THE CROWD FOR LEMONS: VENTURE INVESTORS' PERCEPTIONS OF AN EQUITY PECKING ORDER

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ABSTRACT

Crowd-based means of financing are emerging as a novel way for entrepreneurs to secure scarce early-stage financing. With venture capital still being the most important source of funding for young innovative ventures in later stages, this raises the question of potential interactions between crowdfinancing and traditional forms of start-up funding. In this study, I investigate whether professional venture investors perceive a seed-financing hierarchy by entrepreneurs, and whether this equity pecking order is affected by venture quality and could therefore serve as an uncertainty-reducing signal to prospective investors. Drawing on a choice experimental research design I find causal evidence that VCs believe that "lemons" (low-quality start-ups) have a higher relative likelihood than "peaches" (high-quality start-ups) of turning to crowd-based financing as a first means of external equity funding rather than turning to traditional sources, suggesting a perceived negative selection bias toward crowd-based financing. In addition to extending the pecking order framework and advancing signaling theory in the entrepreneurial setting, this work has implications for capital-seekers, venture investors and policy makers.

Keywords: Crowdfunding, Pecking Order, Signaling, Venture Capital, Vignette Experiment

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INTRODUCTION

Crowd-based means of funding (Ahlers et al., 2015; Fisch, 2018; Mollick, 2014) are emerging as a valid novel way of providing scarce seed-finance for entrepreneurial ventures. Initial theoretical and empirical work on the interplay between these new and traditional forms of venture financing has emphasized the positive effects of an initial crowdfunding on subsequent investments by, e.g., venture capitalists and business angels (Drover et al., 2017b; Kaminski et al., 2016; Sorenson et al., 2016; Strausz, 2017). Through a pecking order theory lens this paper challenges the assumption that venture investors treat prior investments by the crowd as a monolithic positive signal, and provides causal empirical evidence that professional investors perceive a negative selection bias in crowd-based financing channels.

The initiation of new ventures is of vital importance for innovation-based economies as they disproportionally contribute to the promotion of innovation and employment growth (Schumpeter, 1942; Wennekers & Thurik, 1999). One of the biggest obstacles for the creation of new enterprises is proper funding (Ferrary, 2010; Hochberg et al., 2007), making entrepreneurial finance a foundational issue in innovation and entrepreneurship research and a major policy concern. Since start-up companies typically do not generate stable profits, and are characterized by informational opacity and usually cannot offer high-quality collateral to credit lenders, they largely depend on external sources of equity funding (Gompers & Lerner, 2001; Hall & Lerner, 2010). Over the last decades the entrepreneurship literature has therefore emphasized the importance of venture capital and business angels (Bellavitis et al., 2017; Berger & Udell, 1998; Drover et al., 2017a; Wright et al., 2016), which explicitly address the financing needs of young companies with high-growth prospects but high uncertainty. The digital era and its growing appetite to “cut out the middleman” has not only lead the way to new business opportunities, but has also substantially expanded the start-up financing landscape. In particular, new crowd-based forms of financing, such as crowdfunding (e.g., Ahlers et al., 2015; Belleflamme et al., 2014; Mollick, 2014) and initial coin offerings (ICOs) (Catalini & Gans, 2018; Fisch, 2018) enable founders to target a broader group of external equity investors and to directly collect funds from potential consumers by an open call through the internet.

However, it is likely that most growth-oriented ventures cannot (or do not want to) solely rely on these new financing means. Reasons include that venture capitalists can typically invest larger amounts of money necessary for high-technology ventures to thrive than campaigns could raise (Sorenson et al., 2016); and that professional venture investors also provide important connections to crucial resources other than capital (Baum & Silverman, 2004; Ferrary & Granovetter, 2009). The increasingly heterogeneous financing landscape thus makes co-investments from different equity sources more common, raising the question how crowd capital relates to traditional sources of funding. The purpose of this paper is to offer insights into whether the discrete early financing choices of entrepreneurs are used as an uncertainty-reducing signal (Spence, 1973, 2002) by prospective venture investors. More specifically, I aim to shed light on the question whether investors perceive a financing hierarchy in approaching seed-funding channels by entrepreneurs – i.e. an entrepreneurial equity pecking order –, and if so, whether it is affected by a start-up's quality and business model.

While it has been argued that "crowdfunding is still a funding source of last resort, and that more promising projects may have already received, e.g., venture capital" (Ahlers et al., 2015: 975), initial studies on the interactions between crowd-based and traditional venture financing have mainly proposed a positive relationship (Drover et al., 2017b; Sorenson et al., 2016; Strausz, 2017). Yet we still lack an understanding of whether and how venture investors associate an entrepreneurs' choice between competing seed-funding channels with the venture's latent quality, and whether prior funding therefore potentially affects their start-up assessment. It appears important to address this question, since VC money becomes increasingly scarce in early stages (Elitzur & Gavious, 2003; Hellmann & Thiele, 2015; NVCA, 2017; OECD, 2016), and young innovative firms without knowledge of the signaling effects of their choice of alternative options might obstruct their chances for follow-up funding by professional investors.

This paper challenges the view that successful prior funding by the crowd generally transports positive information to prospective investors. Instead, I firstly refer to the pecking order framework (Myers & Majluf, 1984) to argue that professional venture investors perceive that entrepreneurs follow a financing hierarchy when selecting equity funding sources, and that this hierarchy is (in part) determined by venture quality. Secondly, I draw on a signaling perspective (Spence, 1973, 2002) to theorize that prior equity funding can therefore serve as an effective signal of latent firm quality and reduce information asymmetry for subsequent investors. I discuss that low-quality start-ups both may find it relatively harder to identify, approach, and deal with professional investors than high-quality start-ups, and may anticipate relatively higher chances of actually being funded when approaching the crowd rather than traditional investors, e.g., due to less thorough due diligence processes by the crowd. Subsequent venture investors might therefore assume a negative selection bias in crowd-based means of financing, i.e., that "peaches" (high-quality start-ups) tend to seek and attract seed-funding from established investors, whereas "lemons" (low-quality start-ups) have a higher relative likelihood of turning to the crowd. Both pecking order theory – which draws its propositions from the existence of information asymmetries between investors and managers –, and signaling theory – which links asymmetric information to quality – are particularly suitable for this study because the new venture finance setting is characterized by high information asymmetry (Amit et al., 1998; Busenitz et al., 2005).

To probe this line of thinking empirically, I collect data from 376 hypothetical seed-funding choices by 94 venture investors in a choice experimental survey approach called vignette analysis. Such a methodological approach has several advantages with regard to challenges associated with the research context: as a real-time data collection technique, survey experiments overcome the limitations of traditional post-hoc methods (e.g., questionnaires and interviews), which may suffer from people being poor at introspection, having difficulties to recall crucial aspects or being inclined to retrospectively rationalize decisions (Shepherd & Zacharakis, 1999). Furthermore, given that achieving high response rates in studies with venture investors is a challenging task (e.g. Muzyka et al., 1996), choice experiments are able to produce statistically significant results even with a seemingly low sample size. Above all, being an experimental design, vignette analysis makes causal inference a realistic goal; whereas real market data approaches might suffer from an endogeneity problem.

I can disentangle three main findings: First, I find causal evidence that professional venture investors perceive a negative selection in crowd-based means of financing. They appear to believe that low-quality start-ups have a higher relative likelihood than high-quality start-ups of turning to crowdfinancing as a first means of external equity funding rather than turning to traditional sources. Second, the perceived financing hierarchy is also affected by a start-up's business model. Venture investors assume that B2C start-ups have higher relative probability than B2B businesses to opt for reward-based crowdfunding; however not for the securities-based variant. Yet quality considerations appear to be a more important determinant than potential extra-financial benefits from crowdfunding for B2C ventures. Finally, the effect of differing business models is more pronounced for ventures of mediocre quality, implying that professional investors perceive that high-quality start-up firms generally tend to approach established sources of equity funding as first means of financing.

The contributions of this study are both theoretically and practically relevant. It offers contributions to three streams of academic literature: First, it makes an important contribution to the entrepreneurial finance literature by changing our perception of the interconnection between novel crowd-based funding sources and established venture capital (Drover et al., 2017a; Sorenson et al., 2016; Strausz, 2017). Second, the insights extend the stream of research on the role of observable characteristics that signal a new venture's quality in innovation financing (Amit et al., 1990; Baum & Silverman, 2004; Haeussler et al., 2012; Hsu & Ziedonis, 2013; Plummer et al., 2016) by documenting that prior funding type can serve as an (additional) effective quality signal to prospective investors. Finally, this study examines and extends the boundaries of the pecking order perspective by providing first-time evidence on the perception of an entrepreneurial *equity* pecking order (Frank & Goyal, 2003; Myers & Majluf, 1984; Walthoff-Borm et al., 2018).

The results also have implications for entrepreneurs, investors and policy makers. They contribute to the knowledge of capital-seekers on venture investors' decision policies; provide a benchmark for the investors community for comparing their own judgment to that of their peers; and help public policy, which demands for scientific evidence on the new phenomenon crowdfunding with regard to governmental support for entrepreneurial activities.

BACKGROUND LITERATURE AND HYPOTHESES DEVELOPMENT

Crowd-based Financing and the New Equity Funding Landscape

Access to financial resources is one of the main factors determining which new ventures thrive or languish (Gilbert et al., 2006). In particular innovative and growth-oriented start-ups often need considerable amounts of capital for research and development and the scaling of their business. As such new firms usually do not generate (enough) stable internal cash flows to finance high growth (Gompers, 1995), they are reliant on external sources of capital. Debt financing is typically only available to a limited extent, since new ventures – especially in early stages – are characterized by a high level of uncertainty and a lack of collaterals (Gompers & Lerner, 2001; Hall & Lerner, 2010). As a consequence, *equity* (or equity-like) financing is critical to the survival and flourishing of young, innovative firms. Initial funding may be sourced from the founders, friends, or family (Berger & Udell, 1998), but the capital requirements of high-growth start-ups regularly outstrip the abilities of this group (Cassar, 2004; Plummer et al., 2016). Over the last decades the innovation and entrepreneurship literature has therefore emphasized the importance of venture capitalists and business angel (Bellavitis et al., 2017; Berger & Udell, 1998; Drover et al., 2017a).[1]

The digital era has substantially expanded the start-up financing landscape: Crowd-based forms of financing have been portrayed as a valid new route for entrepreneurs to overcome possible financing constraints by enabling founders to target a broader group of investors and to directly collect funds from laypeople and potential consumers by an open call through the internet (Belleflamme et al., 2014; Mollick, 2016; Schwienbacher & Larralde, 2012; Vulkan et al., 2016). In particular, crowd-based financing has been suggested to overcome professional investors' biases and democratize access to capital and thus innovation (Mollick & Robb, 2016). For the purpose of this study, and in line with Belleflamme et al. (2014), I distinguish between two variants of crowd-based financing: *reward-based* and *securities-based.* In this study I defined *(reward-based) crowdfunding (CF)* as an open call, essentially through the internet, for the provision of financial resources either in the form of a donation or in exchange for some form of reward and/or pre-purchase of a product or service, where contributors do not receive any securities (similar descriptions stem from, e.g., Belleflamme et al., 2010: 5, and Mollick, 2014: 1). Distinct from that, I defined *(securities-based) crowdinvesting (CI)* as the funding of a company (not only a project) by selling equity or hybrid financing instruments to many small investors, usually through an online platform, whereby investors obtain a right in future cash-flows (the variant has been similarly defined by, e.g., Ahlers et al., 2015: 955 and Hornuf & Schwienbacher, 2014: 2). In the empirical part of this paper I limit the focus to these two distinct variants. Initial coin offerings (e.g., Fisch, 2018) can be regarded as a blockchain-based form of crowdfinancing, where utility token offerings resemble the pre-purchase concept of reward-based crowdfunding, whereas in security token offerings issued crypto tokens serve as securities, resembling the concept of crowdinvesting. Evidence suggests that the distinction between these two categories for the crowd-based funding of entrepreneurial ventures is appropriate. E.g.,

[1] Governments also often provide assistance for start-ups in many countries, e.g., in form of grants (Howell, 2017) or public venture capital funds (Guerini and Quas, 2016). In this work I focus on market-based financing, i.e., *private* sources of external equity financing.

Vulkan et al. (2016) have shown that equity crowdfunding is a substantially different fundraising phenomenon than reward-based crowdfunding in the view of backers.

Despite the increasing relevance of crowd-based financing, it is likely that most growth-oriented ventures cannot (or do not want to) solely rely on these new financing means. Reasons include that venture capitalists can typically invest larger amounts of money necessary for high-technology ventures to thrive than crowd campaigns could raise (Sorenson et al., 2016). Apart from their deep pockets, professional venture investors provide important connections to other crucial resources (Baum & Silverman, 2004; Ferrary & Granovetter, 2009) and foster the professionalization of young firms (Hellmann & Puri, 2002; Sapienza et al., 1996). Skirnevskiy et al. (2017: 211) see crowd-based funding "as an additional source of entrepreneurial financing that fills the gap between professional capital providers and 'family and friends'", and Drover et al. (2017b) emphasize that crowdfinancing can also parallel the investment stage of business angels. The increasingly heterogeneous financing landscape thus makes co-investments from different equity sources more common, raising the question how crowd capital relates to traditional sources of funding.

Thus far, largely segmented streams of literature have emerged, that consider financing types in isolation (Bellavitis et al., 2017; Block et al., 2018; Drover et al., 2017a). Initial studies on the interactions between crowd-based and traditional venture financing have mainly proposed a positive relationship. For instance, Strausz (2017) discusses a theoretic model in which reward-based crowdfunding campaigns can be used as a screening mechanism to uncover information about future demand for a venture's offering. For empirical evidence, e.g., Sorenson et al. (2016) find that an increase in successful crowdfunding campaigns within a geographic area corresponds to an increase in VC investments in the same region. However, approaches with observational data, even if firm-level data were available, face limitations with regard to deriving causal conclusions, e.g., since high-quality start-ups will find it easier to attract both crowd-based financing and venture capital. Drover et al. (2017b) therefore conduct a conjoint analysis and show that certain characteristics of crowdfunding campaigns, such as a positive track record of a platform or the type of crowdfunding (reward-based in contrast to securities-based), can certify positive venture quality in the minds of VCs when they make due diligence decisions. Yet, the work does not take into account the trade-off between different sources of early financing. Accounting for this and conducting a choice-based conjoint analysis, Moedl (2018) finds causal empirical evidence that previous crowd-based financing ceteris paribus reduces the likelihood of such-funded start-ups to be considered for investment by subsequent professional venture investors, relative to pre-funding by business angels. While these studies provide important insights, we still lack a more thorough understanding of whether and how venture investors associate an entrepreneurs' choice between competing seed-funding channels with the venture's latent quality, and therefore potentially affects their start-up assessment.

To develop my hypotheses, I chiefly draw from two strands of literature: First, by referring to pecking order theory (Myers, 1984; Myers & Majluf, 1984), I argue that venture investors perceive that entrepreneurs follow a financing hierarchy when choosing equity funding sources, and that this hierarchy is (in part) determined by venture quality. Second, I draw from signaling theory (Spence, 1973, 2002) to theorize that prior equity funding can therefore serve as an effective signal of latent venture quality and reduce the information gap for subsequent investors. Both pecking order theory – which draws its propositions from the existence of information asymmetries between investors and managers –, and signaling theory – which links asymmetric information to quality – are particularly suitable for this study because the entrepreneurial finance setting is characterized by high information asymmetry (Amit et al., 1998; Busenitz et al., 2005).

Toward an Entrepreneurial Equity Pecking Order

Risk capital investments are characterized – by definition – by a high degree of uncertainty and a large difference between the knowledge of capital-seeking entrepreneurs and capital-providing investors: naturally, founders are assumed to have better knowledge about the true quality of their venture than external investors (Amit et al., 1998; Busenitz et al., 2005; Cassar, 2004; Gompers & Lerner, 2001). The market for venture financing therefore faces severe ex-ante[2] information asymmetries (Akerlof, 1970), and numerous studies have shown that markets of external equity

[2] Asymmetric information also occurs ex-post in entrepreneurial finance, as investors (principals) cannot perfectly observe the intent and actions of entrepreneurs (agents), leading to a moral hazard problems (e.g., Jensen & Meckling, 1976). Kaplan and Strömberg (2001) provide an overview of how venture capitalists attempt to mitigate principal-agent conflicts, namely through pre-investment screening, sophisticated contracting, and post-investment monitoring.

financing[3] may be associated with a "lemons problem" (e.g., Chan, 1983; Greenwald et al., 1984; Myers & Majluf, 1984).

A prominent concept that relates asymmetric information to financing choices is the pecking order theory of capital structure (Myers, 1984; Myers & Majluf, 1984). In a nutshell, the framework proposes the existence of a financing hierarchy, as due to asymmetric information outside investors face the risk of adverse selection and demand a "lemons" premium (Akerlof, 1970) for the securities offered in exchange for funds. As risk exacerbates the effects of information asymmetry, the more risky the security, the higher the premium will be (Myers, 1984). According to that logic, since equity is a riskier security than debt it should be subject to higher premiums. Myers and Majluf's (1984) model shows that if business managers act in the interest of existing shareholders and try to avoid the cost of financing, firms will prefer funding by retained earnings, which are not subject to asymmetric information. When internal funds are insufficient and they have to turn to outside sources of capital, they will first raise debt and only consider new equity as a last resort (for empirical evidence see, e.g., Frank & Goyal, 2003).

While the traditional pecking order theory focuses on asymmetric information as the principal mechanism that drives financing hierarchies, recent studies suggest that information asymmetry does not necessarily lead to a financing hierarchy (Harris & Raviv, 1991), and may not be the only reason why a pecking order exists. For instance, transaction costs (Myers, 1984), considerations of a potential loss of control rights (Manigart & Struyf, 1997), or a knowledge gap in the entrepreneur's familiarity with funding sources (van Auken, 2001) have been shown to contribute to a financing hierarchy. Encouraged by this previous work, I set out to explore whether professional investors perceive that inherent venture quality is also a determinant of entrepreneurs' financing choices.

While the classic pecking order theory targets mature firms, it has also been validated for the context of young high-growth companies (e.g., Cassar, 2004; Cosh et al., 2009; Vanacker & Manigart, 2010). Recently, Walthoff-Borm et al. (2018) have shown that firms list on crowdfunding platforms as a "last resort", i.e., when they lack internal funds and debt capacity. These studies in particular and pecking order theory in general, however, consider external equity relatively homogeneous and do not account for different types of external equity financing – a

[3] In fact, problems arising from asymmetric information have also been demonstrated to exist in debt markets, see, e.g., Stiglitz and Weiss (1981).

leeway which becomes highly relevant with the increasingly diverse entrepreneurial equity funding landscape. This study thus examines and extends the boundaries of the pecking order perspective by providing first-time evidence on the perception of an entrepreneurial *equity* pecking order.

Signaling Theory in the Entrepreneurial Setting

A theory which is fundamentally concerned with reducing the information gap between two parties, and which has thus been widely applied in innovation and entrepreneurship research, is signaling theory (Spence, 1973, 2002). The adverse selection problem can be mitigated if high-quality types use observable "signals" to communicate their above-average quality by taking some costly action, which cannot easily be imitated by low-quality types.[4] It has been demonstrated that venture investors tend to address the ex-ante asymmetric information problem by relying on signals of quality, that is, attributes that are observable at the time of the investment decision and for which the probability is high that they correlate with the non-observable determinants of the quality of a start-up (Hoenig & Henkel, 2015; Stuart et al., 1999). In fact, venture investors invest significant time and energy in the screening process and the evaluation of quality signals (Amit et al., 1990; Hall & Hofer, 1993). Conversely, entrepreneurs invest in observable attributes which signal the quality of their start-up (Zott & Huy, 2007). Yet, signals cannot only be sent on purpose, but also unintentionally (Janney & Folta, 2003).

In line with Spence's (1973, 2002) definition, signals have to be observable, costly and discriminatory to be effective (Connelly et al., 2011). I propose that prior funding can be an effective signal, since, on the one hand, ownership structure and financing resources are bluntly *observable* from the business plan. On the other, different types of pre-funding, being differently costly to obtain for start-ups of diverging quality, are *discriminatory* and can therefore achieve a separating equilibrium between ventures of different quality. Leland and Pyle (1977) were the first to show that financing structure can signal a firm's true quality. A number of studies have also reasoned that previous external financing can contain information about the quality of a venture and therefore reduce the uncertainty of subsequent investors (Drover et al., 2017b; Elitzur

[4] Another possibility on the other side of the market is that the uninformed party "screens" the market by providing an additional offer which is only attractive to high-quality subjects, as demonstrated for the insurance market by Rothschild and Stiglitz (1976). Hence, in screening theory the less-informed party bears the cost for the signal, while in signaling theory it is the better-informed party for whom the signal is costly. Riley (2001: 474) therefore calls screening and signaling "twin theories".

& Gavious, 2003; Janney & Folta, 2003; Megginson & Weiss, 1991). With crowd-based financing emerging as a novel source of seed-funding next to established players, there is a need for understanding the informational value that the choice of financing in the early-stage funding game transports to subsequent investors.

Study Hypotheses

The derivation of our hypotheses is conceptually guided by both pecking order and signaling theory. If venture investors perceive that entrepreneurs' financing hierarchies are determined by inherent venture quality, then an early-stage financing choice could serve as an effective signal of the latent quality of a firm to subsequent investors.

Venture quality. The signaling cost differential is arguably smaller for receiving crowdfinancing than for receiving funding from professional investors. There are several indications that it is relatively harder (costlier, in signaling theory jargon) for ventures of lower quality relative to ventures of higher quality to obtain seed-funding from, e.g., business angels than from the crowd. First, transaction costs are assumed to be relatively lower for high-quality types: an investment by a business angel may be regarded as an observable proxy for communicating, e.g., a high-quality management team's positive effort and ability in identifying, approaching, negotiating and dealing with investment managers (Elitzur & Gavious, 2003). In contrast, crowd-based financing usually involves standard terms, nearly no search and negotiation costs and is thus almost equally approachable for low- and high-quality start-ups.[5]

Second, the crowd is expected to be less good at selecting promising ventures than professional investors, yielding to a higher probability that low-quality start-ups obtain funding. For instance, due diligence processes by crowd contributors are likely to be less thorough than by professional investors, owing to the facts that they are on average less experienced, cannot rely on face-to-face interactions, and typically invest small(er) sums per individual, reducing the incentives for deep investigations (Agrawal et al., 2014). The latter potentially yields a free-rider problem: While Astebro et al. (2017) and Zhang and Liu (2012) find that herding occurs in equity

[5] Standard terms may also lead to a tendency of average valuations. These are favorable for low-quality firms, thus increasing their incentives of opting for (securities-based) crowdfunding. On the contrary, the "costs" of receiving funds, e.g., giving away a share of equity, could be relatively lower for high-quality start-ups when turning to individual contract negotiations. It also deserves mentioning that some crowdfunding platforms perform a pre-selection. As they, however, benefit from a high deal flow, it is likely that their selection is not as strict as that of venture investors.

crowdfunding and microloan markets, but that it is not naïve or irrational, Vismara (2015) documents that crowdfunders free-ride on the investment decision and back the projects with the greatest number of investments in an information cascade fashion. The weak individual-level possibilities and incentives to perform due diligence might lead the crowd to make less informed selection decisions than professional venture investors. Mohammadi and Shafi (2016) provide evidence from online peer-to-business lending platforms that crowds indeed perform inferior to institutions when screening the creditworthiness of small and medium sized enterprises.

Less informed crowd decisions may yield to a higher relative likelihood of low-quality ventures to successfully close a funding round with the crowd, compared to acquiring funds from professional venture investors. Put differently, the "cost" of obtaining funding from a business angel is seemingly relatively lower for high-quality ventures than for start-ups of lower quality. Indeed, Mollick and Nanda (2016) find that the crowd is willing to fund more projects that experts may reject (despite discovering a remarkable congruence between experts and the crowd). On the other side of the market this view is backed by a large-scale survey among British fundraisers where 64 percent of those using donation-based crowdfunding and 53 percent of those using reward-based crowdfunding state that it is "unlikely" or "very unlikely" they would have been able to get funding elsewhere (Zhang et al., 2014). Subsequent venture investors might, hence, assume that start-ups financed by the crowd have turned to this means of funding because they considered the chance of obtaining funding from traditional sources to be low or because they had previously been rejected. While such cases might have several explanations, above's reasoning for the smaller signaling cost differential for crowdfinancing makes a compelling argument to propose that venture investors assume that one dominant rationale for a start-up "choosing" to get funded by the crowd (or being forced to turn to the crowd as a last resort) is its inferior quality. For all these reasons, professional venture investors could believe that crowd-based financing alternatives may suffer from a negative selection bias. Our first hypothesis is thus:

> *Hypothesis 1. Venture investors perceive that low-quality start-ups have a higher relative likelihood than high-quality start-ups of approaching crowdfinancing rather than approaching professional investors as a first means of external equity funding.*

Venture type. Scholars have suggested that ventures (of any quality) might search for crowd-based funding for reasons not related to resolving financing constraints, such as user feedback (Colombo et al., 2015), market testing and validation (Strausz, 2017; Viotto da Cruz, 2018) and marketing (Schwienbacher & Larralde, 2012). These extra-financial services of crowd-based funding predominantly apply to firms which feature consumers as target customers, since crowd backers are assumed to be primarily consumers. The venture type, i.e., whether a firm has a business-to-consumer (B2C) or business-to-business (B2B) business model, might thus also influence (perceived) financing hierarchies. This argumentation is also in line with signaling theory, as characteristics of the signal sender might influence the receiver's interpretation of a signal (Connelly et al., 2011).

Investors might assume that B2C start-ups anticipate a higher chance of successfully being funded by crowd. A crowd of consumers is likely to have a higher tendency to fund B2C than B2B ventures since, e.g., in reward-based crowdfunding backers oftentimes receive the product the entrepreneur intends to develop in return for their financing. Besides, the crowd's positive appraisal of B2C companies might be seen as a proof of market acceptance for a start-up's offering. Strausz (2017) discusses a model in which reward-based crowdfunding can be used as a screening mechanism to uncover information about future demand for a venture's offering. This pertains to both third parties and the founders themselves. With regard to the latter, Viotto da Cruz (2018) provide empirical support that a successful crowdfunding campaign increases the probability of actually releasing a market offering. Since market demand and customer adoption are important evaluation criteria in the decision making of venture investors (Petty & Gruber, 2011; Shepherd, 1999), successful crowdfinancing campaigns of B2C ventures could serve as informative and relevant signals to subsequent investors. In the same fashion, they might perceive that these are also important criteria for entrepreneurs' funding choices.

This argumentation pertains to a start-ups offering. In case of securities-based crowdfunding, the crowd's investment might *additionally* certify its perception of the value of the firm more generally, e.g., its underlying financial potential. Since it is assumed that average citizens as retail investors are better in assessing B2C than B2B business models, I also expect venture investors to perceive that B2C start-ups have a higher likelihood of successfully closing a crowdinvesting campaign, and thus a relatively higher probability of approaching securities-based crowdfunding.

Conversely, B2B start-ups might have stronger rationales for seeking funding from professionals, e.g., as venture investors are often said to have a strong network in industries they invest in and therefore serve as door-openers to potential key accounts (e.g., Freear et al., 1994). If venture investors share these views, we would expect them to assign a higher probability of choosing crowd-based financing to start-ups with a B2C business model, relative to those with a B2B business. I consequently formulate our second set of hypotheses as follows:

> *Hypothesis 2a. Venture investors perceive that B2C ventures have a relatively higher likelihood than B2B ventures of approaching crowdfunding rather than approaching professional investors as a first means of external equity funding.*

> *Hypothesis 2b. Venture investors perceive that B2C ventures have a relatively higher likelihood than B2B ventures of approaching crowdinvesting rather than approaching professional investors as a first means of external equity funding.*

All in all, I hypothesize two factors that have the potential to shape entrepreneurs' equity pecking order, and concomitantly serve as uncertainty-reducing signals to subsequent investors. Moreover, this study also aims to explore which factor – quality considerations or potential extra-financial benefits, such as a marketing value to potential consumers – has a stronger effect on entrepreneurs' financing choices in the eyes of investors.

DATA AND METHOD

Vignette analysis

In order to shed light on professional investors' expectations on the role and direction of a venture's quality and its business model on founders' rational choice of an initial source of equity funding, I conduct a choice experiment, namely a vignette analysis, also known as factorial survey[6] in sociology (Rossi & Anderson, 1982; Wallander, 2009). In doing so, I heed the recent call by Williams et al. (2018) to apply more experimental methods to advance entrepreneurship research. *Vignettes* are defined as "short descriptions of a person or a social situation which contain precise references to what are thought to be the most important factors in the decision-making or judgment-making processes of respondents" (Alexander & Becker, 1978: 94). In vignette analyses, several versions of systematically varying vignette descriptions are shown to respondents within surveys in order to elicit their judgments about the scenarios' characteristics

[6] The term *factorial survey* has been associated with randomly selecting subpopulations or vignette sets (Atzmüller and Steiner (2010: 130). As in this study's design all respondents are shown the total vignette population, problems of subset selection do not occur.

(Atzmüller & Steiner, 2010). It is therefore a decompositional method of preference measurement that combines the advantages of survey research with the advantages of experimental designs (Auspurg et al., 2009; Auspurg et al., 2017). Numerous studies have demonstrated that the decision making of venture investors can be modelled through stated choice experiments with a high degree of consistency (Franke et al., 2006; Hoenig & Henkel, 2015; Muzyka et al., 1996; Riquelme & Rickards, 1992; Shepherd et al., 2003; Shepherd & Zacharakis, 1998).[7]

I have chosen this approach mainly for three reasons: To begin with, stated choice experiments represent a concurrent method, rather than a retrospective or self-reported, thus potential weaknesses of post-hoc methodologies are avoided (Shepherd & Zacharakis, 1999: 205f.). In contrast to, e.g., rating-scale surveys, there are no inconsistencies in how respondents interpret scales. Moreover, investors are asked to make actual judgments, thus do not think of particular recent start-ups or rate according to social desirability. Second, VC decisions are often subject to cognitive biases (Baum & Silverman, 2004; Ferrary & Granovetter, 2009). In fact, it is questionable whether VCs really understand their decision policies (Zacharakis & Meyer, 1998). In the setting of a vignette analysis there is no problem with respondents lacking insights in their assessment process (e.g. “gut feeling”), since they make actual decisions; and, as data is collected at the same time when the decision is made, people cannot forget important aspects of a former decision-process or retrospectively rationalize their decisions. Third, and probably the most essential feature of vignette analysis is its experimental setting which allows the analysis of causal effects. With a choice experimental approach an omitted variable bias is excluded by construction, the desired signaling effect of a pre-funding structure can be isolated experimentally, and ceteris paribus analyses are possible. Besides, conditions can be controlled for, making survey experiments a quite cost-efficient alternative: “[t]he environment of a hypothetical choice can be precisely specified, with a design which allows straightforward identification of effects” (McFadden, 2001: 373), and several causal hypotheses can be tested in a single study (Hainmueller et al., 2014: 3). This efficiency makes vignette analysis particularly

[7] Studies in entrepreneurship research often employ conjoint analysis which is a special type of vignette study (see, e.g., Aguinis and Bradley, 2014). Notable differences of this study’s experimental design include that it involves a categorical measurement scale, whereas ordinal or metric scales are typical for traditional conjoint analyses; and that in conjoint analysis’ choice sets, information on varying attribute levels is presented in a tabular form, whereas in vignettes it is usually presented as a narrative to respondents (Hainmueller et al. (2015: 2396); Auspurg et al. (2009: 3).

suitable for studying the behavior of hard to obtain and time-scarce subjects, such as venture investors.

Data and Sample

The target population of our online survey is venture capital managers who work at a private independent venture capital company and business angels located in Germany. I focus on *private independent* venture capital and exclude captive VCs (i.e., corporate, bank-owned, governmental or public VCs; see, e.g., Da Rin et al., 2013), as their alternative ownership structures might affect their objectives, funding and strategic decisions (Bottazzi et al., 2008; Da Rin et al., 2013; Pahnke et al., 2015). Data from the German market for venture financing is particularly suitable for investigating the interplay of crowd-based and traditional means of financing since it is a sophisticated market for both reward-based crowdfunding and securities-based variants. The first securities-based crowdfunding campaigns in Germany started relatively early, in mid-2011, and projects have continuously broken worldwide funding records in terms of collected sums and speed. Young firms funded in this way have experienced successful follow-on VC funding rounds as well as significant complications and rejections solely based on their previously collected crowdfunding. Hence, the German venture capital market was able to gain considerable early experience with this new form of start-up financing. This in opposite to, for instance, the United States, where securities-based crowdfunding was not open to non-accredited investors – hence the majority of the "crowd" – until Mid-May 2016 due to a delay in the concretization and promulgation of the JOBS Act regulation by the Securities and Exchange Commission, a hold-up which de facto limited the crowdfinance market to reward-based crowdfunding (see, e.g., U.S. Securities and Exchange Commission/Investor.gov, 2016). While this is a strong rationale for focusing on venture investors located in Germany, the focus might also be considered as a potential threat to the generalizability of our results. In this context, however, it deserves mentioning that the venture investing industry, which emerged in the USA and has since been a role model across the world, is described as quite homogeneous internationally, in particular with regard to decision policies and screening (e.g., Brettel, 2002; Wright et al., 2005).

In order to ensure that a large number of active venture investors had the same chance of being invited to our survey, I solicited participants through a multitude of channels. Efforts included personalized postal letter and e-mail invitations to German private venture capitalists and business angels listed in the PitchBook database and the Financial Yearbook Germany (www.fyb.de), recommendations and invitations sent out to their members by relevant industry associations, such as the *Bundesverband Deutscher Kapitalbeteiligungsgesellschaften e.V.* (BVK – German Private Equity and Venture Capital Association)[8] and the *Business Angels Netzwerk Deutschland e.V.* (BAND – Business angel network Germany)[9], and canvassing at relevant industry events and network meetings. Invitees were also asked to forward the invitation to their respective colleagues (snowballing). I controlled for potential duplicate entries. Venture investors participated in the online survey from 02/2016 to 02/2017. Despite this relatively long sampling period – reflecting the challenge of obtaining a large sample of venture investors – an analysis of variance between late and early respondents revealed no significant difference (see below). Response rates to invitation waves (where identification is possible) were around 30 percent.

The final sample consists of completed vignette experiments from 94 venture investors (60 venture capitalists and 34 business angels), cumulating to a total of 376 seed-funding choices nested within the 94 persons (each respondent answered four vignettes). This sample size can be regarded as relatively satisfying since achieving large samples in surveys among venture investors is considered to be very difficult (Muzyka et al., 1996), and as our sample size well exceeds the average sample size of empirical studies with venture capitalists (for an overview see, e.g., Shepherd & Zacharakis, 1999: 200–202).

Insert Table 1 around here

Descriptive statistics (see table 1) reveal that our sample contains venture investors with a large variety in terms of background, experience and investment routines. To ensure that non-response is not influencing our results and threatening external validity, I apply established procedures for controlling for non-response bias (see, e.g., Dooley & Lindner, 2003; Armstrong & Overton, 1977). Ideally, one would compare characteristics of our sample against the population of venture investors (or a representative sample thereof), but unfortunately I am not aware of the existence of such data. Under these conditions, comparisons are made with available

[8] The BVK is covering about two thirds of all German VC companies and 90% of VC investment volume in Germany.

[9] Reliable data on business angel “population” is hard to obtain, however, according to its own statement all significant German regional business angels organisations are member of BAND, ensuring a wide coverage.

proxy data (see, e.g., Drover et al., 2017b). The characteristics of our sample parallel those of other empirical studies with venture capitalists:[10] with regard to age, our respondents are on average 45 years old, which compares favorably with 46 years in Aggarwal et al. (2015) as well as 47 years in Zacharakis and Shepherd (2001), and which is only slightly younger than in Drover et al. (2017b) who found the average venture capitalist to be 50 across their two conjoint experiments. Likewise, our respondents' start-up financing experience, which averages 12 years, matches Zacharakis and Shepherd (2001) who drew a sample with a mean of 11 years of VC experience, and lies between Aggarwal et al. (2015) (8 years) and Drover et al. (2017b) (14 years). In accordance with the male-dominated VC population the fraction of males in our sample is 94 percent. This disproportion parallels Zacharakis and Shepherd (2001) (94% male) and Drover et al. (2017b) (90%). Finally, our sample is also highly educated, with 79 percent of venture investors holding at least a Master's degree, compared to 75 percent in Drover et al. (2017b). Consequently, I do not find a systematic discrepancy between our sample and venture investors in other studies.

In addition, I conduct an extrapolation method to test for non-response bias. Extrapolation methods are based on the assumption that survey subjects who participate later and only after some follow-up effort (such as reminders) are more similar to non-respondents (Armstrong & Overton, 1977; Pace, 1939). Following this line of reasoning, I statistically compare the first 25 percent (complete) returns with the last 25 percent (complete) returns using tests of difference on demographic control variables. I could not find any demographic differences between early and late investors, neither in terms of age, educational background, hierarchical position, experience, investment focus, risk attitude, nor expertise of or experience with securities-based crowdfunding. Altogether, when checking for non-response bias I find no evidence to suggest that our respondents are systematically different from non-participating venture investors in any observable way that may threaten the validity of my findings.

[10] Note that I compare my sample with studies among US VCs. Two reasons apply: first, I aim to shed light on the generalizability beyond Germany. Second, well published studies using German VC data – as with any country's data apart from the USA – are simply rare. Two notable exceptions are Franke et al. (2008), whose respondents are younger and less experienced than this study's; and Hoenig and Henkel (2015), who do not report comparable socio-demographics, except that their share of respondents holding senior positions in a VC company (58%-73%, depending on their "other" category) is somewhat smaller than this sample's (74%). The same applies to data on business angels, which is even scarcer.

Experimental Design and Variables

It is imperative to design the choice experiment in such a way that all respondents have a common understanding. I created a thought experiment that confronts participating venture investors with hypothetical descriptions of varying decision situations. These scenarios (vignettes) are presented in the format of a short narrative with sufficient context. Respondents are asked to imagine they were chief executive officer of a *growth-oriented*[11] start-up firm looking for a *first* round of *external equity* financing. For each scenario they are asked to indicate the equity financing source they would approach first. Their own preferences in these situations are likely to correspond to their perception of the average entrepreneur's rational preferences. By asking them which first means of external equity they would choose as founders of start-ups, we can thus draw conclusions on the assumptions of venture investors about the rational self-selection of entrepreneurs into a certain equity funding channel.

I specified four financing alternatives, whereby the (discrete) choice of a preferred financing channel represents the *dependent variable*:[12] As traditional forms of financing I offered *business angel (BA)* and *venture capital (VC).* With regard to crowd-based means of financing, as discussed above, I limit the focus to the distinct variants *reward-based (CF)* and *securities-based crowdfunding* (the latter referred to as *crowdinvesting; CI*), which is in line with Belleflamme et al. (2014) and Vulkan et al. (2016).

Across scenarios I systematically manipulate two dichotomous conditions (dimensions) of the start-up, serving as *independent variables*: First, I vary the assumption of the venture's *quality*. In one scenario, participants should consider the start-up as very attractive and therefore believe to have a good chance of obtaining financing from their preferred channel. In the other, respondents are explained that they cannot assess the start-up's attractiveness to potential investors, hence, that it is potentially mediocre. Additionally, the start-up's financial situation is described as urgent and that the management team can only prepare one (more) application to any financing channel. Such a "last resort" scenario is constructed in order to simulate a decision under the trade-off of preference for a funding type and probability of application success under a

[11] This is important, as growth-orientation implies start-ups that are theoretically considered for investment by venture capitalists, in contrast to non-scalable ventures.

[12] Respondents also had the possibility to add own answer categories. Since most respondents stuck to the pre-specified levels, and as the few respondent-specified levels mostly included either non-equity, internal financing, or government grants, I limit the independent variable to the initial four values (preference rankings were recoded where required).

given quality assumption. The second dimension I vary describes the start-up's *business model* or target customers, respectively. The attribute levels here are B2B and B2C ventures. All other potential start-up characteristics are described to be constant throughout all vignettes to ensure that only quality and venture type considerations influence the decisions of respondents.

As the two independent variables are specified as binary variables, I have a 2 x 2 factorial survey, where each respondent was shown the full factorial design, yielding to a total of four decision scenarios per respondent. The restriction of dimensions is favorable in factorial surveys, as this limits complexity for respondents (Rossi & Anderson, 1982). This is also beneficial from a data analysis perspective. As Aguinis and Bradley (2014) highlight, a fundamental advantage of vignette analyses is that it "allows researchers to include factors that are relevant to the research question while excluding those that might confound the results. This amount of control helps to test causal hypotheses that would otherwise be difficult" (Aguinis & Bradley, 2014: 357). Repeated pre-tests by ten venture investors in the presence of the researcher confirmed the experimental setting is realistic, understandable and manageable in a reasonable time frame.

I chose a within-person design, where each participant sees the whole set of vignettes. Such a design could lead to a potential experimenter demand effect (Charness et al., 2012; Quidt et al., 2018; Zizzo, 2010). Therefore, I carefully considered that the setup is not pushing subjects to answer in a specific way. The alternative, a between-person design, where each individual is exposed to only one treatment, tends to be problematic in the context of our research question and in terms of practical implication of the survey experiment. To begin with, between-subject designs are uncommon when judgments are used as dependent variable (Atzmüller & Steiner, 2010). Aguinis and Bradley (2014: 360) point to the glitches associated with between-subject experimental designs: "because participants are only presented with a single rather than multiple vignettes, they lose any chance at comparison that would help to ground responses contextually. Without other vignettes to serve as referent points for their own judgments, responses may not accurately reflect the true judgments of each respondent." Moreover, to achieve the same number of observations in a between-subjects design, our study would have needed four times as many respondents, representing a significant research-economic threat when targeting hard to achieve subjects such as venture investors (Muzyka et al., 1996). Another advantage of within-person designs is that – because respondents offer responses regarding the same vignettes – comparisons can be made across individuals (Aguinis & Bradley, 2014: 361).

Control variables are selected based on prior research suggesting that individual differences can influence how investors assess investment opportunities (Franke et al., 2008; Franke et al., 2006; Matusik et al., 2008; Murnieks et al., 2011; Zacharakis & Shepherd, 2001). I control for (1) type of venture investor (BA or VC), (2) gender, (3) education (holding a PhD degree), (4) risk attitude[13], (5) experience in start-up finance (in years), (6) investment focus with regard to business model (measured on five point scale between extremes only B2C and only B2B), (7) investment focus with regard to phase (measured on five point scale between early and late stage), and – given its newness as a funding form – (8) respondents' knowledge of crowdinvesting (self-reported on a five point scale).

Estimation strategy

In the underlying survey experiment participants face choices from a limited number of options. The outcome (dependent) variable therefore is not continuous but discrete, hence, discrete choice models are to be used. By systematically varying each dimension of the vignettes in an experimental design, one can estimate the variables' causal impact on respondents' decisions. Multinomial logit is an appropriate behavioral model since the dependent variable is discrete and polychotomous (with no natural ordering), and because the independent variables are alternative-invariant, i.e., choice options are the same across scenarios (e.g., Bowen & Wiersema, 2004: 91; Cameron & Trivedi, 2005: 491–500; Maddala, 2008: 41–46).[14] The derived probability of the behavioral model to be estimated here is specified as follows (main effects model).

The probability *P* that individual *n* chooses financing alternative *i* (and not another alternative $j \neq i$) is:

[13] The world of business venturing is characterized by high levels of uncertainty and risk. Various studies have shown that risk attitudes are an important component of individual heterogeneity among entrepreneurs, e.g., with regard to their probability of entry into entrepreneurship, growth and success as a founder, or the likelihood of exiting an entrepreneurial career (for an overview, see Kerr et al. 2017: 23ff.). Here, I employ a self-reported metric validated by Dohmen et al. (2011) which directly asks participating venture investors to make a global assessment of their willingness to take risks. Following the question: 'Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?', respondents are asked to tick a box on a 11-point scale, where the value 0 means: 'not at all willing to take risks' and the value 10 means: 'very willing to take risks'. A crucial concern is whether self-reported survey questions can be meaningfully interpreted in terms of actual risk-taking behavior. Dohmen et al. (2011) conduct a field experiment in which participants answer this general risk question and additionally make choices in a paid lottery experiment. They find that responses to the general risk question are a reliable predictor of actual risky behavior and conclude that "[t]he question about risk taking in general generates the best all-round predictor of risky behavior" (Dohmen et al. 2011: 522).

[14] That in contrast to the conditional logit model (McFadden, 1974), which is the correct specification for alternative-varying independent variables.

$$P_{ni} = \frac{e^{(\alpha_i + \beta_{Qi} Q_n + \beta_{Bi} B_n)}}{e^{(\alpha_i + \beta_{Qi} Q_n + \beta_{Bi} B_n)} + \sum_{j=1}^{3} e^{(\alpha_j + \beta_{Qj} Q_n + \beta_{Bj} B_n)}}, \quad j = 1,\ldots, 3,$$

where Q denotes regressor quality and B denotes business model.

To account for potential threats of the independence of irrelevant alternatives (IIA) assumption (e.g., Hausman & Wise, 1978; Louviere & Woodworth, 1983), I additionally estimate a binomial logit model as robustness check, for which the IIA assumption is not a prerequisite. Since there are four (non-independent) decisions per respondent, I cluster respondent-specific standard errors in the maximum likelihood estimation.

RESULTS

Descriptive Analysis

The statistical analysis draws on four decisions each from 94 respondents, thus yielding to a total of 376 data points. Relative first order choice frequencies for the different scenarios are depicted in figure 1. Across all four scenarios most venture investors in our sample would first apply for seed-funding from a business angel if they were a start-up founder. When they consider their venture as very attractive, almost two thirds prefer business angel funding as a first means of equity financing and another quarter prefers VC financing, illustrating both the superior role of angel financing in early stages and an overall strong preference for established financing forms. In the high-quality scenarios, less than 10 percent of our respondents opt for crowd-based financing as first external equity channel. There is a notable shift in the case of low-quality ventures: when imagining being founders of potentially mediocre start-ups, the fraction of respondents considering applying for crowd-based financing increases to over 30 percent for B2B ventures, and almost 45 percent for B2C ventures. With regard to business models, about twice as many venture investors who conceive starting a B2C business choose crowdfunding as first means of financing compared to B2B entrepreneurs. I do not observe such a shift for crowdinvesting.

Insert Figure 1 around here

Multivariate Analysis

The results of the multinomial logistic regression are presented in table 2. Coefficient interpretation in multinomial logit models – in contrast to conditional logit models – is relative to a base group or reference category of the dependent variable (Cameron & Trivedi, 2005: 494). I defined outcome alternative *business angel* as reference category (and thus normalize it to have coefficients equal to zero), as it is the most frequent outcome. Model 1 estimates multinomial log-odds of main effects only. Model 2 depicts the relative risk ratios, also referred to as multinomial odds ratios, for the same specification. Column 4 predicts relative risk ratios for a model including control variables, and – since the number of observations is reduced for this specification due to missing values for control variables – column 3 presents the results of the main effects model for the same observations as model 4 to ensure comparability (I resign from imputation of missing values and associated potential problems due to only few missing entries). The overall main effects models, both for the total sample (χ^2 = 47.61; degrees of freedom = 6) and the reduced sample (χ^2 = 47.61; *df* = 6), are statistically significant. The fraction of the maximum potential gain in log-likelihood that is achieved by the fitted models (compared to an intercept-only model that estimates the likelihood of each alternative to be the sample average) is about 7 percent. Likewise, the overall model with control variables (χ^2 = 97.15; *df* = 30) is statistically significant; about 17 percent of the potential gain in log-likelihood is achieved by the fitted model. For the different model specifications I do not observe significant changes in outcomes, neither in terms of parameter values nor their statistical significance.

Insert Table 2 around here

Focusing on the main effects model 1, I find two of the three coefficient estimates for covariate start-up quality are statistically significant at the 0.01 level, namely for the two crowd-based forms of financing (relative to business angel funding). With regard to business model the coefficients for VC ($p<0.05$) and for crowdfunding ($p<0.01$) are statistically significant. Since results of individual testing might vary with the omitted reference category, I also perform a Wald test of joint significance of our independent variables. Both quality (χ^2 = 29.76; *df* = 3) and business model (χ^2 = 16.35; *df* = 3) are clearly highly statistically significant. Multinomial log-odds coefficients allow the assessment of the direction of the effects of a change in covariates on venture investors' perception of entrepreneurs' preference for a first type of equity funding. I find that a decrease in a venture's quality increases respondents' likelihood of applying for crowd-based financing relative to business angel financing if they were founders, offering support for hypothesis 1. With regard to a venture's business model venture investors consider entrepreneurs to have a significantly higher probability of choosing venture capital and (reward-based) crowdfunding relative to angel funding, if they head a B2C rather than a B2B start-up, providing support for hypothesis 2a. Interestingly, there is no statistically significant effect for the (securities-based) crowdinvesting variant. I thus do not find support for hypothesis 2b.

Relative risk ratios. While from multinomial logit coefficients only the direction of an effect is directly readable, relative risk ratios have the advantage that they allow an interpretation of the magnitude of variables' effects (Hoetker, 2007: 334). Relative risk ratios here give the proportionate change in the relative risk of choosing a funding alternative rather than angel financing when a start-up's quality or its business model, respectively, change (cf. Cameron & Trivedi, 2010: 500).[15] Column (2) shows the transformed coefficients of model (1) into relative risk ratios. When the business model in the scenarios changes from B2B to B2C, the relative risks of choosing to apply for venture capital rather than angel funding are 14 percent higher than what they were before the change (given the other variables in the model are held constant).[16] The increase in relative risks is larger for crowdfunding: for B2C ventures the relative risks of choosing crowdfunding instead of business angel funding are about 2.6 times the according relative risks for B2B ventures. As stated before, there is no statistically significant change in relative risks for crowdinvesting relative to BA.

A change in the assumed quality of start-up has an even higher impact on venture investors' perceived seed-funding preferences of entrepreneurs: For mediocre start-ups compared to high-quality start-ups, the relative risk of venture investors perceiving that entrepreneurs choose crowdinvesting as a first means of financing relative to angel financing is expected to increase by a factor of 7.2. A decline in quality even leads to a more than 8 times increase in relative risks of choosing the reward-based crowdfunding variant instead of angel funding. So given a change from high to low-quality in the decision scenario, the relative risk of professional

[15] Relative risk ratios are similar to – but not the same as – odds ratios, which is why they are also referred to a as multinomial odds ratios. Only for bivariate logit models relative risk ratios are equivalent to odds ratios. For a detailed derivation of the distinction see, e.g., https://www.stata.com/statalist/archive/2005-04/msg00678.html (last visited 10 September 2017).

[16] The multinomial log-odds coefficient of business model the alternative VC is 0.132 (rounded), and $e^{0.132} = 1.142$ (rounded).

venture investors perceiving that founders apply for crowd-based financing rather than business angel financing is seven to eight times more likely.

Considering the model including control variables (column 4 of table 2) effects for changes in quality and business model become slightly more pronounced. Control variables only become statistically significant for certain coefficients for funding alternative venture capital (versus base category BA). Venture capitalists in our sample have a three times ($p<0.05$) higher relative risk of choosing VC rather than BA, than business angels in our sample. This finding does not come as a surprise when considering that studies have found a similarity preference in venture investors' decision-making (e.g., Franke et al., 2006; Gompers et al., 2016; Murnieks et al., 2011). Also not unexpected, it appears that venture investors who engage in later stages tend to have relative risks of selecting VC (which tends to increasingly specialize in funding later-stage ventures) relative to BA that are 1.5 times ($p<0.10$) higher than those respondents who state an earlier investment phase focus by one standard deviation. Furthermore, one year more experience in start-up finance leads to an 8 percent ($p<0.01$) increase in the relative risk ratio. Finally, given a rise of respondents' risk propensity by one standard deviation, the relative risk for considering that entrepreneurs first apply at financing form venture capital relative to angel funding is expected to decrease by a factor of 0.64 ($p<0.05$). An increased risk adversity, hence, leads to a lower relative probability of believing that founders approach venture capital first – which appears to be sensible, as venture capital is known to feature high rejection rates. Besides, gender (probably in part due to the low number of females in the sample), education, respondents' investment with regard to business model and their self-stated knowledge of crowdinvesting have no statistically significant effect on the perception of entrepreneurs' pre-funding preferences in our model. As these individual characteristics' effects on the relative risk of choosing VC over BA are comparatively low in effect size, and given the fact that there are no statistically significant effects of respondents' characteristics on their relative risk ratios of choosing either crowd-based financing variant over BA, we can conclude that a venture's assumed quality plays the predominant role for our respondents' early-stage funding preferences.

Marginal effects. While relative odds and relative risk ratios have to be interpreted in comparison to a reference category – which can by unintuitive – results can be made more tangible by computing marginal effects (Long & Freese, 2006: 246f.; Williams, 2012). I therefore calculate average marginal effects (Williams, 2012: 324–326). Moreover, it is important to note that a constant change in relative risks does not imply a constant change in choice probabilities (Hoetker, 2007: 334). Relative risk ratios explain the *average* change in relative risks for a change of *one* covariate, but do not look at a specific scenario; the same holds true for average marginal effects which only provide a single estimate for each covariate, even though the effects of, e.g., a change in start-up quality might vary with the business model of the start-up. In order to estimate the effect of a covariate on the change of probability of a choice occurring in a certain scenario, I additionally calculate the (conditional) marginal effects at representative values (Williams, 2012: 326f.). Representative values here are the two respective outcomes of the independent variable that is held constant.

Insert Table 3 around here

Estimates for average (in bold) and conditional marginal effects at specified outcome values are provided in table 3. Let us first focus on established means of financing (VC and BA). Everything else equal, one would expect an 11.7 percentage points decrease in the proportion of respondents who choose venture capital if one changes the vignette from high-quality start-up to mediocre start-up ($p<0.05$). In the same fashion, one would expect the fraction of respondents who would choose business angel funding as first means of financing to decrease by on average 18.6 percentage points ($p<0.01$). The effect of a change in quality is stronger in the scenarios where the business model is set to B2C rather than B2B (decrease by 13% versus 10% for VC, and 22% versus 16 % for BA). The effect of a change of the business model when keeping start-up quality constant is only statistically significant ($p<0.01$) for the choice probability of outcome angel financing, not for VC. A shift from B2B to B2C ventures in the vignettes decreases the fraction of respondents opting for angel funding by on average eight percentage points; they almost exclusively swing to crowdfunding (+8.5%; $p<0.01$), not to venture capital or crowdinvesting. The negative marginal effect thereby is significantly greater for mediocre (-11%; $p<0.01$) than for high-quality start-ups (-5%; $p<0.05$).

Particularly interesting are the effects of a start-up's quality and its business model on venture investors' perceptions of founders' probabilities on opting for crowd-based financing. The assumption about a venture's quality has a large and significant impact: on average the probability of respondents choosing to apply for crowdinvesting is 13 percentage points higher ($p<0.01$), and for crowdfunding even 17 percentage points higher ($p<0.01$), when the venture is considered to be of low-quality than it is for high-quality start-ups. While for crowdinvesting there are no significant differences in the different business model scenarios, the conditional marginal effect of quality on the probability of applying for crowdfunding is almost twice as high in B2C scenarios (22.5%; $p<0.01$) than it is in B2B scenarios (11.6%; $p<0.01$). This also translates into the marginal effects for changes of covariate business model on choice probabilities for crowdfunding: the average marginal effect of an 8.5 percent increase when shifting from B2B to B2C businesses is largely driven by mediocre start-ups: While the fraction of respondents preferring crowdfunding in cases in which their start-up is said to be attractive only rises by 3 percentage points ($p<0.05$), a B2C instead of a B2B business model causes 14 percent more venture investors in our sample to opt for crowdfunding if their start-up is said to be mediocre ($p<0.01$).

Robustness Test

As a robustness check for our results I perform a bivariate logistic regression. A frequent concern raised with the use of multinomial logit models is the assumption of the independence of irrelevant alternatives (IIA), that is that a respondent's choice between two alternatives is unaffected by what other alternatives are available (Cheng & Long, 2007; Fry & Harris, 1996). In other words: adding or subtracting choice options to/from the existing set, or changing characteristics from a third option, should not affect the odds between any two options (practically, when alternatives are close substitutes the IIA assumption may be inappropriate). The IIA assumption is implicit in multinomial logit models as they reduce the choice of one from more than two (here four) outcome alternatives to a series of pairwise comparisons (binary logits) that are, thus, unaffected by the characteristics of alternatives other than the pair under consideration. Hence, the conditional probabilities (odds) do not depend on other alternatives that are available (Cameron & Trivedi, 2005: 503). As the bivariate logit does not impose the IIA assumption, collapsing the number of categories to two and doing a binary logistic regression could confirm the robustness of our findings.

Tests of Independence of Irrelevant Alternatives. Whether the IIA property is violated can be tested by a number of tests (for an overview see, e.g., Fry & Harris, 1996). I perform the two most commonly used tests (Long & Freese, 2006: 243), namely the Hausman-McFadden test (Hausman & McFadden, 1984) and the Small-Hsiao test (Small & Hsiao, 1985). Both are so-called “choice set portioning tests” (Fry & Harris, 1996: 20), which compare the estimated coefficients from the full model to those from a restricted model that excludes at least one of the outcome alternatives. The tests did not provide unambiguous information whether the IIA property holds in our model, however, with a clear tendency towards the IIA *not* being violated. First, when conducting several runs of the Small-Hsiao test I predominantly did not reject the null hypothesis that the IIA holds. Because the Small-Hsiao test randomly divides the sample into two sub-samples of about equal size, results will differ as the sample will be divided differently. For a majority of performed tests assigning random starting seeds in the software package Stata, the test statistic was not significant for all variations of omitted variables, indicating that the IIA holds. Exemplary, I report test statistics for setting seed=100: VC omitted: χ^2=0.271, p=0.6025; BA omitted: χ^2=0.568, p=0.4512; CI omitted: χ^2=0.297, p=0.5857; CF omitted: χ^2=0.607, p=0.4360. Second, in the Hausmann-McFadden test none of the three tests for our model with BA as base category rejected the H_0 that IIA holds (VC omitted: χ^2=-0.018, p=1.000; CI omitted: χ^2=0.010, p=1.000; CF omitted: χ^2=-0.001, p=1.000). The fourth test with regard to omitting variable BA is computed by refitting the model using the largest remaining outcome as the base category. For the refitted model test statistics indicate a rejection of H_0 (χ^2=95.763, p=0.000). Conflicting outcomes are not uncommon with these tests (see, e.g., Long & Freese, 2006: 243) and some studies, such as by Cheng and Long (2007), even conclude that they are not useful for assessing violations of the IIA assumption. In sum, I did not find clear indication the IIA property has been violated in our multinomial logit model.

Combining outcome variables. As a robustness check for our findings I nevertheless additionally run a binary logistic regression, which does not impose the IIA assumption. For a binomial logit model one has to collapse the number of outcome alternatives to two. Two meta-categories in our factorial survey, that “can plausibly be assumed to be distinct and weighted independently in the eyes of each decision maker” (Daniel McFadden, 1973, cited from Long & Freese, 2006: 243), are crowd-based financing, consisting of alternatives crowdinvesting (CI) and crowdfunding (CF), versus traditional/professional means of financing, consisting of venture capital (VC) and business angel (BA). Apart from this qualitative intuition there is also statistical indication: I conduct Wald tests of whether two outcome categories in our multinomial logit model can be combined. The test statistics for a given pair of outcome alternatives are provided in table 4. The null hypothesis that all coefficients (except intercepts) associated with a given pair of outcomes are zero, i.e., categories can be collapsed, (only) holds for pairs VC-BA and CI-CF. The collapsed outcome alternatives of the dependent variable in our binomial logit model are thus – in accordance with theoretical rationales – traditional means of financing and crowd-based financing.

Insert Table 4 around here

Bivariate logistic regression. I conduct a bivariate logistic regression with the independent variables again being the scenario variables quality and business model (plus control variables), and with the dependent variable being preferred first funding mechanism, with binary outcome alternatives traditional means of financing (0) or crowdfinancing (1). Table 5 shows the results of the regression with coefficients being displayed as odds ratios for easier interpretability. Model 5 is the main effects only model, model 7 includes control variables, and model 6 depicts a main effects only model with the reduced sample size of model 6 due to missing values in control variables. Throughout all model specifications the coefficients for main variables quality and business model are highly statistically significant ($p<0.01$). Control variables do not have a significant effect on the odds of respondents choosing traditional or crowd-based financing, as in the multinomial logit model (there I only found an effect for the relative risk of choosing VC rather than BA, both now being in the traditional category). The odds of crowd-based financing being chosen as preferred first funding channel for low quality start-ups is more than 8 times that of high quality start-ups. When business model changes from B2B to B2C, the odds ratio is 1.7. These results compare favorably in terms of significance, direction and effect size to the relative risk ratios from the multinomial logit models. Our findings thus appear to be robust.

Insert Table 5 around here

DISCUSSION

Summary, Interpretation and Contribution

Crowdfunding's entering of the arena has changed the entrepreneurial funding landscape. The purpose of this study has been to investigate whether venture investors perceive a systematic bias in entrepreneurs' hierarchies of approaching initial sources of equity financing. More specifically, I aimed at collecting quantitative empirical evidence on professional investors' expectations on the role and direction of a venture's quality and its business model on founders' choice of an initial source of equity funding. The results of this paper are impactful because they enhance our understanding of the relationship between a novel form of early-stage funding, to which a large number of new ventures (aim to) turn, and later-stage professional investors, which are critical to further development of innovative entrepreneurial firms.

The study's experimental design allows us to gain insights how venture investors perceive entrepreneurs' hierarchy of approaching equity funding sources. By asking them which first means of external equity they would choose as founders of hypothetical start-ups in varying scenarios, one can draw causal conclusions about the assumptions of venture investors on the rational self-selection of entrepreneurs in certain early-stage financing channels. I thereby heed the recent call by Williams et al. (2018) to apply more experimental methods to advance entrepreneurship research. I can disentangle three major findings: First and foremost, professional venture investors perceive an entrepreneurial equity pecking order in which crowd-based funding comes in last. If they were founders of a high-quality start-up, more than 90 percent of respondents would choose a traditional financing form as first funding channel, thereof two thirds first approach a business angel. However, their likelihood to opt for a crowdfinancing variant increases when venture quality decreases: If they considered themselves to be CEO of a start-up of potentially lower quality, on average their probability of choosing to apply for one of the crowd-based variants of financing would be more than 30 percent higher (17 percent for crowdfunding, 13 percent for crowdinvesting) than if they were heading a high-quality venture. This indicates that professional venture investors perceive a negative quality selection in crowd-based means of financing.

Second, the perceived choice of seed-funding appears to be also affected (to a lesser extent) by a start-up's business model. If venture investors were entrepreneurs, they would have a higher probability of opting for reward-based crowdfunding in case they head a B2C rather than B2B venture. Interestingly, I do not find an increased willingness to apply for an initial (securities-based) crowdinvesting. Yet, in the eyes of venture investors, a start-up's quality appears to be a far more important driver of a founder's financing choice than the firm's business model. Thus, quality considerations prevail potential extra-financial benefits, such as the much-conjured marketing value of crowd-based funding.

Third, the analysis of marginal effects at representative values reveals that the decision criteria of a firm's quality and business model interact. The positive effect of a change of the business model from B2B to B2C in the likelihood of selecting crowdfunding is more pronounced for low-quality than for high-quality start-ups. This means that venture investors have a tendency to believe that good start-ups predominantly approach traditional financing regardless of their venture type, while target customer considerations play a more important role only for mediocre start-ups in determining their first application for equity funding. The clear connection between quality and perceived entrepreneurial equity pecking order indicates that prior funding choices can act as a quality signal to prospective investors.

From a theoretical perspective, this study contributes to several streams of academic literature. First, it makes an important contribution to the innovation financing literature by enhancing our knowledge on how established and novel crowd-based funding sources interact (Drover et al., 2017b; Kaminski et al., 2016; Moedl, 2018; Shafi & Colombo, 2017; Sorenson et al., 2016). In doing so, the study also contributes to breaking down the "silos" of research on entrepreneurial finance types that developed in the management literature (Bellavitis et al., 2017; Block et al., 2018; Drover et al., 2017a; McKenny et al., 2017). My findings challenge the common perception of a unidirectional positive relationship between crowdfunding and venture capital by indicating that a start-up's turning to crowd-based means of financing may initially be regarded as a negative signal of venture quality by subsequent professional venture investors. While crowdfunding has been suggested as a tool to overcome professional investors' biases and democratize entrepreneurial finance and thus innovation (e.g., Mollick & Robb, 2016), it might in itself be subject to bias.

Second, the analysis extends the stream of research on signaling in venture financing (Amit et al., 1990; Baum & Silverman, 2004; Conti et al., 2013; Haeussler et al., 2012; Hoenig & Henkel, 2015; Hsu & Ziedonis, 2013; Plummer et al., 2016) by adding a new aspect to the signaling framework in the entrepreneurial setting. The perceived negative selection bias toward crowd-based funding I document in this study implies that prior funding can serve as an (additional) quality signal to prospective investors.

Finally, the emergence of new forms of financing and the concomitantly increasingly diverse equity funding landscape require a more nuanced view of corporate finance hierarchies that extends classical concepts such as the pecking order theory (Frank & Goyal, 2003; Myers, 1984; Myers & Majluf, 1984; Vanacker & Manigart, 2010; Walthoff-Borm et al., 2018). This study's insights advance the perception of firms' financing hierarchies beyond the traditional triad profits, debt and external equity. By accounting for heterogeneous types of external equity and providing first-time evidence on the perception of an *equity* pecking order, I extend the boundaries of the pecking order perspective. I hope that my documented findings will further stimulate scholars to investigate the interplay of different means of equity financing.

Managerial Implications

This study may be useful for entrepreneurs, venture investors and policy makers. Entrepreneurs with high-growth ambitions should be aware that venture investors associate their choice of a first means of external equity financing with firm quality. The results indicate that sourcing seed money from the crowd can thus be a double-edged sword; while crowdfinancing provides necessary funds to become "VC ready", it might backfire when it discourages scale up funding as subsequent professional investors see lemons in crowdfunded ventures. In particular, managers of B2B firms should take into account that professional investors tend to treat an initial choice for crowd-based financing almost exclusively as a negative signal of firm quality, whereas they appear to show more understanding for B2C ventures that their business model may be an additional rationale to opt for reward-based crowdfunding. Accordingly, founders should be wary that the funds they gain from the crowd may become an anchor around their neck when they are looking for follow-up venture capital.

The results also have implications for venture investors. As their decision making is oftentimes lead by "gut feeling", investors can take the findings as an empirical basis to compare their own judgments to that of their peers. Finally, fostering entrepreneurship by creating an active market for venture financing is increasingly becoming a focal agenda of governments around the world (OECD, 2017). Policy makers can thus draw from the results to understand the consequences of early-stage funding with regard to the current tendency of regulatory exemptions for new funding alternatives and in order to design their start-up sector support programs.

Limitations and Future Research

The study's limitations offer several opportunities for future research. To begin with, one needs to consider that survey experiments are just simplified models of real-life decision-making. For instance, only a limited number of attributes can be included in the choice design (Mitchell & Shepherd, 2010: 151). While limiting the analysis to only the most important variables from a theory perspective is favorable for the comprehensibility of the survey experiment (as suggested by, e.g., Rossi & Anderson, 1982), I acknowledge that other mechanisms are conceivable, too. For instance, it has been proposed that homophily is a major driver for venture capitalists' syndication decisions when choosing an investment partner (Gompers et al., 2016). Since business angels arguably share more characteristics with potential prospective venture investors than a crowd of presumably laypeople, this might in part explain a (perceived) preference for professional pre-investors. While I cannot exclude that, e.g., such "birds-of-a-feather-flock-together" effects play a role, my analysis clearly indicates that quality-signaling considerations are one important component of venture investors' decision policies. In particular, vignette analysis does not suffer from an omitted variable bias since all the variables not included are set equal in a reference scenario.

Further, decisions made in a choice experiment are never actual choices (revealed preferences), but only stated preferences. The most frequent criticism survey experiments face – that they lack external validity owing to the choice situation not being realistic – is addressed in this study by extensive pre-testing which confirmed that the experimental setting is realistic and understandable. In general, scholars have shown that choice experiments significantly reflect decision policies employed by individuals (Hammond & Adelman, 1976), and in particular by VCs (Shepherd et al., 2003; Shepherd & Zacharakis, 1998). Despite the boundaries choice experiments thus appear to be particularly suitable to expose whether venture investors perceive a hierarchy in approaching equity financing forms by entrepreneurs. Nonetheless, and even though best practices were closely followed, I recognize that every research design choice implies trade-offs. Other methodological tools that counter the limitations of stated choice experiments, such as case studies, represent viable paths to examine venture investors' perceptions of entrepreneurs' financing hierarchies in a complementary light.

Moreover, the research design derives the perceptions of venture investors from their own seed-funding preferences if they were in the shoes of entrepreneurs. While I cannot think of a meaningful explanation why investors should assume that an entrepreneur's rational seed-funding decision should systematically differ – especially since we care about entrepreneurs investors are potentially willing to invest in – this has to be kept in mind when interpreting the results. I considered a more challenging interpretability to be minor compared to an otherwise less intuitive scenario description for respondents. Nonetheless, the findings trigger a question that has not been answered, yet: While I found indication that venture investors *assume* that low-quality start-ups tend to select themselves into crowdfinancing, I do not have evidence whether they really *do*. While I leave this question subject to further research, it is worth mentioning that for a signaling mechanism to be effective, crowdfinancing need not even actually have to suffer from negative selection, it is sufficient if subsequent investors believe so – as I have shown with this analysis.

Finally, for the findings to hold in the long run, venture investors' perceptions need to be consistent with a reality in which crowdfunded projects really perform worse to projects funded by professionals – otherwise, prospective investors' assumptions might change over time. However, as it has been shown that obtaining venture capital increases young innovative firms' chances of survival and growth (Gilbert et al., 2006; Hellmann & Puri, 2002; Sapienza et al., 1996), nowadays' assumptions by professional investors about the inferior quality of crowdfinanced firms might become self-fulfilling prophecy. Yet – and even though the nature of venture capital has been pretty stable (Gompers & Lerner, 2001, 2004) – it could be valuable to check upon my results once crowd-based financing mechanisms might have gained further legitimacy.

Conclusion

This study indicates that venture quality appears to be one discriminatory factor for the rational initial financing choice of entrepreneurs in the eyes of venture investors. In particular, they are prejudiced against crowdfinancing and perceive a negative selection bias: professional venture investors – as potential prospective signal receivers – assume that "lemons" (low-quality start-ups) have a higher relative likelihood than "peaches" (high-quality start-ups) of turning to crowd-based financing as a first means of external equity funding rather than turning to traditional sources. This perceived equity pecking order is a fundamental prerequisite for a negative signaling mechanism of crowd-based financing relative to established sources of funding. The findings provide important implications for entrepreneurs, venture investors and policy makers. Founders need to be aware that their choice of early-stage funding might affect the likelihood of receiving venture capital at a later stage. Venture investors may take the results as a benchmark and interpret them in comparison to their own decision-making. Policy makers, finally, need to understand the consequences of early-stage financing in their pursuit of fostering entrepreneurship by creating active markets for venture financing.

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TABLE 1

Selected demographics of venture investors

Quantitative variables	Obs.	Mean	SD	Min.	Max.
Age	92	44.95	12.05	23	76
Experience (years in startup finance)	94	11.95	8.01	0.5	40
Business model focus (1=only B2B ; 5=only B2C)	94	2.74	0.73	1	4
Phase focus (1=only early stages ; 5=only later stages)	94	2.30	0.91	1	5
average no. of co-investors per investment	91	3.27	5.61	0	50
Bplan rejection rate after first screening (in %)	94	87.50	9.90	30	99.5
Risk attitude (1=totally risk-averse; 11=totally risk-seeking)	94	8.38	1.31	5	11
Self-reported state of knowledge of securities-based crowdfunding (1=none; 5= very good)	92	3.45	1.12	1	5

Nominal variables		Obs.	Freq.	Percent
Sex	male	93	87	93.6%
	female		6	6.5%
Nationality	German	93	89	95.7%
	Austrian		1	1.1%
	American		1	1.1%
	Dutch		1	1.1%
	Swiss		1	1.1%
Education: highest degree	Mittlere Reife/Secondary Education	93	1	1.1%
	Abitur/High School		5	5.4%
	Bachelor		13	14.0%
	Master/Diploma/State Exam.		48	51.6%
	Doctoral degree/Ph.D.		26	28.0%
Education:	Management/Economics	94	72	76.6%
field(s) of highest degree(s)	Engineering		20	21.3%
[multiple response possible]	Natural Sciences		13	13.8%
	Law		5	5.3%
	Other		6	6.4%
Type of venture investor	(Private) VC	94	60	63.8%
[single response]	Business Angel		34	36.2%
Position [only VCs]	Senior (Partner/Principal)	59	42	71.2%
	Junior (Associate/Analyst)		17	28.8%

FIGURE 1

First order choice frequencies for 2 x 2 scenarios

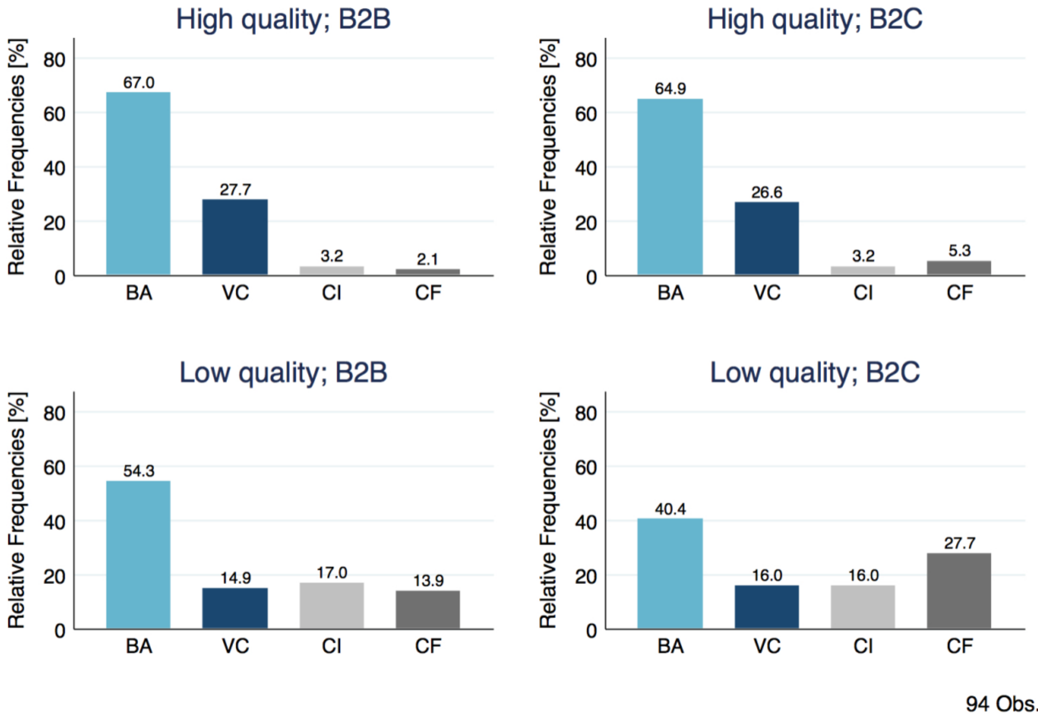

TABLE 2

Results of multinomial logistic regression

	MNL, multinomial log-odds			MNL, relative risk ratios								
	(1)			(2)			(3)			(4)		
	main effects (total sample)			main effects (total sample)			main effects (sample of model 4)			with controls		
Variables	VC | BA	CI | BA	CF | BA	VC | BA	CI | BA	CF | BA	VC | BA	CI | BA	CF | BA	VC | BA	CI | BA	CF | BA
quality	-0.228	1.980 ***	2.086 ***	0.796	7.244 ***	8.049 ***	0.782	7.345 ***	8.173 ***	0.711	8.065 ***	8.901 ***
(high → low)	(0.332)	(0.573)	(0.532)	(0.265)	(4.147)	(4.285)	(0.274)	(4.223)	(4.371)	(0.293)	(4.878)	(5.045)
business model	0.132 **	0.155	0.937 ***	1.142 **	1.168	2.553 ***	1.147 **	1.179	2.577 ***	1.179 **	1.176	2.760 ***
(B2B → B2C)	(0.066)	(0.150)	(0.232)	(0.075)	(0.175)	(0.592)	(0.079)	(0.179)	(0.602)	(0.096)	(0.181)	(0.663)
Gender (female)										0.329	3.648	2.159
										(0.241)	(3.707)	(1.592)
Education (PhD degree)										0.431	0.730	0.489
										(0.228)	(0.487)	(0.272)
Risk propensity [1)]										0.644 **	1.402	0.988
										(0.138)	(0.360)	(0.249)
Investor type (VC)										3.040 **	0.756	1.575
										(1.693)	(0.421)	(0.779)
Years in start-up finance										1.079 ***	0.989	1.006
										(0.031)	(0.027)	(0.025)
Focus b'model [1)]										1.017	1.131	0.689
(B2B→B2C)										(0.253)	(0.419)	(0.169)
Focus phase [1)]										1.534 *	1.115	1.495
(early→late)										(0.343)	(0.323)	(0.401)
CI knowledge [1)]										0.91	1.125	0.787
										(0.206)	(0.285)	(0.179)
Constant	0.385 ***	0.043 ***	0.033 ***	0.385 ***	0.043 ***	0.033 ***	0.381 ***	0.046 ***	0.032 ***	0.081 ***	0.050 ***	0.022 ***
	(0.092)	(0.025)	(0.018)	(0.092)	(0.025)	(0.018)	(0.093)	(0.026)	(0.018)	(0.055)	(0.039)	(0.018)
Model parameters:												
Log-pseudolikelihood			-396.175			-396.175			-385.063			-346.907
Wald Chi²(df)			47.41(6)			47.41(6)			47.61(6)			97.15(30)
Prob > Chi²			0.000			0.000			0.000			0.000
McFadden's pseudo-R²			0.0728			0.0728			0.0755			0.1671
Observations			376			376			364			364

Note: Dependent variable category 'BA' as reference category for multinomial logit model. Robust standard errors clustered by respondent in parentheses. *** p<0.01; ** p<0.05; * p<0.1

[1)] Standardized coefficients, such that they have standard deviations as their units.

TABLE 3

Average and conditional marginal effects

Dependent Variable	Covariate	Representative value	ME		SE	P-value	95% Conf. Interval	
Venture Capital	Quality	**Average marginal effect**	**-0.117**	**	**0.049**	**0.018**	**-0.214**	**-0.020**
	(high → low)	Business model=B2B	-0.101	**	0.050	0.044	-0.200	-0.003
		Business model=B2C	-0.133	***	0.049	0.007	-0.229	-0.037
	Business model	**Average marginal effect**	**-0.000**		**0.008**	**1.000**	**-0.015**	**0.015**
	(B2B → B2C)	Quality=high	0.016		0.012	0.144	-0.005	0.037
		Quality=low	-0.016	*	0.008	0.052	-0.032	0.000
Business Angel	Quality	**Average marginal effect**	**-0.186**	***	**0.066**	**0.005**	**-0.315**	**-0.057**
	(high → low)	Business model=B2B	-0.155	**	0.067	0.021	-0.287	-0.023
		Business model=B2C	-0.217	***	0.067	0.001	-0.348	-0.086
	Business model	**Average marginal effect**	**-0.080**	***	**0.023**	**0.001**	**-0.125**	**-0.035**
	(B2B → B2C)	Quality=high	-0.049	**	0.020	0.013	-0.087	-0.01
		Quality=low	-0.111	***	0.031	0.000	-0.172	-0.05
Crowdinvesting	Quality	**Average marginal effect**	**0.133**	***	**0.038**	**0.000**	**0.059**	**0.207**
	(high → low)	Business model=B2B	0.141	***	0.040	0.000	0.062	0.220
		Business model=B2C	0.125	***	0.037	0.001	0.052	0.198
	Business model	**Average marginal effect**	**-0.005**		**0.012**	**0.656**	**-0.029**	**0.018**
	(B2B → B2C)	Quality=high	0.003		0.005	0.574	-0.006	0.012
		Quality=low	-0.013		0.020	0.504	-0.052	0.026
Crowdfunding	Quality	**Average marginal effect**	**0.170**	***	**0.040**	**0.000**	**0.091**	**0.249**
	(high → low)	Business model=B2B	0.116	***	0.034	0.001	0.049	0.182
		Business model=B2C	0.225	***	0.052	0.000	0.124	0.326
	Business model	**Average marginal effect**	**0.085**	***	**0.019**	**0.000**	**0.047**	**0.123**
	(B2B → B2C)	Quality=high	0.030	**	0.014	0.028	0.003	0.057
		Quality=low	0.140	***	0.036	0.000	0.074	0.206

Obs. = 376; Robust standard errors clustered by respondent. *** p<0.01; ** p<0.05; * p<0.1

TABLE 4

Wald tests for combining outcome categories

Categories tested		χ^2	dF	$p > \chi^2$
VC	**BA**	**0.991**	**2**	**0.609**
VC	CI	19.250	2	0.000
VC	CF	26.791	2	0.000
BA	CI	18.008	2	0.000
BA	CF	28.254	2	0.000
CI	**CF**	**2.967**	**2**	**0.227**

TABLE 5

Results of bivariate logistic regression

Variables	Binomial logit [2], odds ratios (5) main effects (total sample)	(6) main effects (n=364)	(7) with controls (n=364)
quality *(high → low)*	8.162 *** (3.203)	8.317 *** (3.282)	9.150 *** (3.664)
business model *(B2B → B2C)*	1.717 *** (0.246)	1.732 *** (0.252)	1.783 *** (0.268)
Gender (female)			3.193 (2.512)
Education (PhD degree)			0.716 (0.342)
Risk propensity [1]			1.294 (0.255)
Investor type (VC)			0.870 (0.364)
Years in start-up finance			0.979 (0.022)
Focus b'model [1] *(B2B→B2C)*			0.805 (0.170)
Focus phase [1] *(early→late)*			1.223 (0.273)
CI knowledge [1]			0.945 (0.191)
Constant			0.072 *** (0.041)
Model parameters:			
Log-pseudolikelihood	-169.367	-166.045	-159.074
Wald Chi²(df)	37.08(2)	37.09(2)	56.96(10)
Prob > Chi²	0.000	0.000	0.000
McFadden's pseudo-R²	0.1466	0.1503	0.1860
Observations	376	364	364

*** $p<0.01$; ** $p<0.05$; * $p<0.1$

Note: Robust standard errors clustered by respondent in parentheses.

[1] Standardized coefficients, such that they have standard deviations as their units.

[2] Bivariate logit with traditional financing (BA and VC) as reference category versus crowd-based financing (CI and CF).