital acquisition: Can entrepreneurs compensate for the spatial proximity benefits of South East England and 'star'golden-triangle universities? Environment and Planning A 44, 281-296.
Nuscheler, D., Engelen, A., Zahra, S.A., 2019. The role of top management teams in transforming technology-based new ventures' product introductions into growth. Journal of Business Venturing 34, 122-140.
Packard, M.D., Clark, B.B., Klein, P.G., 2017. Uncertainty types and transitions in the entrepreneurial process. Organization Science 28, 840-856.
Pecota, M., 2018. Why only 1.3% of Kickstarter campaigns reach $100K. https://www.launchboom.com/blog/why-only-1-3-of-kickstarter-campaigns-reach-100k-6f2f71d34346/.
Petty, J.S., Gruber, M., 2011. "In pursuit of the real deal". A longitudinal study of VC decision making. Journal of Business Venturing 26, 172-188.
Piva, E., Rossi-Lamastra, C., 2018. Human capital signals and entrepreneurs' success in equity crowdfunding. Small Business Economics 51, 667-686.
Plummer, L.A., Allison, T.H., Connelly, B.L., 2016. Better together? Signaling interactions in new venture pursuit of initial external capital. Academy of Management Journal 59, 1585-1604.
Pollack, J.M., Rutherford, M.W., Nagy, B.G., 2012. Preparedness and cognitive legitimacy as antecedents of new venture funding in televised business pitches. Entrepreneurship Theory and Practice 36, 915-939.
Powell, W.W., Koput, K., Bowie, J.I., Smith-Doerr, L., 2002. The spatial clustering of science and capital: Accounting for biotech firm-venture capital relationships. Regional Studies 36, 291-305.
Putnam, R.D., 2000. Bowling alone: The collapse and revival of American community. Simon and Schuster, New York.
PwC, 2014. MoneyTree report Q3 2014, in: Association, N.V.C. (Ed.).
Ragozzino, R., Reuer, J.J., 2011. Geographic distance and corporate acquisitions: signals from IPO firms. Strategic Management Journal 32, 876-894.
Reagans, R., McEvily, B., 2003. Network structure and knowledge transfer: The effects of cohesion and range. Administrative Science Quarterly 48, 240-267.
Reese, D., Rieger, V., Engelen, A., 2020. Should competencies be broadly shared in new ventures' founding teams? Strategic Entrepreneurship Journal, forthcoming.
Roma, P., Gal-Or, E., Chen, R.R., 2018. Reward-based crowdfunding campaigns: Informational value and access to venture capital. Information Systems Research 29, 679-697.
Roma, P., Messeni Petruzzelli, A., Perrone, G., 2017. From the crowd to the market: The role of reward-based crowdfunding performance in attracting professional investors. Research Policy 46, 1606-1628.

Rosenbaum, P.R., Rubin, D.B., 1984. Reducing bias in observational studies using subclassification on the propensity score. Journal of the American Statistical Association 79, 516-524.
Scheaf, D.J., Davis, B.C., Webb, J.W., Coombs, J.E., Borns, J., Holloway, G., 2018. Signals' flexibility and interaction with visual cues: Insights from crowdfunding. Journal of Business Venturing 33, 720-741.
Shane, S., Cable, D., 2002. Network ties, reputation, and the financing of new ventures. Management Science 48, 364-381.
Short, J.C., Ketchen, D.J., McKenny, A.F., Allison, T.H., Ireland, R.D., 2017. Research on crowdfunding: Reviewing the (very recent) past and celebrating the present. Entrepreneurship Theory and Practice 41, 149-160.
Sorenson, O., Stuart, T.E., 2001. Syndication networks and the spatial distribution of venture capital investments. American Journal of Sociology 10, 1546-1588.
Spence, M., 1973. Job market signaling. The Quartely Journal of Economics 87, 355-374.
Stanko, M.A., Henard, D.H., 2017. Toward a better understanding of crowdfunding, openness and the consequences for innovation. Research Policy 46, 784-798.
Stern, I., Dukerich, J.M., Zajac, E., 2014. Unmixed signals: How reputation and status affect alliance formation. Strategic Management Journal 35, 512-531.
Strausz, R., 2017. A theory of crowdfunding: A mechanism design approach with demand uncertainty and moral hazard. American Economic Review 107, 1430-1476.
Stuart, T.E., Hoang, H., Hybels, R., 1999. Interorganizational endorsements and the performance of entrepreneurial ventures. Administrative Science Quarterly 44, 315-349.
Tartari, V., Perkmann, M., Salter, A., 2014. In good company: The influence of peers on industry engagement by academic scientists. Research Policy 43, 1189-1203.
Tartari, V., Salter, A., 2015. The engagement gap:: Exploring gender differences in University–Industry collaboration activities. Research Policy 44, 1176-1191.
Thies, F., Huber, A., Bock, C., Benlian, A., Kraus, S., 2019. Following the crowd—Does crowdfunding affect venture capitalists' selection of entrepreneurial ventures? Journal of Small Business Management 57, 1378-1398.
Tian, X., 2011. The causes and consequences of venture capital stage financing. Journal of Financial Economics 101, 132-159.
Townsend, D.M., Hunt, R.A., McMullen, J.S., Sarasvathy, S.D., 2018. Uncertainty, knowledge problems, and entrepreneurial action. Academy of Management Annals 12, 659-687.
Vanacker, T., Forbes, D.P., Knockaert, M., Manigart, S., 2020. Signal strength, media attention, and resource mobilization: evidence from new private equity firms. Academy of Management Journal 63, 1082-1105.
Viotto da Cruz, J., 2018. Beyond financing: crowdfunding as an informational mechanism. Journal of Business Venturing 33, 371-393.
Vismara, S., 2018. Information cascades among investors in equity crowdfunding. Entrepreneurship Theory and Practice 42, 467-497.
Walthoff-Borm, X., Schwienbacher, A., Vanacker, T., 2018. Equity crowdfunding: First resort or last resort? Journal of Business Venturing 33, 513-533.
Wang, W., Mahmood, A., Sismeiro, C., Vulkan, N., 2019. The evolution of equity crowdfunding: Insights from co-investments of angels and the crowd. Research Policy 48(8), 103727.
Wooldridge, J.M., 2010. Econometric analysis of cross section and panel data. MIT press.
Yang, L., Wang, Z., Hahn, J., 2020. Scarcity strategy in crowdfunding: An empirical exploration of reward limits. Information Systems Research 31, 1107-1131.
Zacharakis, A.L., Meyer, G.D., 2000. The potential of actuarial decision models: Can they improve the venture capital investment decision? Journal of Business Venturing 15, 323-346.
Zelner, B.A., 2009. Research notes and commentaries using simulation to interpret results from logit, probit, and other nonlinear models. Strategic Management Journal 30, 1335-1348.
Zhang, J., 2011. The advantage of experienced start-up founders in venture capital acquisition: Evidence from serial entrepreneurs. Small Business Economics 36, 187-208.
Zider, B., 1998. How venture capital works. Harvard Business Review 76, 131-139.

Table 1. Descriptive statistics for the full sample (threshold for crowdfunded new ventures on the raised amount set equal to $5,000)

	PANEL A New ventures engaging in crowdfunding (325 observations)				PANEL B New ventures not engaging in crowdfunding (300 observations)			
Variables	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
Subsequent Funding from VCs (Dep. variable)	0.188	0.391	0	1	0.593	0.492	0	1
Top Startup Ecosystems	0.471	0.500	0	1	0.477	0.500	0	1
Average Industry Experience	7.458	6.096	0	33.5	13.410	9.081	1	38
MBA	0.101	0.302	0	1	0.233	0.424	0	1
PhD	0.111	0.314	0	1	0.227	0.419	0	1
Size of the Entrepreneurial Team	1.585	0.866	1	6	1.830	0.847	1	5
Previous New Ventures	0.400	0.491	0	1	0.553	0.498	0	1
Entrepreneur Past Successful Funding Experience	0.086	0.281	0	1	0.183	0.387	0	1
Patents	0.037	0.189	0	1	0.117	0.321	0	1
Affiliation with a Prestigious Partner	0.077	0.267	0	1	0.103	0.305	0	1
B2B (used for treatment effect regression model)	0.258	0.438	0	1	0.473	0.500	0	1
Consumer Electronics & Hardware	0.738	0.440	0	1	0.740	0.439	0	1
3D Printing & Robotics	0.225	0.418	0	1	0.070	0.255	0	1
Medical Devices	0.006	0.078	0	1	0.177	0.382	0	1
Aerospace Applications	0.031	0.173	0	1	0.013	0.115	0	1
Year of Est. 2005	0.028	0.164	0	1	0.080	0.272	0	1
Year of Est. 2006	0.028	0.164	0	1	0.080	0.272	0	1
Year of Est. 2007	0.025	0.155	0	1	0.080	0.272	0	1
Year of Est. 2008	0.028	0.164	0	1	0.087	0.282	0	1
Year of Est. 2009	0.074	0.262	0	1	0.107	0.309	0	1
Year of Est. 2010	0.114	0.318	0	1	0.113	0.317	0	1
Year of Est. 2011	0.157	0.364	0	1	0.200	0.401	0	1
Year of Est. 2012	0.273	0.447	0	1	0.083	0.277	0	1
Year of Est. 2013	0.181	0.386	0	1	0.120	0.325	0	1
Year of Est. 2014	0.092	0.290	0	1	0.050	0.218	0	1

Table 2. Descriptive statistics for the matched sample (threshold for crowdfunded new ventures on the raised amount set equal to $5,000)

	PANEL A New ventures engaging in Crowdfunding (156 observations)	PANEL B New ventures not engaging in Crowdfunding (156 observations)	
Variables	**Mean**	**Mean**	**Two sample T-Test with groups (p-value)**
Top Startup Ecosystems	0.538	0.506	0.572
Average Industry Experience	9.868	9.054	0.409
MBA	0.154	0.141	0.750
PhD	0.141	0.141	1.000
Size of the Entrepreneurial Team	1.782	1.744	0.216
Previous New Ventures	0.526	0.519	0.910
Entrepreneur Past Successful Funding Experience	0.147	0.135	0.745
Patents	0.051	0.045	0.792
Affiliation with a Prestigious Partner	0.096	0.064	0.299
Consumer Electronics & Hardware	0.897	0.872	0.480
3D Printing & Robotics	0.064	0.083	0.517
Medical Devices	0.013	0.026	0.411
Aerospace Applications	0.026	0.019	0.703
Year of Est. 2005	0.051	0.045	0.792
Year of Est. 2006	0.051	0.051	1.000
Year of Est. 2007	0.045	0.038	0.778
Year of Est. 2008	0.045	0.055	0.609
Year of Est. 2009	0.122	0.103	0.592
Year of Est. 2010	0.122	0.109	0.724
Year of Est. 2011	0.237	0.224	0.789
Year of Est. 2012	0.077	0.128	0.136
Year of Est. 2013	0.179	0.173	0.882
Year of Est. 2014	0.071	0.071	1.000

Table 3. Probit regression models for the matched sample (threshold for crowdfunded new ventures on the raised amount set equal to $5,000)

	No interactions	*Crowdfunding* interacted with *Patents*	*Crowdfunding* interacted with *Entrepreneur Past Successful Funding Experience*	*Crowdfunding* interacted with *Affiliation with a Prestigious Partner*	All interactions
Top Startup Ecosystems	0.159	0.142	0.175	0.159	0.157
	(0.167)	(0.168)	(0.168)	(0.167)	(0.169)
Average Industry Experience	-0.026*	-0.025*	-0.027**	-0.026*	-0.027**
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
MBA	0.386*	0.387*	0.431	0.386*	0.428*
	(0.226)	(0.230)	(0.233)	(0.226)	(0.237)
PhD	0.285	0.299	0.362	0.285	0.377
	(0.240)	(0.246)	(0.241)	(0.243)	(0.249)
Size of the Entrepreneurial Team	0.226**	0.234**	0.250***	0.226**	0.254***
	(0.090)	(0.092)	(0.092)	(0.090)	(0.094)
Previous New Ventures	0.151	0.150	0.151	0.151	0.154
	(0.174)	(0.175)	(0.180)	(0.174)	(0.181)
Entrepreneur Past Successful Funding Experience	0.670***	0.630**	0.080	0.670***	0.082
	(0.257)	(0.261)	(0.328)	(0.256)	(0.327)
Patents	0.680*	-0.380	0.602	0.680*	-0.381
	(0.405)	(0.445)	(0.400)	(0.405)	(0.423)
Affiliation with a Prestigious Partner	-0.113	-0.090	-0.128	-0.107	-0.058
	(0.285)	(0.288)	(0.292)	(0.442)	(0.423)
Crowdfunding	-1.057***	-1.168***	-1.262***	-1.056***	-1.347***
	(0.166)	(0.173)	(0.328)	(0.171)	(0.197)
Crowdfunding X Patents	-	2.048***	-	-	1.966***
	-	(0.712)	-	-	(0.700)
Crowdfunding X Entrepreneur Past Successful Funding Experience	-	-	1.242***	-	1.168***
	-	-	(0.455)	-	(0.454)
Crowdfunding X Affiliation with a Prestigious Partner	-	-	-	-0.010	-0.086
	-	-	-	(0.570)	(0.588)
Year of Establishment (dummies)	Included	Included	Included	Included	Included
Subcategories (dummies)	Included	Included	Included	Included	Included
Constant	-0.758	-0.782	-0.926	-0.757	-0.925
	(0.696)	(0.694)	(0.688)	(0.699)	(0.688)
N. obs initial sample	625	625	625	625	625
N. obs initial sample of crowdfunded new ventures	325	325	325	325	325
N. obs one-to-one matched sample	312	312	312	312	312
Pseudo R^2	0.215	0.233	0.231	0.215	0.247

Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. Treatment effect regression models (threshold for crowdfunded new ventures on the raised amount set equal to $5,000)

	No interaction		*Crowdfunding* interacted with *Patents*		*Crowdfunding* interacted with *Entrepreneur Past Successful Funding Experience*		*Crowdfunding* interacted with *Affiliation with a Prestigious Partner*		All interactions	
	2nd stage	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage	1st stage
Top Startup Ecosystems	0.047	-0.094	0.047	-0.095	0.046	-0.093	0.045	-0.094	0.045	-0.094
	(0.034)	(0.121)	(0.034)	(0.121)	(0.034)	(0.121)	(0.034)	(0.121)	(0.033)	(0.121)
Average Industry Experience	-0.003	-0.045***	-0.002	-0.045***	-0.003	-0.045***	-0.003	-0.045***	-0.002	-0.045***
	(0.003)	(0.009)	(0.003)	(0.009)	(0.003)	(0.009)	(0.003)	(0.009)	(0.003)	(0.009)
MBA	0.086*	-0.369**	0.087*	-0.369**	0.093*	-0.367**	0.087*	-0.369**	0.093**	-0.367**
	(0.048)	(0.169)	(0.048)	(0.169)	(0.048)	(0.169)	(0.048)	(0.169)	(0.047)	(0.169)
PhD	0.132***	-0.237	0.128***	-0.235	0.139***	-0.237	0.133***	-0.236	0.135***	-0.235
	(0.048)	(0.169)	(0.048)	(0.169)	(0.048)	(0.169)	(0.048)	(0.169)	(0.047)	(0.169)
Size of the Entrepreneurial Team	0.098***	-0.185***	0.099***	-0.185***	0.101***	-0.185***	0.097***	-0.185***	0.101***	-0.185***
	(0.021)	(0.070)	(0.021)	(0.070)	(0.021)	(0.070)	(0.021)	(0.070)	(0.021)	(0.070)
Previous New Ventures	0.071*	-0.240*	0.073**	-0.240*	0.063*	-0.241*	0.072*	-0.240*	0.065*	-0.241*
	(0.037)	(0.129)	(0.037)	(0.129)	(0.037)	(0.129)	(0.037)	(0.129)	(0.037)	(0.129)
Entrepreneur Past Successful Funding Experience	0.123**	-0.137	0.103*	-0.141	0.003	-0.139	0.124**	-0.137	-0.000	-0.142
	(0.054)	(0.188)	(0.054)	(0.188)	(0.064)	(0.188)	(0.054)	(0.188)	(0.064)	(0.188)
Patents	0.135**	0.039	0.002	0.020	0.117*	0.040	0.137**	0.039	0.001	0.020
	(0.067)	(0.417)	(0.078)	(0.420)	(0.067)	(0.413)	(0.067)	(0.417)	(0.077)	(0.418)
Affiliation with a Prestigious Partner	0.041	-0.171	0.024	-0.170	0.033	-0.170	0.073	-0.170	0.067	-0.169
	(0.060)	(0.214)	(0.060)	(0.214)	(0.060)	(0.214)	(0.080)	(0.213)	(0.079)	(0.213)
B2B	-	-0.704***	-	-0.703***	-	-0.707***	-	-0.704***	-	-0.705***
	-	(0.127)	-	(0.127)	-	(0.127)	-	(0.127)	-	(0.127)
Crowdfunding	-0.249**	-	-0.284***	-	-0.269***	-	-0.242**	-	-0.288***	-
	(0.102)	-	(0.102)	-	(0.097)	-	(0.102)	-	(0.098)	-
Crowdfunding X Patents	-	-	0.476***	-	-	-	-	-	0.434***	-
	-	-	(0.144)	-	-	-	-	-	(0.145)	-
Crowdfunding X Entrepreneur Past Successful Funding	-	-	-	-	0.350***	-	-	-	0.314***	-

Experience										
	-	-	-	-	(0.104)	-	-	-	(0.104)	-
Crowdfunding X Affiliation with a Prestigious Partner	-	-	-	-	-	-	-0.074	-	-0.110	-
	-	-	-	-	-	-	(0.119)	-	(0.118)	-
Year of Establishment (dummies)	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Subcategories (dummies)	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Constant	0.433***	-0.830*	0.448***	-0.828*	0.439***	-0.839*	0.429***	-0.830*	0.446***	-0.839*
	(0.111)	(0.479)	(0.111)	(0.479)	(0.110)	(0.480)	(0.112)	(0.479)	(0.110)	(0.480)
N. obs. initial sample	625	625	625	625	625	625	625	625	625	625
N. obs initial sample of crowdfunded new ventures	325	325	325	325	325	325	325	325	325	325
LR test of independent equations (p-value)	0.486	-	0.545	-	0.325	-	0.483	-	0.378	-

Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Note that, in the first stage regression, when necessary, the variables are computed right before the time of the first funding to properly capture their influence on the decision to use CF.

Table 5. Probit regression models for matched sample (threshold for crowdfunded new ventures on the goal set equal to $5,000)

	No interactions	*Crowdfunding* interacted with *Patents*	*Crowdfunding* interacted with *Entrepreneur Past Successful Funding Experience*	*Crowdfunding* interacted with *Affiliation with a Prestigious Partner*	All interactions
Top Startup Ecosystems	0.242	0.214	0.223	0.241	0.203
	(0.139)	(0.167)	(0.165)	(0.163)	(0.169)
Average Industry Experience	-0.016	-0.013	-0.017	-0.016	-0.014
	(0.012)	(0.013)	(0.012)	(0.012)	(0.013)
MBA	0.292	0.276	0.368	0.312	0.352
	(0.237)	(0.242)	(0.242)	(0.236)	(0.247)
PhD	0.346	0.436*	0.390	0.354	0.483*
	(0.248)	(0.253)	(0.252)	(0.250)	(0.255)
Size of the Entrepreneurial Team	0.240***	0.269***	0.267***	0.236***	0.289***
	(0.091)	(0.094)	(0.091)	(0.091)	(0.094)
Previous New Ventures	0.059	0.090	0.034	0.069	0.082
	(0.170)	(0.174)	(0.175)	(0.171)	(0.180)
Entrepreneur Past Successful Funding Experience	0.714***	0.632**	0.038	0.709***	0.047
	(0.270)	(0.283)	(0.350)	(0.270)	(0.371)
Patents	0.523	-0.708	0.439	0.534	-0.671
	(0.390)	(0.476)	(0.398)	(0.389)	(0.491)
Affiliation with a Prestigious Partner	-0.131	0.117	0.127	0.368	0.283
	(0.270)	(0.278)	(0.274)	(0.369)	(0.376)
Crowdfunding	-0.902***	-1.112***	-1.122***	-0.861***	-1.272***
	(0.164)	(0.176)	(0.182)	(0.171)	(0.198)
Crowdfunding X Patents	-	3.129***	-	-	3.034***
	-	(0.781)	-	-	(0.806)
Crowdfunding X Entrepreneur Past Successful Funding Experience	-	-	1.454***	-	1.307***
	-	-	(0.482)	-	(0.505)
Crowdfunding X Affiliation with a Prestigious Partner	-	-	-	-0.472	-0.325
	-	-	-	(0.538)	(0.564)
Year of Establishment (dummies)	Included	Included	Included	Included	Included
Subcategories (dummies)	Included	Included	Included	Included	Included
Constant	-1.036	-1.290*	-1.184*	-1.035	-1.411**
	(0.723)	(0.707)	(0.708)	(0.709)	(0.686)
N. obs initial sample	613	613	613	613	613
N. obs initial sample of crowdfunded new ventures	313	313	313	313	313
N. obs one-to-one matched sample	302	302	302	302	302
Pseudo R^2	0.181	0.227	0.203	0.183	0.244

Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6. Treatment effect regression models (threshold for crowdfunded new ventures on the goal set equal to $5,000)

	No interaction		*Crowdfunding* interacted with *Patents*		*Crowdfunding* interacted with *Entrepreneur Past Successful Funding Experience*		*Crowdfunding* interacted with *Affiliation with a Prestigious Partner*		All interactions	
	2nd stage	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage	1st stage
Top Startup Ecosystems	0.043	-0.079	0.044	-0.080	0.043	-0.078	0.042	-0.079	0.042	-0.080
	(0.035)	(0.122)	(0.034)	(0.122)	(0.034)	(0.122)	(0.035)	(0.122)	(0.034)	(0.122)
Average Industry Experience	-0.003	-0.046***	-0.002	-0.047***	-0.003	-0.046***	-0.003	-0.046***	-0.002	-0.047***
	(0.003)	(0.009)	(0.003)	(0.009)	(0.003)	(0.009)	(0.003)	(0.009)	(0.003)	(0.009)
MBA	0.087*	-0.349**	0.087*	-0.349**	0.093*	-0.347**	0.087*	-0.349**	0.093*	-0.347**
	(0.049)	(0.171)	(0.048)	(0.171)	(0.048)	(0.171)	(0.049)	(0.171)	(0.048)	(0.171)
PhD	0.135***	-0.267	0.130***	-0.266	0.142***	-0.268	0.136***	-0.267	0.138***	-0.266
	(0.049)	(0.171)	(0.048)	(0.172)	(0.048)	(0.171)	(0.049)	(0.171)	(0.048)	(0.171)
Size of the Entrepreneurial Team	0.098***	-0.186***	0.099***	-0.185***	0.101***	-0.186***	0.097***	-0.186***	0.101***	-0.186***
	(0.021)	(0.071)	(0.021)	(0.071)	(0.021)	(0.071)	(0.021)	(0.071)	(0.021)	(0.071)
Previous New Ventures	0.072*	-0.239*	0.073**	-0.239*	0.064*	-0.240*	0.073*	-0.239*	0.066*	-0.240*
	(0.038)	(0.131)	(0.037)	(0.131)	(0.038)	(0.130)	(0.038)	(0.131)	(0.037)	(0.130)
Entrepreneur Past Successful Funding Experience	0.120**	-0.107	0.100*	-0.110	0.002	-0.108	0.121**	-0.107	-0.002	-0.111
	(0.054)	(0.189)	(0.054)	(0.189)	(0.065)	(0.189)	(0.054)	(0.189)	(0.064)	(0.189)
Patents	0.133**	0.054	0.001	0.035	0.116*	0.056	0.136**	0.054	0.001	0.036
	(0.067)	(0.420)	(0.078)	(0.423)	(0.067)	(0.415)	(0.067)	(0.420)	(0.078)	(0.421)
Affiliation with a Prestigious Partner	0.037	-0.146	0.021	-0.146	0.030	-0.146	0.073	-0.145	0.067	-0.144
	(0.061)	(0.214)	(0.061)	(0.214)	(0.061)	(0.215)	(0.081)	(0.214)	(0.079)	(0.214)
B2B	-	-0.736***	-	-0.736***	-	-0.739***	-	-0.736***	-	-0.737***
	-	(0.129)	-	(0.129)	-	(0.129)	-	(0.129)	-	(0.129)
Crowdfunding	-0.245**	-	-0.281**	-	-0.263***	-	-0.237**	-	-0.282***	-
	(0.104)	-	(0.104)	-	(0.098)	-	(0.104)	-	(0.100)	-
Crowdfunding X Patents	-	-	0.473***	-	-	-	-	-	0.432***	-
	-	-	(0.145)	-	-	-	-	-	(0.146)	-

Crowdfunding X Entrepreneur Past Successful Funding Experience	-	-	-	-	0.345***	-	-	-	0.309***	-
	-	-	-	-	(0.105)	-		-	(0.105)	-
Crowdfunding X Affiliation with a Prestigious Partner	-	-	-	-	-	-	-0.081	-	-0.116	-
	-	-	-	-	-	-	(0.120)	-	(0.119)	-
Year of Establishment (dummies)	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Subcategories (dummies)	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Constant	0.431***	-0.794*	0.445***	-0.791	0.435***	-0.803*	0.426***	-0.794*	0.442***	-0.802*
	(0.113)	(0.481)	(0.112)	(0.481)	(0.112)	(0.482)	(0.113)	(0.481)	(0.111)	(0.483)
N. obs. initial sample	613	613	613	613	613	613	613	613	613	613
N. obs initial sample of crowdfunded new ventures	313	313	313	313	313	313	313	313	313	313
LR test of independent equations (p-value)	0.502	-	0.569	-	0.334	-	0.498	-	0.393	-

Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Note that, in the first stage regression, when necessary, the variables are computed right before the time of the first funding to properly capture their influence on the decision to use CF

Table 7. Probit regression models for the matched sample (threshold for crowdfunded new ventures on the raised amount set equal to $10,000)

	No interactions	*Crowdfunding* interacted with *Patents*	*Crowdfunding* interacted with *Entrepreneur Past Successful Funding Experience*	*Crowdfunding* interacted with *Affiliation with a Prestigious Partner*	All interactions
Top Startup Ecosystems	0.286*	0.275*	0.282*	0.286*	0.271
	(0.166)	(0.167)	(0.167)	(0.165)	(0.168)
Average Industry Experience	-0.026**	-0.024*	-0.027**	-0.025**	-0.025**
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
MBA	0.320	0.344	0.339	0.321	0.353
	(0.227)	(0.226)	(0.235)	(0.227)	(0.233)
PhD	0.163	0.180	0.198	0.165	0.216
	(0.238)	(0.236)	(0.238)	(0.238)	(0.238)
Size of the Entrepreneurial Team	0.247***	0.262***	0.285***	0.246***	0.295***
	(0.088)	(0.090)	(0.089)	(0.088)	(0.091)
Previous New Ventures	0.192	0.186	0.185	0.194	0.185
	(0.169)	(0.169)	(0.176)	(0.169)	(0.176)
Entrepreneur Past Successful Funding Experience	0.674**	0.607**	0.052	0.673**	0.024
	(0.265)	(0.270)	(0.344)	(0.265)	(0.343)
Patents	0.503	-0.156	0.390	0.506	-0.202
	(0.364)	(0.450)	(0.371)	(0.364)	(0.454)
Affiliation with a Prestigious Partner	-0.092	-0.110	-0.119	-0.041	-0.096
	(0.275)	(0.279)	(0.280)	(0.384)	(0.388)
Crowdfunding	-0.922***	-1.041***	-1.140***	-0.914***	-1.236***
	(0.162)	(0.169)	(0.181)	(0.169)	(0.193)
Crowdfunding X Patents	-	1.662**	-	-	1.592**
	-	(0.687)	-	-	(0.699)
Crowdfunding X Entrepreneur Past Successful Funding Experience	-	-	1.371***	-	1.315***
	-	-	(0.474)	-	(0.476)
Crowdfunding X Affiliation with a Prestigious Partner	-	-	-	-0.097	-0.063
	-	-	-	(0.540)	(0.559)
Year of Establishment (dummies)	Included	Included	Included	Included	Included
Subcategories (dummies)	Included	Included	Included	Included	Included
Constant	-0.784	-0.815	-0.882	-0.781	-0.895
	(0.737)	(0.735)	(0.718)	(0.735)	(0.716)
N. obs initial sample	616	616	616	616	616
N. obs initial sample of crowdfunded new ventures	316	316	316	316	316
N. obs one-to-one matched sample	312	312	312	312	312
Pseudo R^2	0.195	0.210	0.215	0.195	0.228

Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8. Probit regression models for matched sample (threshold for crowdfunded new ventures on the raised amount set equal to $20,000)

	No interactions	*Crowdfunding* interacted with *Patents*	*Crowdfunding* interacted with *Entrepreneur Past Successful Funding Experience*	*Crowdfunding* interacted with *Affiliation with a Prestigious Partner*	All interactions
Top Startup Ecosystems	0.202	0.185	0.220	0.198	0.200
	(0.168)	(0.171)	(0.170)	(0.168)	(0.174)
Average Industry Experience	-0.010	-0.008	-0.011	-0.010	-0.009
	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)
MBA	0.206	0.161	0.248	0.208	0.198
	(0.242)	(0.239)	(0.243)	(0.243)	(0.242)
PhD	0.252	0.348	0.298	0.248	0.385
	(0.252)	(0.255)	(0.255)	(0.252)	(0.259)
Size of the Entrepreneurial Team	0.229**	0.246**	0.250**	0.223**	0.258**
	(0.099)	(0.101)	(0.100)	(0.099)	(0.103)
Previous New Ventures	0.206	0.236	0.194	0.216	0.239
	(0.179)	(0.181)	(0.183)	(0.179)	(0.186)
Entrepreneur Past Successful Funding Experience	1.235***	1.133***	0.635*	1.232***	0.578
	(0.288)	(0.292)	(0.361)	(0.287)	(0.359)
Patents	0.468	-0.477	0.363	0.483	-0.505
	(0.433)	(0.528)	(0.449)	(0.432)	(0.530)
Affiliation with a Prestigious Partner	-0.058	-0.096	-0.083	0.137	0.042
	(0.264)	(0.267)	(0.265)	(0.356)	(0.350)
Crowdfunding	-1.069***	-1.213***	-1.219***	-1.030***	-1.324***
	(0.178)	(0.184)	(0.196)	(0.187)	(0.214)
Crowdfunding X Patents	-	2.522***	-	-	2.521***
	-	(0.859)	-	-	(0.892)
Crowdfunding X Entrepreneur Past Successful Funding Experience	-	-	1.162**	-	1.112**
	-	-	(0.486)	-	(0.487)
Crowdfunding X Affiliation with a Prestigious Partner	-	-	-	-0.461	-0.382
	-	-	-	(0.526)	(0.551)
Year of Establishment (dummies)	Included	Included	Included	Included	Included
Subcategories (dummies)	Included	Included	Included	Included	Included
Constant	-1.182*	-1.217*	-1.320*	-1.163*	-1.328*
	(0.670)	(0.684)	(0.687)	(0.663)	(0.700)
N. obs initial sample	590	590	590	590	590
N. obs initial sample of crowdfunded new ventures	290	290	290	290	290
N. obs one-to-one matched sample	296	296	296	296	296
Pseudo R^2	0.241	0.266	0.252	0.242	0.277

Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9. Probit regression models for matched sample (threshold for crowdfunded new ventures on the raised amount set equal to $100,000)

	No interactions	*Crowdfunding* interacted with *Patents*	*Crowdfunding* interacted with *Entrepreneur Past Successful Funding Experience*	*Crowdfunding* interacted with *Affiliation with a Prestigious Partner*	All interactions
Top Startup Ecosystems	0.483**	0.523**	0.460**	0.477**	0.496**
	(0.213)	(0.213)	(0.215)	(0.212)	(0.215)
Average Industry Experience	-0.012	-0.001	-0.007	-0.013	0.001
	(0.019)	(0.018)	(0.018)	(0.019)	(0.018)
MBA	0.134	0.233	0.258	0.122	0.326
	(0.269)	(0.270)	(0.272)	(0.272)	(0.282)
PhD	0.517*	0.554*	0.542*	0.512*	0.576*
	(0.294)	(0.308)	(0.313)	(0.292)	(0.324)
Size of the Entrepreneurial Team	0.311***	0.314***	0.347***	0.300***	0.327***
	(0.111)	(0.114)	(0.111)	(0.110)	(0.111)
Previous New Ventures	-0.221	-0.207	-0.299	-0.190	-0.238
	(0.230)	(0.233)	(0.241)	(0.234)	(0.248)
Entrepreneur Past Successful Funding Experience	0.755**	0.726**	0.122	0.762**	0.163
	(0.334)	(0.342)	(0.407)	(0.335)	(0.399)
Patents	0.700	-0.490	0.702	0.716*	-0.542
	(0.431)	(0.536)	(0.440)	(0.432)	(0.488)
Affiliation with a Prestigious Partner	-0.310	-0.354	-0.391	0.028	-0.032
	(0.303)	(0.338)	(0.314)	(0.413)	(0.421)
Crowdfunding	-0.952***	-1.159***	-1.211***	-0.904***	-1.336***
	(0.199)	(0.217)	(0.214)	(0.207)	(0.235)
Crowdfunding X Patents	-	2.266***	-	-	2.372***
	-	(0.751)	-	-	(0.725)
Crowdfunding X Entrepreneur Past Successful Funding Experience	-	-	1.479**	-	1.369**
	-	-	(0.588)	-	(0.593)
Crowdfunding X Affiliation with a Prestigious Partner	-	-	-	0.745	-1.107
	-	-	-	(0.649)	(0.928)
Year of Establishment (dummies)	Included	Included	Included	Included	Included
Subcategories (dummies)	Included	Included	Included	Included	Included
Constant	0.024	-0.223	-0.464	0.213	-0.328
	(0.886)	(0.888)	(0.938)	(0.874)	(0.940)
N. obs initial sample	442	442	442	442	442
N. obs initial sample of crowdfunded new ventures	142	142	142	142	142
N. obs one-to-one matched sample	206	206	206	206	206
Pseudo R^2	0.252	0.283	0.274	0.255	0.307

Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10. Treatment effect regression models (threshold for crowdfunded new ventures on the raised amount set equal to $100,000)

	No interaction		*Crowdfunding* interacted with *Patents*		*Crowdfunding* interacted with *Entrepreneur Past Successful Funding Experience*		*Crowdfunding* interacted with *Affiliation with a Prestigious Partner*		All interactions	
	2nd stage	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage	1st stage
Top Startup Ecosystems	0.084*	-0.127	0.088**	-0.130	0.085**	-0.126	0.084*	-0.127	0.089**	-0.128
	(0.043)	(0.146)	(0.043)	(0.146)	(0.043)	(0.146)	(0.043)	(0.146)	(0.043)	(0.146)
Average Industry Experience	-0.003	-0.042***	-0.002	-0.042***	-0.002	-0.042***	-0.003	-0.042***	-0.002	-0.042***
	(0.003)	(0.010)	(0.003)	(0.011)	(0.003)	(0.010)	(0.003)	(0.010)	(0.003)	(0.010)
MBA	0.076	-0.148	0.072	-0.150	0.084	-0.147	0.076	-0.148	0.080	-0.148
	(0.055)	(0.191)	(0.055)	(0.192)	(0.055)	(0.191)	(0.055)	(0.191)	(0.054)	(0.192)
PhD	0.134**	-0.243	0.125**	-0.245	0.138**	-0.241	0.134**	-0.243	0.129**	-0.242
	(0.059)	(0.203)	(0.058)	(0.204)	(0.058)	(0.203)	(0.059)	(0.203)	(0.058)	(0.203)
Size of the Entrepreneurial Team	0.096***	-0.126	0.095***	-0.125	0.101***	-0.126	0.096***	-0.126	0.100***	-0.126
	(0.026)	(0.084)	(0.026)	(0.084)	(0.026)	(0.084)	(0.026)	(0.084)	(0.025)	(0.084)
Previous New Ventures	0.035	-0.151	0.040	-0.147	0.023	-0.155	0.035	-0.151	0.029	-0.151
	(0.048)	(0.159)	(0.047)	(0.160)	(0.048)	(0.159)	(0.048)	(0.159)	(0.047)	(0.159)
Entrepreneur Past Successful Funding Experience	0.117*	0.009	0.098	-0.005	0.010	-0.002	0.116*	0.009	0.005	-0.007
	(0.062)	(0.215)	(0.061)	(0.216)	(0.070)	(0.212)	(0.062)	(0.215)	(0.069)	(0.212)
Patents	0.109	0.438	-0.007	0.403	0.092	0.430	0.109	0.438	-0.010	0.399
	(0.078)	(0.420)	(0.084)	(0.424)	(0.075)	(0.414)	(0.076)	(0.420)	(0.083)	(0.422)
Affiliation with a Prestigious Partner	0.070	-0.067	0.055	-0.066	0.060	-0.068	0.068	-0.068	0.063	-0.067
	(0.073)	(0.245)	(0.072)	(0.245)	(0.072)	(0.245)	(0.086)	(0.245)	(0.085)	(0.245)
B2B	-	-0.668***	-	-0.673***	-	-0.667***	-	-0.668***	-	-0.670***
	-	(0.156)	-	(0.155)	-	(0.155)	-	(0.156)	-	(0.155)
Crowdfunding	-0.176	-	-0.259	-	-0.213	-	-0.176	-	-0.274	-
	(0.169)	-	(0.183)	-	(0.158)	-	(0.170)	-	(0.170)	-
Crowdfunding X Patents	-	-	0.532***	-	-	-	-	-	0.477***	-
	-	-	(0.174)	-	-	-	-	-	(0.174)	-
Crowdfunding X	-	-	-	-	0.412***	-	-	-	0.371***	-

Entrepreneur Past Successful Funding Experience										
	-	-	-	-	(0.130)	-	-	-	(0.130)	-
Crowdfunding X Affiliation with a Prestigious Partner	-	-	-	-	-	-	0.006	-	-0.049	-
	-	-	-	-	-	-	(0.158)	-	(0.156)	-
Year of Establishment (dummies)	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Subcategories (dummies)	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Constant	0.412***	-0.779	0.432***	-0.759	0.409***	-0.785	0.412***	-0.779	0.424***	-0.771
	(0.131)	(0.504)	(0.131)	(0.502)	(0.128)	(0.504)	(0.131)	(0.504)	(0.128)	(0.503)
N. obs. initial sample	442	442	442	442	442	442	442	442	442	442
N. obs initial sample of crowdfunded new ventures	142	142	142	142	142	142	142	142	142	142
LR test of independent equations (p-value)	0.589	-	0.788	-	0.469	-	0.589	-	0.637	-

Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Note that, in the first stage regression, when necessary, the variables are computed right before the time of the first funding to properly capture their influence on the decision to use CF.

Table 11. Probit regression models for the matched sample (matching and controlling also for the amount raised in the first round)

	No interactions	*Crowdfunding* interacted with *Patents*	*Crowdfunding* interacted with *Entrepreneur Past Successful Funding Experience*	*Crowdfunding* interacted with *Affiliation with a Prestigious Partner*	All interactions
Top Startup Ecosystems	0.274	0.282	0.233	0.276	0.238
	(0.222)	(0.225)	(0.226)	(0.223)	(0.228)
Average Industry Experience	-0.019	-0.011	-0.018	-0.020	-0.011
	(0.016)	(0.017)	(0.016)	(0.016)	(0.017)
MBA	0.136	0.176	0.231	0.131	0.245
	(0.327)	(0.326)	(0.329)	(0.327)	(0.328)
PhD	0.246	0.212	0.220	0.258	0.192
	(0.319)	(0.326)	(0.337)	(0.318)	(0.343)
Size of the Entrepreneurial Team	0.214*	0.245**	0.254**	0.221*	0.275**
	(0.118)	(0.122)	(0.120)	(0.119)	(0.123)
Previous New Ventures	0.161	0.180	0.154	0.145	0.184
	(0.232)	(0.231)	(0.238)	(0.228)	(0.235)
Amount raised in the first round (Ln)	0.104	0.110	0.112	0.100	0.112
	(0.080)	(0.081)	(0.081)	(0.080)	(0.081)
Entrepreneur Past Successful Funding Experience	1.587***	1.553***	0.758	1.616***	0.810
	(0.430)	(0.431)	(0.514)	(0.436)	(0.537)
Patents	0.749*	-0.305	0.670	0.755*	-0.226
	(0.446)	(0.605)	(0.470)	(0.442)	(0.632)
Affiliation with a Prestigious Partner	-0.027	-0.004	0.096	-0.193	0.090
	(0.396)	(0.376)	(0.388)	(0.474)	(0.460)
Crowdfunding	-0.989***	-1.171***	-1.183***	-1.023***	-1.325***
	(0.216)	(0.232)	(0.233)	(0.226)	(0.253)
Crowdfunding X Patents	-	1.889***	-	-	1.695**
	-	(0.734)	-	-	(0.779)
Crowdfunding X Entrepreneur Past Successful Funding Experience	-	-	1.754***	-	1.571**
	-	-	(0.646)	-	(0.632)
Crowdfunding X Affiliation with a Prestigious Partner	-	-	-	0.417	-0.010
	-	-	-	(0.802)	(0.847)
Year of Establishment (dummies)	Included	Included	Included	Included	Included
Subcategories (dummies)	Included	Included	Included	Included	Included
Constant	-2.470*	1.907	1.775	2.714**	1.410
	(1.359)	(1.384)	(1.414)	(1.345)	(1.444)
N. obs initial sample	562	562	562	562	562
N. obs initial sample of crowdfunded new ventures	325	325	325	325	325
N. obs one-to-one matched sample	196	196	196	196	196
Pseudo R^2	0.315	0.334	0.334	0.315	0.348

Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12. Probit regression models for the matched sample (matching and controlling also for the product price)

	No interactions	*Crowdfunding* interacted with *Patents*	*Crowdfunding* interacted with *Entrepreneur Past Successful Funding Experience*	*Crowdfunding* interacted with *Affiliation with prestigious partner*	All interactions
Top Startup Ecosystems	0.149	0.125	0.127	0.144	0.101
	(0.181)	(0.183)	(0.181)	(0.181)	(0.182)
Average Industry Experience	-0.023*	-0.020	-0.021*	-0.022*	-0.019
	(0.013)	(0.013)	(0.012)	(0.012)	(0.013)
MBA	0.138	0.184	0.226	0.155	0.269
	(0.277)	(0.275)	(0.277)	(0.277)	(0.277)
PhD	0.424*	0.430*	0.443*	0.419*	0.441*
	(0.242)	(0.246)	(0.253)	(0.242)	(0.256)
Size of the Entrepreneurial Team	0.313***	0.326***	0.358***	0.311***	0.362***
	(0.101)	(0.103)	(0.105)	(0.101)	(0.106)
Previous New Ventures	0.227	0.231	0.211	0.240	0.230
	(0.183)	(0.183)	(0.191)	(0.183)	(0.192)
Entrepreneur Past Successful Funding Experience	0.718**	0.640**	0.056	0.715**	0.044
	(0.288)	(0.296)	(0.390)	(0.288)	(0.389)
Patents	0.701*	0.178	0.611	0.695*	0.175
	(0.403)	(0.472)	(0.394)	(0.404)	(0.462)
Affiliation with a Prestigious Partner	-0.037	-0.049	-0.049	0.184	0.132
	(0.300)	(0.298)	(0.298)	(0.428)	(0.402)
Product price (Ln)	-0.049	-0.044	-0.053	-0.050	-0.050
	(0.050)	(0.051)	(0.051)	(0.050)	(0.051)
Crowdfunding	-1.123***	-1.218***	-1.355***	-1.100***	-1.398***
	(0.178)	(0.185)	(0.200)	(0.183)	(0.212)
Crowdfunding X Patents	-	1.669**	-	-	1.511**
	-	(0.746)	-	-	(0.707)
Crowdfunding X Entrepreneur Past Successful Funding Experience	-	-	1.308***	-	1.205**
	-	-	(0.500)	-	(0.507)
Crowdfunding X Affiliation with a Prestigious Partner	-	-	-	-0.399	-0.360
	-	-	-	(0.602)	(0.605)
Year of Establishment (dummies)	Included	Included	Included	Included	Included
Subcategories (dummies)	Included	Included	Included	Included	Included
Constant	-0.404	-0.511	-0.551	-0.387	-0.600
	(0.866)	(0.865)	(0.851)	(0.864)	(0.851)
N. obs initial sample	608	608	608	608	608
N. obs initial sample of crowdfunded new ventures	325	325	325	325	325
N. obs one-to-one matched sample	278	278	278	278	278
Pseudo R^2	0.244	0.256	0.262	0.245	0.268

Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13. Treatment effect regression models controlling for product price

	No interaction		*Crowdfunding* interacted with *Patents*		*Crowdfunding* interacted with *Entrepreneur Past Successful Funding Experience*		*Crowdfunding* interacted with *Affiliation with prestigious partner*		All interactions	
	2nd stage	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage	1st stage
Top Startup Ecosystems	0.047	-0.097	0.047	-0.099	0.047	-0.097	0.046	-0.097	0.045	-0.098
	(0.034)	(0.124)	(0.034)	(0.124)	(0.034)	(0.124)	(0.035)	(0.125)	(0.034)	(0.124)
Average Industry Experience	-0.004	-0.043***	-0.003	-0.043***	-0.003	-0.043***	-0.004	-0.043***	-0.003	-0.043***
	(0.003)	(0.009)	(0.003)	(0.009)	(0.003)	(0.009)	(0.003)	(0.009)	(0.003)	(0.009)
MBA	0.093*	-0.402**	0.094*	-0.402**	0.098**	-0.400**	0.093*	-0.402**	0.099**	-0.399**
	(0.049)	(0.173)	(0.048)	(0.173)	(0.048)	(0.173)	(0.049)	(0.173)	(0.048)	(0.173)
PhD	0.137***	-0.236	0.133***	-0.234	0.145***	-0.237	0.137***	-0.236	0.141***	-0.234
	(0.049)	(0.174)	(0.049)	(0.174)	(0.049)	(0.174)	(0.049)	(0.174)	(0.049)	(0.174)
Size of the Entrepreneurial Team	0.099***	-0.152**	0.100***	-0.152**	0.103***	-0.152**	0.099***	-0.153**	0.103***	-0.152**
	(0.021)	(0.073)	(0.021)	(0.073)	(0.021)	(0.073)	(0.021)	(0.073)	(0.021)	(0.073)
Previous New Ventures	0.066*	-0.265**	0.067*	-0.265**	0.056	-0.265**	0.067*	-0.264**	0.059	-0.264**
	(0.038)	(0.133)	(0.038)	(0.133)	(0.038)	(0.133)	(0.038)	(0.133)	(0.037)	(0.133)
Entrepreneur Past Successful Funding Experience	0.131**	-0.176	0.111**	-0.179	0.005	-0.181	0.132**	-0.177	-0.001	-0.183
	(0.055)	(0.190)	(0.055)	(0.190)	(0.066)	(0.190)	(0.055)	(0.189)	(0.065)	(0.190)
Patents	0.144**	0.112	0.003	0.089	0.124*	0.107	0.146**	0.112	0.000	0.083
	(0.069)	(0.419)	(0.081)	(0.424)	(0.068)	(0.415)	(0.069)	(0.419)	(0.080)	(0.421)
Affiliation with a Prestigious Partner	0.029	-0.108	0.013	-0.107	0.021	-0.107	0.057	-0.107	0.053	-0.105
	(0.061)	(0.224)	(0.061)	(0.225)	(0.061)	(0.225)	(0.082)	(0.224)	(0.081)	(0.224)
B2B	-	-0.574***	-	-0.572***	-	-0.579***	-	-0.574***	-	-0.576***
	-	(0.132)	-	(0.133)	-	(0.132)	-	(0.132)	-	(0.132)
Product Price (Ln)	0.005	-0.153***	0.005	-0.153***	0.004	-0.153***	0.004	-0.153***	0.003	-0.153***
	(0.011)	(0.036)	(0.011)	(0.036)	(0.010)	(0.036)	(0.011)	(0.036)	(0.010)	(0.036)
Crowdfunding	-0.219**	-	-0.253**	-	-0.248**	-	-0.215**	-	-0.268***	-
	(0.104)	-	(0.105)	-	(0.100)	-	(0.105)	-	(0.100)	-
Crowdfunding X Patents	-	-	0.476***	-	-	-	-	-	0.434***	-
	-	-	(0.146)	-	-	-	-	-	(0.146)	-
Crowdfunding X Entrepreneur Past	-	-	-	-	0.361***	-	-	-	0.327***	-

Successful Funding Experience	-	-	-	-	(0.105)	-	-	-	(0.105)	-
Crowdfunding X Affiliation with a Prestigious Partner	-	-	-	-	-	-	-0.061	-	-0.099	-
	-	-	-	-	-	-	(0.121)	-	(0.119)	-
Year of Establishment (dummies)	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Subcategories (dummies)	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Constant	0.402***	-0.057	0.423***	-0.058	0.418***	-0.062	0.402***	-0.058	0.435***	-0.065
	(0.136)	(0.519)	(0.135)	(0.520)	(0.134)	(0.520)	(0.136)	(0.519)	(0.133)	(0.520)
N. obs. initial sample	608	608	608	608	608	608	608	608	608	608
N. obs initial sample of crowdfunded new ventures	325	325	325	325	325	325	325	325	325	325
LR test of independent equations (p-value)	0.345	-	0.382	-	0.232	-	0.347	-	0.270	-

Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Note that, in the first stage regression, when necessary, the variables are computed right before the time of the first funding to properly capture their influence on the decision to use CF.

Table 14. Probit regression models for the matched sample using CEM (threshold for crowdfunded new ventures on the raised amount set equal to $5,000)

	No interactions	*Crowdfunding* interacted with *Patents*	*Crowdfunding* interacted with *Entrepreneur Past Successful Funding Experience*	*Crowdfunding* interacted with *Affiliation with prestigious partner*	All interactions
Top Startup Ecosystems	0.348*	0.362*	0.324	0.345*	0.336
	(0.206)	(0.206)	(0.209)	(0.206)	(0.207)
Average Industry Experience	-0.014	-0.011	-0.014	-0.014	-0.011
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
MBA	0.745*	0.776*	0.783*	0.743*	0.803*
	(0.413)	(0.413)	(0.415)	(0.412)	(0.413)
PhD	0.299	0.377	0.390	0.286	0.454
	(0.471)	(0.480)	(0.446)	(0.470)	(0.454)
Size of the Entrepreneurial Team	0.404***	0.416***	0.428***	0.402***	0.439***
	(0.112)	(0.113)	(0.113)	(0.111)	(0.114)
Previous New Ventures	-0.116	-0.111	-0.154	-0.108	-0.142
	(0.215)	(0.216)	(0.220)	(0.215)	(0.222)
Entrepreneur Past Successful Funding Experience	0.616*	0.549	0.016	0.618*	-0.043
	(0.356)	(0.359)	(0.412)	(0.356)	(0.421)
Patents	0.053	-0.760	-0.105	-0.037	-0.780
	(0.469)	(0.516)	(0.476)	(0.469)	(0.522)
Affiliation with a Prestigious Partner	-0.136	-0.207	-0.182	-0.015	-0.133
	(0.375)	(0.375)	(0.378)	(0.495)	(0.495)
Crowdfunding	-0.802***	-0.893***	-0.931***	-0.776***	-0.994***
	(0197)	(0.205)	(0.211)	(0.206)	(0.225)
Crowdfunding X Patents	-	1.671**	-	-	1.690**
	-	(0.757)	-	-	(0.765)
Crowdfunding X Entrepreneur Past Successful Funding Experience	-	-	1.287**	-	1.299**
	-	-	(0.638)	-	(0.637)
Crowdfunding X Affiliation with a Prestigious Partner	-	-	-	-0.421	-0.395
	-	-	-	(0.730)	(0.723)
Year of Establishment (dummies)	Included	Included	Included	Included	Included
Subcategories (dummies)	Included	Included	Included	Included	Included
Constant	-0.813	-0.606	-0.742	-0.837	-0.555
	(0.766)	(0.809)	(0.767)	(0.767)	(0.810)
N. obs initial sample	625	625	625	625	625
N. obs initial sample of crowdfunded new ventures	325	325	325	325	325
N. obs one-to-one matched sample	276	276	276	276	276
Pseudo R^2	0.213	0.225	0.225	0.213	0.238

Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

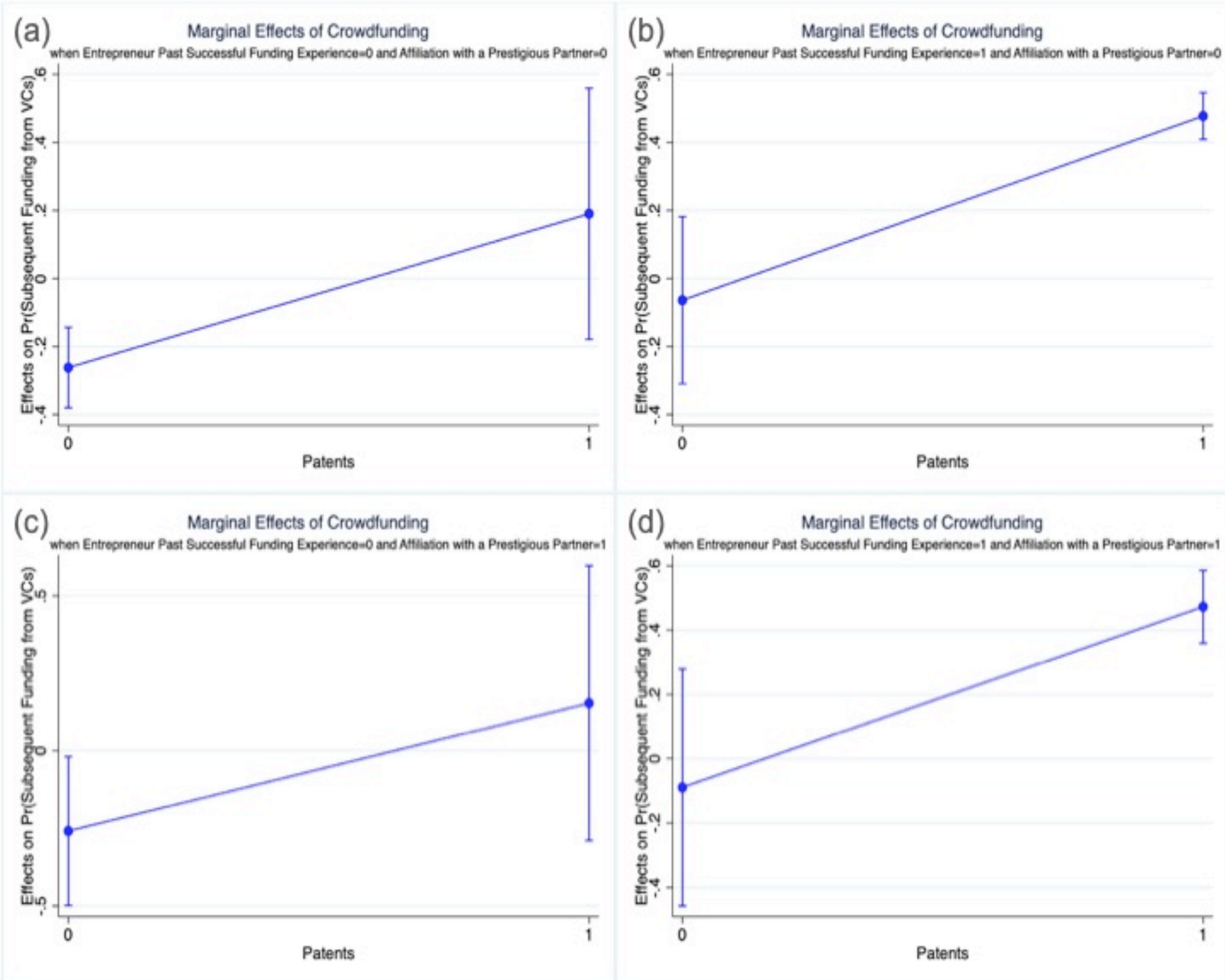

Figure 1. The effect of a marginal change in the variable *Crowdfunding* computed for the matched sample at different values of the variables *Patents* when *Entrepreneur Past Successful Funding Experience* and *Affiliation with a Prestigious Partner* are set equal to 0 and equal to 1, respectively. In all cases, the remaining variables are set equal to zero if binary (except for the dummies *Consumer Electronics & Hardware, Year of Establishment 2012, Previous New Ventures*, which are set equal to 1, the latter only when *Entrepreneur Past Successful Funding Experience* is equal to 1) or to their sample mean if continuous or integer.

Appendix Table 1. Correlation Matrix

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	**Crowdfunding**													
(2)	**Top Startup Ecosystems**	-0.017												
(3)	**Average Industry Experience**	-0.364*	-0.015											
(4)	**MBA**	-0.182*	0.041	0.076										
(5)	**PhD**	-0.155*	-0.035	0.123*	-0.035									
(6)	**Size of the Entrepreneurial Team**	-0.149*	0.071	0.005	0.141*	0.143*								
(7)	**Previous New Ventures**	-0.160*	0.083*	0.101*	0.091*	0.074	0.219*							
(8)	**Entrepreneur Past Successful Funding Experience**	-0.147*	0.058	0.166*	0.082*	0.041	0.170*	0.348*						
(9)	**Patents**	-0.154*	-0.024	0.239*	0.087*	-0.029	-0.033	-0.001	0.068					
(10)	**Affiliation with a Prestigious Partner**	-0.046	-0.017	-0.029	0.012	0.161*	0.056	-0.006	0.026	0.038				
(11)	**Consumer Electronics & Hardware**	-0.001	-0.006	0.009	-0.011	-0.016	0.036	0.017	-0.036	0.017	-0.094*			
(12)	**3D Printing & Robotics**	0.216*	-0.019	-0.123*	-0.091*	-0.023	-0.055	-0.036	0.018	-0.069	0.040	-0.712*		
(13)	**Medical Devices**	-0.303*	-0.031	0.155*	0.122*	0.043	0.018	0.047	0.030	0.084*	0.021	-0.520*	-0.130*	
(14)	**Aerospace Applications**	0.057	0.031	-0.023	0.021	0.020	-0.009	-0.055	0.005	-0.043	0.142*	-0.253*	-0.064	-0.047

The significance level is equal to 0.05. For ease of exposition, we do not include the coefficients related to the *Year of Establishment* dummies which, however, do not display correlation coefficients larger than 0.25.