Badge of Honor or Scarlet Letter? Unpacking Investors' Judgment of Entrepreneurs' Past Failure

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Abstract

Research shows that most ventures fail, yet it has devoted limited attention to the consequences of entrepreneurs' past failure for investors' decisions. Our motivating insight is that failure can be due to bad luck, lack of skill or both. Therefore, failure conveys ambiguous information about skill. We predict that investors will discount entrepreneurs that experienced past failure. However, in the presence of a signal of skill, the magnitude of the failure discount is reduced. We test our predictions using an online experiment where respondents are potential investors in seed stage ventures via equity crowdfunding. Respondents evaluate a realistic investment opportunity in a between-subjects design, where we decompose the effect of failure into luck and skill. Our results indicate that investors discount entrepreneurs who have experienced failure. Past failure in the presence of a signal of skill, however, is not discounted. The findings indicate no discount of failure based on the "failed" label only. Overall, our analysis sheds light on the rationality of investors. In a world where entrepreneurial failure is prevalent, we find that investors are sensitive to its core drivers: luck and skill.

Keywords: entrepreneur, venture, failure, luck, skill, investors, crowdfunding, experiment

INTRODUCTION

Entrepreneurship success is scarce because it requires both a set of entrepreneurial skills and good luck; as a consequence, failure is much more widespread (Gompers et al. 2010). For example, the rate of failure for VC-backed startups within the first five years is around 75% (Bernardo & Welch 2001). Many ultimately successful entrepreneurs have failed in the past (Arora and Nandkumar 2011). The entrepreneurship literature has focused instead on entrepreneurial success, but failure is also worth of scholarly attention per se (Kerr & Nanda 2009). We do not fully understand the pathways through which past failure affects future entrepreneurial activities. The lacuna is noteworthy because failure does not only weed out the incompetent entrepreneurs, but "also threatens or actually overtakes many an able man" (Schumpeter 1942, p. 74). More precisely, we do not know whether investors recognize – and discern – those who fail due to limited skill from those who simply experienced bad luck.

The purpose of this paper is to examine if and to what extent investors distinguish luck from skill in their assessment of an entrepreneur's past failure. When investors evaluate entrepreneurs, they infer their skill from the information available, such as past performance. Entrepreneurial skills (which we simply refer to in the paper as "skill"), are only one ingredient to success, the other one is good luck. Whereas success indicates the presence of both skill and luck (Frank 2016), past failure can be due to lack of skill, bad luck, or both. Because it is often impossible to discern skill from luck, one would expect that, on average, investors will discount entrepreneurs who experienced past failure. If the discounting behavior is rational, one would further expect that in the presence of information about skill, the investor will diminish their failure discount. If the failure discount persists in the presence of a skill signal, one would argue that the investor exhibits a behavioral disutility in dealing with someone carrying the "failed" label. This is what economists might sometimes call "stigma of failure" (Landier 2005).[1]

We test our hypotheses using a "framed online field" experiment (Harrison and List 2004), using a 2x2 between-subjects design. The four treatments differentiate the entrepreneurs leading the venture. One treatment dimension is past failure (due to bad luck) against past

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[1] We are aware of the various definitions of 'stigma of failure' in the different literatures (i.e., most notably sociology and economics), see for instance Link and Phelan (2001). We cautiously use the (always quoted) phrase "stigma of failure" to indicate the phenomenon that investors discount entrepreneurs with past failure, while investors have full information that these entrepreneurs have the skill to succeed but carry the "failure" label, purely due to bad luck.

success in the previous startup experience. The other treatment dimension is information about the role of skill in the performance of the past venture against no information about the role of skill. Respondents with relevant investment experience –we call them "investors"- review an investment opportunity, similar to the ones commonly presented on an equity crowdfunding platform. Each respondent is randomly assigned to one of the four treatments and responds about their willingness to invest and the amount they would invest. The design of the experiment enables us to identify how investors behave differently when observing different combinations of past performance (failure -due to bad luck- or success) and information about skill. Our results document the discounting behavior of investors with respect to their assessment of failure due to bad luck. Investors shun entrepreneurs who experienced failure because it creates ambiguity about their skill. However, when a signal of skill co-occurs, past failure is not penalized. We conclude that there is no "stigma of failure".

Our study contributes to the entrepreneurship literature by shedding light on investors' assessment of past entrepreneurial failure. Our results expand and corroborate earlier quantitative studies about entrepreneurial experience through novel experimental evidence about failure. First, we theorize and test that past failure is not symmetric to past success as an indicator of skill. We identify the costs of failure compared to success and we decompose it into its latent drivers; lack of skill and bad luck. Failure is a less precise indicator of skill and investors discount past failed entrepreneurs due to the greater ambiguity. Second, we measure the impact of past failure on investors' assessment, in the absence – and presence – of further information regarding its root cause. When investors can access further information about skill, the discount due to past failure disappears. Third, through our setting, we provide evidence that crowdfunding investors are not exposed to behavioral biases and they are rational in their investment decisions, alleviating some concerns over investors from new alternative sources of finance (Chemmanur and Fulghieri 2014).

The study is organized as follows. Section 2 reviews the literature and develops theory and hypotheses. Section 3 describes the experimental design, the context and the procedure. Section 4 shows the results. Finally, section 5 discusses our findings and concludes.

THEORETICAL BACKGROUND

We ask the following research question: "Do investors distinguish (bad) luck from skill in their assessment of an entrepreneur's past failure?" We explore whether investors discount entrepreneurs having experienced past failure and further investigate whether the cost of

failure is mitigated by the provision of a signal of skill. In order to answer our research question, we take the investors' perspective. Our theory development follows three steps. First, we present a clear definition of failure. Second, we review the literature on signals in venture financing. Finally, we build on existing theories to derive four hypotheses.

Failure and its roots

To build our theoretical argument, we employ an explicit definition of entrepreneurial failure. We draw on Ucbasaran et al. (2013) and define entrepreneurial failure as the "cessation of the founders' involvement due to discontinuity of operations".[2] Our definition is more conservative than the one in Ucbasaran et al. (2013); it calls not only to the termination of an entrepreneur's employment with the venture, but also for the termination of the venture itself. This working definition exhibit several advantages. First, it avoids confusion about the reasons for the entrepreneur's end of employment with the venture. Put simply, the fact the venture has been terminated is an unambiguous signal of entrepreneurial failure. Second, and relatedly, it is a characteristic of the career history of the entrepreneur that is observable to prospective investors. Finally, it is an empirically observable phenomenon to the academic researcher.

It is noteworthy that the potential causes of failure are manifold. They can be broadly decomposed into two types; failure due to limited entrepreneurial skill, or failure due to bad luck (van Praag 2003, Landier 2005, Gompers et al. 2010). This observation echoes Schumpeter (1942) who claims that failure overtakes "many an able man," suggesting that skill may not be a sufficient condition for success. Below, we present brief anecdotes to illustrate the role of these two factors in entrepreneurial failure. On the one hand, failure can be due to lack of skills, for example poor risk management. Consider Plain Vanilla, an entrepreneurial venture that developed a successful interactive mobile game named QuizUp in 2012. The startup raised $ 40 million in venture capital in four years but was sold in December 2016 for only $ 1.2 million. In a post-mortem analysis, the founder comments:[3]

"We placed our bets on the extensive collaboration with the television giant NBC. One could say that we placed too many eggs in the NBC basket. […] When I received the message from NBC that they were

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[2] Shepherd (2003, p.318) employs a similar definition: Failure is the event when "a fall in revenues and/or a rise in expenses are of such a magnitude that the firm becomes insolvent and is unable to attract new debt or equity funding; consequently, it cannot continue to operate under the current ownership and management".

[3] https://www.cbinsights.com/blog/startup-failure-post-mortem/

canceling the production of the show, it became clear that the conditions for further operation, without substantial changes, were gone."

The founder acknowledged a poor strategy: the lack of effort towards diversifying the client base was at the core of their failure.

On the other hand, failure can be due to bad luck, for example a regulatory change hitting one specific market. Consider HomeHero, a platform founded in 2013 to connect families and caregivers. The platform could offer competitive prices by employing caregivers as independent contractors. In June 2015, the platform worked with 1,200 caregivers and the entrepreneurs raised $ 20 million in Series A funding. Less than three months later, an unanticipated federal regulatory change required HomeHero to treat the caregivers as employees and not contractors. The regulatory shift raised the costs for users, forced the platform to become an employer of caregivers, and resulted in termination of 95% of the contracts with caregivers. By the end of February 2017, HomeHero ceased its operations. Absent the federal regulatory change, HomeHero had a competitive advantage common to many marketplaces and would have survived.

Understanding the roots of failure -- either bad luck, lack of skill, or both – is important to make inferences about the skill of the entrepreneur and to judge the likelihood of success in subsequent startup endeavors.

Signals in Venture Financing

Investors in entrepreneurial ventures face substantial problems due to information asymmetries (Hsu 2007, Chatterji 2009). In particular, entrepreneurs have private information about their skills that investors cannot observe. As a consequence, investors have difficulty to assess the quality of a startup and they necessarily rely on whatever signals are available about the entrepreneurs and their proposed venture (Stuart et al. 1999).

The literature identifies a number of signals of skill. Patents are a notable example. They are costly to obtain and it is virtually impossible to obtain them when the required knowledge base and the necessary funds are absent. Therefore, investors can use entrepreneurs' patent ownership to make inferences about the value of the venture and its underlying knowledge base (Hsu and Ziedonis 2013, Conti et al. 2013).

Signals are not limited to the firm but can also pertain to the entrepreneurs' social and human capital. Entrepreneurs with higher levels of social capital are more likely to have prior ties to investors and they can access resources more easily (Stuart et al. 1999, Hsu 2007). Entrepreneurs with higher levels of human capital have better industry employers. Affiliation to prominent employers related to informational advantage (Higgins and Gulati 2006) and better industry knowledge (Chatterji 2009). Thus, entrepreneurs with desirable characteristics in their social and human capital can leverage it to signal higher skill.

Although entrepreneurial failure is commonplace, we have limited understanding of its signaling implications. It is often implicitly assumed that, since past success is a signal of skill, past failure signals the absence of entrepreneurial skill (Gompers et al. 2010). Hochberg et al. (2014) explicitly argue that when failure occurs frequently, investors are more likely to infer lack of skills to justify it. Building on the previous section, we note that failure may be due to the lack of skill, but may also be the result of bad luck. It follows that the inferences about entrepreneurial skill from observing entrepreneurial failure are more ambiguous. Of course, if an entrepreneur has failed many times, the likelihood of the entrepreneur lacking skill is very high (Hochberg et al., 2014). However, most entrepreneurs fail only once or perhaps twice. In this very common case, the failure event is a noisy signal of lack of entrepreneurial skill. Indeed, Eggers and Song, (2015), make a related assertion that the implications of past failure are not simply a mirror of past success.

So far, the existing literature has remained relatively silent on the information value of past failure. We theorize that the information value of past failure is not symmetric to past success. In the remainder of this section, we develop a parsimonious framework and four hypotheses.

Theory Development

We assume that entrepreneurial success requires both luck and skill.[4] It follows that investors perceive an entrepreneur who was previously successful, as endowed with skill. That is, success unambiguously identifies a high level of skill.[5] Investors are faced with a more

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[4] We find empirical support for this assumption in our experiment (when testing hypothesis 3). Of course, we realize that in real life there are exceptional cases in which succes can sometimes be due an entrepreneur having good luck but low levels of skill (or vice versa).

[5] In this framework, we refrain from considerations about learning. We further assume that investors believe that the learning experiences of past failed and past successful entrepreneurs are similar (Arora and Gambardella 1997, Minniti and Bygrave 2001). Empirical studies provide support for the fact that learning takes place under failure too (Chen 2013, Eggers and Song 2015).

ambiguous signal in the presence of (one event of) past entrepreneurial failure. It may be due to an entrepreneur's lack of skills (e.g., Plain Vanilla developed a poor strategy by "placing too many eggs in one basket"), or to bad luck (e.g., regulatory shock inflected on HomeHero), see Table 1.

*** INSERT TABLE 1 HERE ***

Absent any information about entrepreneurs' skills, investors tend to rely on observable information. For instance, Pope and Sydnor (2017) show that investors on a crowdfunding platform charge differential interest rates to distinct groups of borrowers, based on their beliefs about the repayment skills of these groups. They infer repayment skills from observable characteristics of each group, namely from the borrowers' pictures. Once investors receive less ambiguous information, the discount or premium associated with group membership tends to decline or disappear (Altonji and Pierret, 2001). If investors discount failure because of its information about skill, they should not discount failure due to bad luck when a signal of skill co-occurs. In other words, the discount of failure originates from its ambiguity. Thus, we hypothesize:

Hypothesis 1. Investors attach a lower value to venture proposals by entrepreneurs with past failure experience than by entrepreneurs with success experience, in the absence of additional signals of skill.

Hypothesis 2. Investors attach a higher value to venture proposals by entrepreneurs with past failure experience in the presence of a positive signal of skill than in the absence of such a signal.

And while past success inevitably signals skills, past failure does not. The key insight is that bad luck can lead to failure even in the presence of entrepreneurial skill. It follows that if the investor obtains an independent and credible signal of entrepreneurial skill, they will be able to discern the root cause of the failure and correctly attribute it to bad luck. In other words, a signal of skill may change an investor's perception of an individual who experienced past entrepreneurial failure. On the contrary, a signal of skill will have no effect on the perception of entrepreneurs who have experienced success. We hypothesize:

Hypothesis 3. The positive effect of a signal of skill on an investor's evaluation of a venture proposal is higher given past failure experience (due to bad luck) than past success experience of the entrepreneur.

Please note that if the additional information content of a signal of skill in case of past success is zero, there is support for the assumption that success requires both skill and luck. More precisely, the assumption is actually shared by investors.

The hypotheses so far are based on the assumption that investors incorporate entrepreneurial signals rationally in their behavior. This is not necessarily the case. For instance, investors may have a low tolerance for failure, irrespective of its cause and assign a cost to failure *per se* (Tian and Wang 2014). Regardless of the information about skill, investors may still discriminate entrepreneurs carrying the "failed" label. Discrimination theory defines this phenomenon of intrinsic discount as taste-based discrimination (Altonji and Pierret 2001), while the theory about "stigma of bankruptcy" documents discounting behavior irrespective of the observed qualities of the stigmatized individual (Sutton and Callahan 1987). Therefore, we hypothesize:

Hypothesis 4. In the presence of a positive signal of skill for entrepreneurs with past failure (due to bad luck), investors still evaluate the venture proposal of entrepreneurs who experienced failure in the past to be of lower value than equal proposals of those with success experience.

In the next section, we discuss the experiment we have designed to test these four hypotheses.

EXPERIMENT

Context

The setting of our experiment is the equity crowdfunding market in the United Kingdom. Equity crowdfunding is a particular form of crowdfunding where ventures ask capital to a pool of small investors in exchange of equity through an online platform (Ahlers et al., 2015). Equity crowdfunding is a desirable setting for four reasons.

First, ventures on equity crowdfunding platforms are usually in their seed stage, where information asymmetry is largest. Second, crowdfunding platforms are characterized by a limited impact of traditional constraints such as geography (Agrawal et al. 2015) and, to some extent, to social capital too (Dushnitsky and Klueter 2011). Third, traditional investments in entrepreneurial ventures such as by business angels and venture capitalists are dynamic and

hard to capture in an experiment. Crowdfunding platforms are more static and investors have a lower degree of involvement after their investment decision (Chemmanur and Fulghieri 2014). Fourth, investors' reactions to information provided seems similar to traditional resource gatekeepers (Mollick and Nanda 2015). Finally, unlike other types of crowdfunding platforms like Kickstarter or Kiva, which are reward and donation-based, investments on equity crowdfunding platforms are driven by financial considerations only (Cholakova and Clarysse 2015).

We run our experiment in the United Kingdom because it is the largest and most developed market for equity crowdfunding at the time of writing. In 2015, the market for equity crowdfunding of UK was estimated between £167 million and £330 million (Crowdfundinghub 2016), while the market in the US was estimated around $34 million.[6]

Design

We design a randomized 2x2 (plus one) between-subjects experiment. Respondents who evaluate an investment opportunity are randomly assigned to one of the four treatments. A treatment consists in a controlled manipulation of the previous startup experience of the team (failure, success) in combination with or without a signal of skill. We complement these four manipulations with a baseline with no experience and no signal of quality.

Respondents are not only randomly assigned to one of the four (plus one) treatments, but also to one of two investment opportunities that we selected from an established equity crowdfunding platform. In an attempt to control for the quality of the actual venture, we selected one successful and one unsuccessful venture. Both ventures are digital platforms, one dealing with restaurant bookings and one dealing with rental of storage space. The successful project asked for £ 350,000 and the unsuccessful £ 150,000, for an equity share of 19% and 17% respectively. These values are similar to the average requested amount on the platform (Vulkan et al. 2016). For privacy concerns, we anonymized the names of the ventures, the names of the entrepreneurs, and their faces. We informed respondents about this anonymization.

In order to implement our treatments and make the remaining characteristics of the proposals identical across the treatments, we edit the two original investment proposals. We restrict the

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[6] Source: http://www.inc.com/ryan-feit/equity-crowdfunding-by-the-numbers.html The US market grows slowly due to a sluggish regulatory process (Bruton et al. 2015).

size of the founding team to two members, the most common team size (Coad and Timmermans 2014). We label one entrepreneur with managerial background as CEO and the other entrepreneur with technological experience as COO. In this way, we control for confounding elements like team composition (Beckman et al. 2007) and symbols like the job title (Zott and Huy 2007). A further manipulation in the team section makes sure that each of the entrepreneurs in a team had their previous experience in the same startup for two years. The information about the past startup is limited to its name, suggesting that the past venture was in the same industry as the proposed one.

Respondents read about the venture in three sections: business idea, founding team, and Q&A (see Appendix Figures A1-A3). These three sections represent the essential information available to an investor on an equity crowdfunding platform. The first section is an executive summary of the business idea and provides information about the business model, the market, the use of proceedings, and the milestones achieved. It states the requested amount, the amount per share, and a pre-money valuation of the business (Figure A1). The second section looks like a short resume of each of the two entrepreneurs. Respondents read about the entrepreneurs' education, their alma mater, and the year of graduation. Investors also observe entrepreneurs' last employer, the associated job title, and the past venture they founded (Figure A2). The third section is a Q&A wall, a common feature on crowdfunding platforms (Mollick 2014). The Q&A section (Figure A3) is important because it allows investors and entrepreneurs to interact publicly. Investors request information or challenge them before making their investment decision. Entrepreneurs usually tend to respond timely and sincerely because of the public nature of the Q&A section. No answer or dodging the questions might undermine their fundraising effort. This disclosure induced by third parties in a public space is typically perceived as more reliable information than self-reports of past performance (Gomulya and Mishina 2017).

*** INSERT TABLE 2 HERE ***

The Q&A section is the best place where information about past failure can be credibly revealed. Thus, our treatments are based on the question of a fellow investor about the outcome of the early venture the team founded before.

For the information about past success or failure due to bad luck, we combine a closed form question about the venture's outcome (either positive or negative) with an open question to disclose the reason. The closed form for the type of outcome controls for decoupling attempts

through grammar and linguistics (Crilly et al. 2016). In the failure treatment, the entrepreneur selects the failure option in the closed form and explains that the startup "ran out of business because [their] main business partner, key to the previous business, died in a car crash". Thus, we mimic bad luck by choosing a scenario as exogenous as possible. In the case of past success, the entrepreneur selects the success option in the closed part of the answer and explains that the past venture "was successfully sold for £ 500,000." While the sum does not represent an exceptional success (Groupon reached the valuation of $ 1.35 billion in two years), we chose an amount that would not bias the perception about the additional liquidity and resources of the entrepreneurs.

For the information about skill, the answer to the open question includes an additional sentence where we provide information about the performance of the past venture before its exit: "[the past startup's] sales trajectory was growing double digit when, [success/failure occurred]." We prefer this one over other more established signals like intellectual property (Conti et al. 2013, Hsu and Ziedonis 2013) because previous research has shown that these are ineffective signals in the equity crowdfunding setting (Ahlers et al. 2015). Table 2 shows an overview of how the four treatments are revealed in the Q&A section: a dimension for past failure versus success (rows) and a dimension where a signal of skill is absent versus present (columns).

Procedure

We recruited our respondents on Prolific, an online UK-based platform for survey and experiment tasks, the highest quality platform at the time of our writing (Peer et al., 2017).[7] We offered a monetary compensation of £ 1, the average payment for an 11 minutes task on Prolific.[8] For the selection of target respondents, i.e, people with investment experience or willing to invest in crowdfunding in the near future, this is a very small, probably negligible incentive. Compared to other platforms like Mturk, Prolific focuses on scientific studies and offers its participants to "help advance human knowledge." Intrinsic motivation may partially compensate for incentives.

We applied a prescreening of subjects living in the European Union or the United Kingdom who had investment experience in the past. We recruited 600 prescreened respondents who

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[7] The experiment is available through http://goo.gl/cxSNep
[8] Initially we had the idea of incentivizing investors by rewarding correct estimates of the percentage pledged for the business case on the real equity crowdfunding platform. However, due to the manipulations to the team composition, a truthful comparison was impossible and we decided to refrain from implementing further incentives.

opened the questionnaire including the business proposal and answered questions about their investment decision and socio-demographic information. After their responses about investments and before providing their background information, respondents answer two attention checks in order to screen out those who answered carelessly.[9] We further excluded those whose completion time was two standard deviations below and two standard deviations above the average due to a possible lack of attention or focus. Finally, we excluded respondents providing inconsistent information (e.g., being professional investors at the age of 18 or opposite gender to the one reported to Prolific). All in all, this resulted in a valid sample of 328 respondents.

In the introductory part of the experiment, respondents are informed about the object of the study and the fictitious nature of the investment task. On the next page, subjects read the three sections about the venture: idea, team, and Q&A. In order to discourage subjects from searching the projects online, these anonymized pages are presented in "png" format.

After reading the venture description, respondents answer questions about their investment choice. Respondents answer whether they would consider investing in the venture, and, if so, how much money. Moreover, a closed-form question requires respondents to rank potential drivers of their investment, i.e. the market, the business idea, or the entrepreneurial team.

We further collect information about respondents' behavior related to financial decision making in general; about their private and professional past investments, and their participation both as a backer and requester in crowdfunding platforms. We administer respondents' risk aversion based on a non-incentivized version of the multiple price list elicitation method, where respondents choose between a risky lottery ticket and a certain equivalent (Holt and Laury, 2002). A final block of questions administered respondents' socio-demographics, to be used as control variables in the analysis. Beyond information such as age, gender, education, employment status, and location, we added a question about house ownership as a proxy of wealth. To avoid a bias due to the sequence of responses, the order in which response possibilities for all closed form questions are shown is randomized.

Investors as Unit of Analysis
We are interested in the investor's perspective. In this section, we provide three reasons to motivate such perspective as a desirable unit of analysis both theoretically and empirically.

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[9] We allowed for the use of a "back" button so that respondents could reread information.

First, they are the key stakeholders of a startup in a seed stage: capital and liquidity can be vital resources for ventures still lacking operations and a customer base. Second, investors' perspectives are the earliest "hard" indicator we can study: convincing investors and obtaining finance is one of the first goals of early stage startups that is fundamental to achieve growth. Earlier experimental studies (Brooks et al. 2014, Hoenig and Henkel 2015) and studies in finance and strategy (Hsu 2007, Chatterji 2009) widely adopted investment propensity as their focal outcome variable. Third, those who invest in equity have an unbiased view on the proceeds of the venture, unlike entrepreneurs themselves, who may have different motives such as enjoying non-pecuniary benefits like autonomy or status (Sauermann and Roach, 2015). These motives may stifle the acceptance of failure.

All in all, the investors' perspective is a tractable and timely variable for seed stage ventures[10]. We will study the investors' behavior both on the extensive and the intensive margins. Thus, our main outcome variables of interest are the investor's willingness to invest in a given venture and the amount invested in the venture.

Variables

Dependent variables. We operationalize subjects' investment decisions with two variables. The first variable is a Likert scale derived from the questionnaire indicating subjects' likelihood to invest in the venture on a scale from 1 to 5. This variable represents the extensive margin. The second variable represents the hypothetical amount invested (if any). We performed winsorization of the variable at the 95th percentile to mitigate outliers' effect. The 95th percentile of the variable is £ 2,000. This variable represents the intensive margin.

Treatment variables. Each but one of the experimental conditions may be represented by a dummy variable, namely (b) "Failure, no signal of skill"; (c) "failure, signal of skill"; (d) "Success, signal of skill", whereas the condition (a) "Success, no signal of skill" is the baseline. Also, we include "No Experience" for completeness. The effect on investors' evaluations of each of the treatments (b), (c), and (d) is estimated in comparison to the baseline condition (a), "Success with no signal of skill" to be able to test hypotheses.

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[10] Alternative performance measures of startups like revenues, revenue growth and size are lagging indicators of performance. They would require a longer time for ventures to be realized or researchers should rely on forecasts or simulations. For example, Hoogendoorn et al. (2013) study the effect of gender diversity in teams of students. Their measure of sales and profits appears after one year and ventures are liquidated afterwards.

In order to test *Hypothesis 1,* we compare the conditions (a) and (b). Since the baseline is (a), the coefficient (b) < *0* would lend support to Hypothesis 1. In the absence of additional signals, investors attach a lower value to entrepreneurial proposals by entrepreneurs with past failure experience (due to bad luck) than by entrepreneurs with successful experience.

To test *Hypothesis 2* we compare the coefficients *(b)* and *(c)*. Meeting the condition *(c) – (b) < 0* would lend support to *Hypothesis 2*. Investors attach a higher value to entrepreneurial proposals by entrepreneurs with startup failure experience in the presence of a positive signal of skill than in the absence of such a signal.

Support for *Hypothesis 3* comes down to *(c) – (b) > (d)*. The positive effect of a signal of skill on an investor's evaluation of an entrepreneurial proposal is higher given past failure experience (due to bad luck) than past successful experience of the entrepreneur.

In the same fashion: *(c) – (d) < 0* would lend support to *Hypothesis 4*. In the presence of a signal of skill for entrepreneurs with past failure (due to bad luck), investors still evaluate the entrepreneurial startup proposal of these entrepreneurs to be of lower value than equal proposals of those with success experience.

Control variables. All models include a dummy variable for the successful project. We further control for all sociodemographic characteristics, risk aversion, place of residence (London and Outside UK dummies), and professional investment experience. We also control for a full set of dummies for experience in crowdfunding investment (ranging from 1 "never invested and not interested" to 4 "serial investor").

RESULTS

Descriptive Statistics

Table 3 shows the descriptive statistics of the experiment. The first two rows of Pane A describe the dependent variables. Our respondents are on average likely to consider investment in the opportunity offered (3.6 out of 5) and they would invest on average 300 pounds, which is close to the amount surveyed on a major equity crowdfunding platform in the UK (Vulkan et al., 2016). The rest of Panel A describes the control variables. Respondents are on average 37 years old, 84% of them have at least college education, and their risk profile is quite conservative, 3.2 out of 10. Slightly more than half (56%) own their house. The share of males in our sample, 57%, is similar to the share of male backers detected on other major crowdfunding platforms,

like Kickstarter (Greenberg & Mollick, 2016). Looking at the geography, 13% of the sample live outside the UK and 15% lives in London.

Pane B of the table reports crowdfunding experiences and attitudes of the participants. Panel A already showed that 14% of respondents has professional investment experience. Because we excluded from the sample investors who reported to be "not interested" in all the categories of crowdfunding, we have limited the sample to those "at risk of investing" in crowdfunding, of any sort. The average profile of our sample shows a selection of wealthier and more educated individuals, traditionally more "at risk" of investing in equity and crowdfunding.

*** INSERT TABLE 3 HERE ***

In Table 4, we report the variables of interest along our experimental treatment. We check whether attrition has unbalanced the samples. The number of respondents who passed the attention check is lower for the conditions with the skill signal. The skill signal required reading and understanding an additional question, which raised the bar for passing. The samples are relatively balanced though in terms of the distribution of characteristics of respondents. Within some pairs of the main treatments, differences are present in terms of age, education, wealth, and foreign status, but mainly compared to the benchmark "treatment" of no experience (which required even less reading and understanding). Due to the attrition, we control for the unbalanced variables in our regression estimations (King et al., 2011).

*** INSERT TABLE 4 HERE ***

Main Results

Table 5 shows the results of the experiment. All the specifications are OLS regressions with robust standard errors.[11] The baseline is the condition (a) "Success without Signal of Skill". Specifications w.1 to w.3 estimate effects on the extensive margin, i.e., the likelihood of investing. Specifications s.1-s.3 estimate the intensive margin – the amount invested. Each specification includes a dummy controlling for the higher quality. The positive and significant coefficient of project quality in each specification indicates that the respondents we pooled

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[11] Because of the nature of the data (ordered categorical variable for investment propensity, count variable for amount invested), we also replicated the specifications using ordered logit regression and negative binomial regression with no substantial difference in the results. Due to space constraints, the results are available on request.

behave similarly to the investors on the equity crowdfunding platform we used. Specifications s.1 and w.1 include no further controls. specifications w.2 and s.2 include controls balancing the variables that were different across manipulations (King et al., 2011), and specifications w.3 and s.3 include additional controls at the investor level.

*** INSERT TABLE 5 HERE ***

We intended to use the condition "No experience" as a control. The results compared to the baseline (a) are not significant across all specifications. We cannot infer meaningful comparisons from this condition because of confounding elements. Individuals with no entrepreneurial experience for two years (negative effect) compensate with extra industry and functional experience (positive effect) as employees. This could explain the negative yet insignificant effect both on the extensive and the intensive margin. Therefore, we will focus our attention on the four treatments with entrepreneurial experience that we need for testing our hypotheses 1-4. The results from testing these hypotheses are shown in Table 6.

*** INSERT TABLE 6 HERE ***

In order to test *Hypothesis 1,* we compare the conditions (a) and (b). The coefficient (b) < *0* would lend support to Hypothesis 1 since (a) is the benchmark. As Table 5 shows, failure without any signal of skill (b) has a negative effect both on the extensive and intensive margin. For the extensive margin, the negative coefficient becomes significant once we balance the samples by using controls. Investors give a lower average score ranging between 0.37 and 0.39, which is around 10% of the baseline. For the intensive margin, the coefficient is consistently negative and significant. Investors would apply a discount between £ 140 and £ 185, which is around 47% and 62% of the baseline. This lends support to Hypothesis 1, see Table 6.

To test *Hypothesis 2,* that a signal of skill reduces the discount of failure, we compare coefficients *(b)* and *(c)*. Meeting the condition *(c) – (b)* < 0 would lend support to *Hypothesis 2*. In Table 5, we observe that the coefficient (c) is not significant compared to the baseline condition (a) past success. Since the coefficient (b) is negative and significant across specifications, there is qualitative evidence supporting Hypothesis 2. Table 6 formalizes the comparison. We compare coefficients using a Wald test and find strong empirical support to Hypothesis 2. The only exception is specification w.1, which suffers from the randomization unbalance.

Table 5 provides intuitive evidence supporting *Hypothesis 3*, i.e., the positive effect of a signal of skill is higher given past failure experience (due to bad luck) than past successful experience: *(c) – (b) > (d)*. The additional signal of skill reduces the discount due to past failure, turning the effect of condition (c) not significant. However, condition (d) is not significantly different from condition (a). The additional signal of skill does not add any premium to past success. In Table 6, we compare the differences formally. The evidence is less strong but significant in our third specifications: the significance holds for the extensive margin ($p<0.10$ for the specifications controlling for investors' characteristics) and less for the intensive margin (s.2 would be significant with a one-tailed test, and only s.3 has $p<0.05$).

Results from Hypothesis 3 are particularly interesting as they show validity of our assumption. Earlier, we assumed that success requires both skill and luck. The insignificance of condition (d) suggests that investors do not perceive that success can take place due to good luck only. If this were so, additional information about skill would be beneficial. Indeed, the coefficient (d) in the first three columns of the upper panel of Table 6 is insignificantly different from the baseline case of previous success with no signal of skill. This implies that investors attach no value at all to the signal of skill in the case of business success.

Finally, we test the "label" or "stigma" hypothesis, i.e., *(c) – (d) < 0*. When past failure is due to bad luck and information about skill is available, a discount of failure compared to success suggests disutility in dealing with "failed" entrepreneurs. The results from Table 5 compare the two conditions (c) and (d): both are not significantly different from the condition (a) of past success with no information. In Table 6 we test and find no difference between conditions (c) and (d), i.e., when information about skill is available, the "failed" label carries no discount. We reject Hypothesis 4.

Additional Analysis

We identify two possible mechanisms underlying our results by estimating two alternative specifications. A third alternative specification addresses the role of perceptions. Table 7 reports the formal testing of our four hypotheses as in Table 6, but using the three alternative specifications.[12]

A first alternative mechanism that drives the result that failure due to bad luck is not punished (when there is a signal of skill) is compassion. Investors could feel compassioned about the

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[12] The underlying regression table can be found as Appendix Table A1.

exogenous failure and give entrepreneurs a second chance. This behavior could especially make sense in a setting where sense of community plays a role for investors (Agrawal et al., 2014). If compassion drives the results, once controlling for it, the effect of the signal of skill should be null for past failure. We do not have information about investors' compassion, but we can control for reciprocity (Colombo et al., 2015). Entrepreneurs who raised crowdfunding money tend to back others' campaigns as they perceive mutual identification and share a supportive behavior towards peers (Butticè et al., 2017). In models wr.1 and sr.1 table 7, we test the hypothesis from a supplementary specification with a full set of dummies for each crowdfunding experience of investors as a pledger. The results for our experimental conditions do not change substantially, suggesting that compassion is not likely to be the driving force of our results.

A second potential mechanism is similarity bias. This bias originates from the raters' tendency to favor disproportionally similar individuals (Byrne, 1971). Unobserved heterogeneity in raters' experiences could be the driver of our results. If this were the case, we would observe our coefficients lose size and significance after controlling for similarity. Past literature showed presence of this bias among venture capitalists in terms of functional and industry background (Franke et al., 2006). In order to take this into account, we create a set of four dummy variables, two controlling for the team and two for the industry. One variable takes on the value one if the investor has the same study background as one of the founders (business administration or computer science) and zero otherwise. Another variable indicates if the team characteristics (rather than industry or business idea) drove the investment decision. Together, these two dummy variables should control for the similarity between investors and teams in their functional background. We further create one dummy variable that takes the value of one if the industry experience of the investor matches the industry of the projects and zero otherwise. Also, we controlled for whether the investor's decision was driven by industry consideration (opposed to team or business idea). We use this set of dummy variables as an indicator of the similarity between investors and the industry of the investment proposal. We find some evidence of similarity bias due to industry experience (see Table A1 of the Appendix). However, Table 7 shows that controlling for it does not affect the results in support of our hypotheses.

Finally, we investigate whether investors' perceptions are driving the results by using perceived instead of actual treatments as alternative explanatory variables. We used the response to the attention check about the outcome of the past venture rather than our treatment. By incorporating the people who failed the attention test, the sample increases to 526 respondents. The size of the coefficients of interest do not change substantially, but the estimates are more

precise, probably due to the larger sample (see Table A1 in the Appendix). Table 7 shows overall support for our earlier findings using the perceived rather than the actual treatments. What investors perceive turns out to be an important explanation of the discount of failure. This adds credibility to the findings and the robustness of our results.

Overall, our main results keep standing. Discount of failure seems to originate from ambiguity over the founder's skill (Hypothesis 1). Information about founders' skill has an effect in removing any discount (Hypothesis 2). We found also evidence of the effect of the signal of skill to be more effective under failure than under success (Hypothesis 3). The fact that the signal of skill has actually zero value with past success confirms our assumption that investors do not perceive success with good luck and poor skill as a possibility. Finally, we found no evidence of discount due to the "failed" label only (Hypothesis 4).

DISCUSSION AND CONCLUSION

Failure is the most common feature of entrepreneurial life. Yet, we have little evidence about how critical resource providers – investors – judge the founders' past venture experience. If investors misattribute failure to lack of skill, it may prevent skilled yet once unlucky entrepreneurs from re-entering entrepreneurship (Landier 2005, Eberhart et al. 2017). Moreover, to the extent that innovative and exploratory ventures are the ones more likely to fail (Manso 2011, Tian and Wang 2014), the ultimate outcome may impede the pace of innovation. Accordingly, this study seeks to understanding investors' perception of failure. We have studied the consequences of failure experience for the likelihood of obtaining finance and the amount received for a subsequent venture in an experimental study.

In our framework, we start from the assumption that success requires both luck and skill (Frank 2016) while failure can result from bad luck or lack of skill. Consequently, success is an unambiguous signal of skill and failure is ambiguous. Failure "threatens or actually overtakes many an able man" (Schumpeter 1942 p. 74) and pools them with people lacking skill. Even in the case of obvious bad luck, investors are not certain about the skill of the entrepreneurs.

How do investors judge past failure of entrepreneurs? We argue that, on average, investors will discount entrepreneurs who experienced past failure because of ambiguity over entrepreneurs' skill (Hochberg et al., 2014). When investors observe an additional signal of skill, the discount may decreases or even disappear. These predictions suggest that investors are rationally using

failure to infer skill. We also acknowledge the possibility that investors may discount entrepreneurs who failed in the past (even when it was solely due to bad luck) even when they receive information about their skill. Such behavior would highlight something similar to a "stigma of failure" (Landier 2005).

Testing our theory and teasing out skill and luck in an observational dataset would be challenging, We overcome limitations of an observational dataset via a framed online field experiment (Harrison and List 2004) that matches treatments to our hypotheses. We exploit the setting of equity crowdfunding in the UK because it maximizes tractability and generalizability at the same time. We run our experiment on respondent who had investment experience, invested, or consider investing in crowdfunding.

The results confirm our hypotheses about the information content of failure. Entrepreneurs who have experienced failure due to bad luck obtain lower valuations than past successful entrepreneurs. However, when a positive signal of their skill is provided, the penalty vanishes and previously failed entrepreneurs are not valued differently than previously successful entrepreneurs. We find no evidence of "stigma of failure". Rather than failure per se, investors rationally discount ambiguity over skill.

Our study answers a call for a better understanding of persistence in entrepreneurship (Gompers et al. 2010). We provided a theoretical and empirical assessment of past entrepreneurial failure for investors. Our theory provides a fundamental insight about the information past failure reveals: it is not symmetric to past success and it is more ambiguous. Investors can discount past failure either due to the ambiguity over skills or due to the "failed" label. We show that information about failure is not negative when an additional signal co-occurs.

Through our setting, our study also contributes to the literature about equity crowdfunding platforms. Our results about the rationality of investors contribute to build an argument for the "wisdom of the crowd" (Mollick and Nanda 2015). Professional investors seem to be aware of sheer bad luck as cause of failure[13] (Cope et al. 2004). Similarly, equity crowdfunding investors recognize that failure may take place due to bad luck only and do not discount it. This alleviates concerns over small uninformed investors the entrepreneurial finance literature pointed out (Chemmanur and Fulghieri 2014).

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[13] https://about.crunchbase.com/news/heres-likely-startup-get-acquired-stage/

Finally, our results about the rationality of seed stage investors are informative to other related literatures. For example, we did not find anything that could recall the "stigma of failure" (Sutton and Callahan 1987). In other words, we performed a test of discrimination against entrepreneurs with bad luck by investors. If the discount of past failure had not been removable, it would have been taste discrimination. Because the discount of past failure goes away with additional information about skill, it is due to statistical discrimination (Aigner and Cain 1977, Altonji and Pierret 2001). This is one of the first experimental studies testing for type of discrimination (Pope and Sydnor 2011).

Our study has some relevant boundary conditions. First, it may be that our finding that investors do not discount the "failed" label only applies to small startups at the seed stage, only involving the entrepreneur and investors. There might be cases where "stigma of failure" bites harder like in mature firms that involve layoffs, losses for pension funds, and other damages to society. This would reconcile our results with findings about lower quality of stakeholders for entrepreneurs who experienced bankruptcy (Sutton and Callahan 1987). We expect, though, that failure due to bad luck at later stages when the firm grows, becomes progressively less likely.

Second, our experiment tests for investors' evaluation of the second attempt of an entrepreneur. It may be that investors make different decisions depending on the degree of the founders' persistence in terms of number of attempts (Fontana et al., 2016) or length of the spell (Parker, 2013). Longer spells could make the information about the skill stronger, while more past ventures could make the inference about skill from failure more reliable as consecutive failures due to bad luck are less likely. Further research could investigate differential effects based on the spell of past entrepreneurship or the number of earlier attempts.

Third, the study focuses on investors based in the United Kingdom. By and large, there are country and regional differences in how failure is perceived (Saxenian, 1996). Our results are based on a country where the literature reports lower levels of failure tolerance compared to the United States (Cope et al., 2004). Thus, these results are a conservative estimate. We argue that a replication in the United States would strengthen our findings or we could even find a premium when past failure occurs with information about skill.

Finally, our information about skill is far from being a signal in the Spence (1973) sense. It was not costly and easy to imitate. We expect that with a proper credible signal of skill the results would be even stronger. However, our findings show that perception of failure and skill is what drives the results. Individuals used information that is rather weak to form perceptions that

shaped their investment decision. This finding echoes the research of Ambuehl and Li (2014), where they found that individuals over-value low quality information.

Our results have implications for both entrepreneurs and platform owners. At the seed stage, entrepreneurs may choose to be less reluctant about disclosing past failure. Past failure disclosure should be accompanied by an adequate signal of skill. We obtained our results using a rather weak signal of skill and we expect larger effects with stronger signals. The discussion as to whether and how to reveal previous failure experience to investors is an actual one among entrepreneurs. In an interview, Matthew Cain, author of the book "Made to Fail – 13 Surprising Start-up Lessons", discusses how to report business failure and suggests[14]: "A start-up failure can be an interesting conversation with the right person. But it isn't necessarily. Because failing doesn't necessarily teach you anything. You'll have to persuade the recruiter of what you learnt – and that it's valuable for their business". The advice recommends that failure disclosure needs to occur in a conversation and that some additional information needs to co-occur.

This study may offer insights to equity crowdfunding platforms. The way to mitigate the cost of failure is to provide opportunities for less noisy signals that contribute to reduction of information asymmetries. Platforms can improve the design and the options for interaction between investors and founders on the platform. Platforms should allow for certified skill signals from founders or "safe spaces" where disclosing past failure may increase the investment opportunities for the entrepreneur.

We showed that ambiguity about skill is the main driver of discount of past failure. All in all, conditional on more information about skill, founding teams run by entrepreneurs who failed in the past can carry their past failures as a badge of honor rather than a scarlet letter.

REFERENCES

Agrawal, A., Catalini, C., & Goldfarb, A. (2015). Crowdfunding: Geography, social networks, and the timing of investment decisions. *Journal of Economics & Management Strategy*, *24*(2), 253-274.

Agrawal, A., Catalini, C., & Goldfarb, A. (2014). Some simple economics of crowdfunding. *Innovation Policy and the Economy*, *14*(1), 63-97.

Ahlers, G. K., Cumming, D., Günther, C., & Schweizer, D. (2015). Signaling in equity crowdfunding. *Entrepreneurship Theory and Practice*, *39*(4), 955-980.

Aigner, D. J., & Cain, G. G. (1977). Statistical theories of discrimination in labor markets. *ILR Review*, *30*(2), 175-187.

Altonji, J. G., & Pierret, C. R. (2001). Employer Learning and Statistical Discrimination. *The Quarterly Journal of Economics*, *116*(1), 313-350.

Ambuehl, S., & Li, S. (2014). Belief updating and the demand for information. *Working Paper*.

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[14] http://www.ukstartupjobs.com/career-advice/mention-failed-startup-cv/

Arora, A., & Gambardella, A. (1997). Public policy towards science: picking stars or spreading the wealth?. *Revue d'économie industrielle*, *79*(1), 63-75.

Arora, A., Gambardella, A., Magazzini, L., & Pammolli, F. (2009). A breath of fresh air? Firm type, scale, scope, and selection effects in drug development. *Management Science*, *55*(10), 1638-1653.

Arora, A., & Nandkumar, A. (2011). Cash-out or flameout! Opportunity cost and entrepreneurial strategy: Theory, and evidence from the information security industry. *Management Science*, *57*(10), 1844-1860.

Azoulay, P., Bonatti, A., & Krieger, J. L. (2015). *The career effects of scandal: evidence from scientific retractions* (No. w21146). National Bureau of Economic Research.

Beckman, C. M., Burton, M. D., & O'Reilly, C. (2007). Early teams: The impact of team demography on VC financing and going public. *Journal of Business Venturing*, *22*(2), 147-173.

Bernardo, A. E., & Welch, I. (2001). On the evolution of overconfidence and entrepreneurs. *Journal of Economics & Management Strategy*, *10*(3), 301-330.

Bernstein, S., Korteweg, A., & Laws, K. (2017). Attracting Early-Stage Investors: Evidence from a Randomized Field Experiment. *The Journal of Finance*.

Brooks, A. W., Huang, L., Kearney, S. W., & Murray, F. E. (2014). Investors prefer entrepreneurial ventures pitched by attractive men. *Proceedings of the National Academy of Sciences*, *111*(12), 4427-4431.

Bruton, G., Khavul, S., Siegel, D., & Wright, M. (2015). New financial alternatives in seeding entrepreneurship: Microfinance, crowdfunding, and peer-to-peer innovations. *Entrepreneurship Theory and Practice*, *39*(1), 9-26.

Butticè, V., Colombo, M. G., & Wright, M. (2017). Serial crowdfunding, social capital, and project success. *Entrepreneurship Theory and Practice*, *41*(2), 183-207.

Byrne, D. E. (1971). *The attraction paradigm.* New York: Academic Press

Chatterji, A. K. (2009). Spawned with a silver spoon? Entrepreneurial performance and innovation in the medical device industry. *Strategic Management Journal*, *30*(2), 185-206.

Chemmanur, T. J., & Fulghieri, P. (2014). Entrepreneurial finance and innovation: An introduction and agenda for future research. *Review of Financial Studies*, *27*(1), 1-19.

Chen, J. (2013). Selection and serial entrepreneurs. *Journal of Economics & Management Strategy*, *22*(2), 281-311.

Cholakova, M., & Clarysse, B. (2015). Does the possibility to make equity investments in crowdfunding projects crowd out reward-based investments?. *Entrepreneurship Theory and Practice*, *39*(1), 145-172.

Coad, A., & Timmermans, B. (2014). Two's Company: Composition, Structure and Performance of Entrepreneurial Pairs. *European Management Review*, *11*(2), 117-138.

Colombo, M. G., Franzoni, C., & Rossi-Lamastra, C. (2015). Internal social capital and the attraction of early contributions in crowdfunding. *Entrepreneurship Theory and Practice*, *39*(1), 75-100.

Conti, A., Thursby, M., & Rothaermel, F. T. (2013). Show Me the Right Stuff: Signals for High-Tech Startups. *Journal of Economics & Management Strategy*, *22*(2), 341-364.

Cope, J., Cave, F., & Eccles, S. (2004). Attitudes of venture capital investors towards entrepreneurs with previous business failure. *Venture Capital*, *6*(2-3), 147-172.

Crilly, D., Hansen, M., & Zollo, M. (2016). The grammar of decoupling: A cognitive-linguistic perspective on firms' sustainability claims and stakeholders' interpretation. *Academy of Management Journal*, *59*(2), 705-729.

Dushnitsky, G., & Klueter, T. (2011). Is there an eBay for ideas? Insights from online knowledge marketplaces. *European Management Review*, *8*(1), 17-32.

Eberhart, R. N., Eesley, C. E., & Eisenhardt, K. M. (2017). Failure Is an Option: Institutional Change, Entrepreneurial Risk, and New Firm Growth. *Organization Science*, *28*(1), 93-112.

Eggers, J. P., & Song, L. (2015). Dealing with failure: Serial entrepreneurs and the costs of changing industries between ventures. *Academy of Management Journal*, *58*(6), 1785-1803.

Fontana, R., Malerba, F., & Marinoni, A. (2016). Pre-entry experience, technological complementarities, and the survival of de-novo entrants. Evidence from the US telecommunications industry. *Economics of Innovation and New Technology*, *25*(6), 573-593.

Frank, R. H. (2016). *Success and luck: Good fortune and the myth of meritocracy*. Princeton University Press.

Franke, N., Gruber, M., Harhoff, D., & Henkel, J. (2006). What you are is what you like—similarity biases in venture capitalists' evaluations of start-up teams. *Journal of Business Venturing*, *21*(6), 802-826.

Gompers, P., Kovner, A., Lerner, J., & Scharfstein, D. (2010). Performance persistence in entrepreneurship. *Journal of Financial Economics*, *96*(1), 18-32.

Gomulya, D., & Mishina, Y. (2017). Signaler credibility, signal susceptibility, and relative reliance on signals: How stakeholders change their evaluative processes after violation of expectations and rehabilitative efforts. *Academy of Management Journal*, *60*(2), 554-583.

Greenberg, J., & Mollick, E. (2016). Activist Choice Homophily and the Crowdfunding of Female Founders. *Administrative Science Quarterly*, 0001839216678847.

Harrison, G. W., & List, J. A. (2004). Field experiments. *Journal of Economic Literature*, *42*(4), 1009-1055.

Higgins, M. C., & Gulati, R. (2006). Stacking the deck: The effects of top management backgrounds on investor decisions. *Strategic Management Journal*, *27*(1), 1-25.

Hochberg, Y. V., Ljungqvist, A., & Vissing-Jørgensen, A. (2013). Informational holdup and performance persistence in venture capital. *The Review of Financial Studies*, *27*(1), 102-152.

Hoenig, D., & Henkel, J. (2015). Quality signals? The role of patents, alliances, and team experience in venture capital financing. *Research Policy*, *44*(5), 1049-1064.

Hoogendoorn, S., Oosterbeek, H., & Van Praag, M. (2013). The impact of gender diversity on the performance of business teams: Evidence from a field experiment. *Management Science*, *59*(7), 1514-1528.

Holt, C. A., & Laury, S. K. (2002). Risk aversion and incentive effects. *American economic review*, *92*(5), 1644-1655.

Hsu, D. H. (2007). Experienced entrepreneurial founders, organizational capital, and venture capital funding. *Research Policy*, *36*(5), 722-741.

Hsu, D. H., & Ziedonis, R. H. (2013). Resources as dual sources of advantage: Implications for valuing entrepreneurial-firm patents. *Strategic Management Journal*, *34*(7), 761-781.

Kerr, W. R., & Nanda, R. (2009). Democratizing entry: Banking deregulations, financing constraints, and entrepreneurship. *Journal of Financial Economics*, *94*(1), 124-149.

King, G., Nielsen, R., Coberley, C., Pope, J. E., & Wells, A. (2011). Avoiding randomization failure in program evaluation, with application to the Medicare Health Support program. *Population health management*, *14*(S1), S-11.

Landier, A. (2005). Entrepreneurship and the Stigma of Failure. *Working Paper*

Link, B. G. & Phelan J. C. (2001) Conceptualizing Stigma. *Annual Review of Sociology* 27, 363-385.

Manso, G. (2011). Motivating innovation. *The Journal of Finance*, *66*(5), 1823-1860.

McGrath, R. G. (1999). Falling forward: Real options reasoning and entrepreneurial failure. *Academy of Management review*, *24*(1), 13-30.

Minniti, M., & Bygrave, W. (2001). A dynamic model of entrepreneurial learning. *Entrepreneurship: Theory and practice*, *25*(3), 5-5.

Mollick, E. (2014). The dynamics of crowdfunding: An exploratory study. *Journal of business venturing*, *29*(1), 1-16.

Mollick, E., & Nanda, R. (2015). Wisdom or madness? Comparing crowds with expert evaluation in funding the arts. *Management Science*, *62*(6), 1533-1553.

Nielsen, K., & Sarasvathy, S. D. (2016). A market for lemons in serial entrepreneurship? Exploring type I and type II errors in the restart decision. *Academy of Management Discoveries*, *2*(3), 247-271.

Parker, S. C. (2013). Do serial entrepreneurs run successively better-performing businesses?. *Journal of Business Venturing*, *28*(5), 652-666.

Peer, E., Brandimarte, L., Samat, S., & Acquisti, A. (2017). Beyond the Turk: alternative platforms for crowdsourcing behavioral research. *Journal of Experimental Social Psychology*, *70*, 153-163.

Pope, D. G., & Sydnor, J. R. (2011). What's in a Picture? Evidence of Discrimination from Prosper. com. *Journal of Human Resources*, *46*(1), 53-92.

Rocha, V., Carneiro, A., & Varum, C. A. (2015). Serial entrepreneurship, learning by doing and self-selection. *International Journal of Industrial Organization*, *40*, 91-106.

Roach, M., & Sauermann, H. (2015). Founder or joiner? The role of preferences and context in shaping different entrepreneurial interests. *Management Science*, *61*(9), 2160-2184.

Saxenian, A. (1996). *Regional advantage*. Harvard University Press.

Schumpeter, J. A. (1950). *Capitalism, Socialism, and Democracy. 3d Ed.* New York, Harper [1962].

Semadeni, M., Cannella Jr, A. A., Fraser, D. R., & Lee, D. S. (2008). Fight or flight: Managing stigma in executive careers. *Strategic Management Journal*, *29*(5), 557-567.

Shepherd, D. A. (2003). Learning from business failure: Propositions of grief recovery for the self-employed. *Academy of management Review*, *28*(2), 318-328.

Skowronski, J. J., & Carlston, D. E. (1989). Negativity and extremity biases in impression formation: A review of explanations. *Psychological bulletin*, *105*(1), 131.

Spence, M. (1973). Job market signaling. *The quarterly journal of Economics*, *87*(3), 355-374.

Stuart, T. E., Hoang, H., & Hybels, R. C. (1999). Interorganizational endorsements and the performance of entrepreneurial ventures. *Administrative science quarterly*, *44*(2), 315-349.

Sutton, R. I., & Callahan, A. L. (1987). The stigma of bankruptcy: Spoiled organizational image and its management. *Academy of Management journal*, *30*(3), 405-436.

Ucbasaran, D., Shepherd, D. A., Lockett, A., & Lyon, S. J. (2013). Life after business failure: The process and consequences of business failure for entrepreneurs. *Journal of Management*, *39*(1), 163-202.

Van Praag, C. M. (2003). Business survival and success of young small business owners. *Small business economics*, *21*(1), 1-17.

Vogel, R., Puhan, T. X., Shehu, E., Kliger, D., & Beese, H. (2014). Funding decisions and entrepreneurial team diversity: A field study. *Journal of Economic Behavior & Organization*, *107*, 595-613.

Vulkan, N., Åstebro, T., & Sierra, M. F. (2016). Equity crowdfunding: A new phenomena. *Journal of Business Venturing Insights*, *5*, 37-49.

Zott, C., & Huy, Q. N. (2007). How entrepreneurs use symbolic management to acquire resources. *Administrative Science Quarterly*, *52*(1), 70-105.

Table 1. Success is an Unambiguous Indicator of High Skill, Failure is Ambiguous.

Luck/skill	Low skill	High skill
Bad luck	Failure	Failure
Good luck	Failure	Success

Table 2. Overview of the Treatments

Manipulation	No skill signal	Skill signal
Success	"2014-2016 Co-founder and CEO of [*Alpha*]." "2012-2014 Co-founder and CEO of [*Beta*]." "2010-2012 Manager of [*Sigma*]." *What happened to Beta?* • Ran out of business • <u>Successful exit</u> *Why did it happen?* "The startup was successfully sold for £ 500,000"	"2014-2016 Co-founder and CEO of [*Alpha*]." "2012-2014 Co-founder and CEO of [*Beta*]." "2010-2012 Manager of [*Sigma*]." *What happened to Beta?* • Ran out of business • <u>Successful exit</u> *Why did it happen?* "We were growing double digit, when the startup was successfully sold for £ 500,000"
Failure	"2014-2016 Co-founder and CEO of [*Alpha*]." "2012-2014 Co-founder and CEO of [*Beta*]." "2010-2012 Manager of [*Sigma*]." *What happened to Beta?* • <u>Ran out of business</u> • Successful exit *Why did it happen?* "Our main business partner, who was key to that specific business, died in a car accident"	"2014-2016 Co-founder and CEO of [*Alpha*]." "2012-2014 Co-founder and CEO of [*Beta*]." "2010-2012 Manager of [*Sigma*]." *What happened to Beta?* • <u>Ran out of business</u> • Successful exit *Why did it happen?* "We were growing double digit, when our main business partner, who was key to that specific business, died in a car accident"

Table 3. Descriptive Statistics

Pane A Dependent and Control Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Investment Propensity	328	3.604	1.005	1	5
Amount Invested	328	297.796	523.935	0	2000
Age	328	36.921	10.865	21	67
College Degree or Higher	328	0.841	0.366	0	1
Risk Aversion	328	3.159	2.607	0	10
Owns House	327	0.563	0.497	0	1
Male	327	0.566	0.496	0	1
Living outside U.K.	328	0.131	0.338	0	1
Living in London	328	0.152	0.360	0	1
Professional Investor	328	0.143	0.351	0	1

Pane B Crowdfunding Experience of the Respondents

Type of Crowdfunding	Invested		Raised	
Donation				
* Not Interested	46.9%	151	62.6%	204
* Potential Investor	38.8%	125	34.0%	111
* Investor	7.8%	25	3.1%	10
* Serial Investor	6.5%	21	0.3%	1
Reward				
* Not Interested	26.4%	83	56.7%	186
* Potential Investor	42.4%	133	38.4%	126
* Investor	13.4%	42	3.0%	10
* Serial Investor	17.8%	56	1.8%	6
Equity				
* Not Interested	38.0%	123	63.7%	209
* Potential Investor	51.9%	168	33.5%	110
* Investor	7.7%	25	1.8%	6
* Serial Investor	2.5%	8	0.9%	3
Debt				
* Not Interested	38.3%	118	59.5%	194
* Potential Investor	51.3%	158	36.5%	119
* Investor	7.5%	23	3.7%	12
* Serial Investor	2.9%	9	0.3%	1

Table 4. Randomization Checks

Variable	No Experience N	No Experience Mean	Failure w/o Sig N	Failure w/o Sig Mean	Failure w/ Sig N	Failure w/ Sig Mean	Success w/o Sig N	Success w/o Sig Mean	Success w/ Sig N	Success w/ Sig Mean
Age[c]	82	35.195	66	36.515	52	37.173	97	38.588	31	36.710
College Degree or Higher[c,f,h]	82	0.890	66	0.879	52	0.885	97	0.763	31	0.806
Risk Aversion	82	3.012	66	3.212	52	2.962	97	3.505	31	2.677
Owns Housing Solution[f,g,h,i]	81	0.556	66	0.455	52	0.481	97	0.639	31	0.710
Professional Investor[d,i]	81	0.593	66	0.500	52	0.538	97	0.577	31	0.645
Male	82	0.146	66	0.197	52	0.077	97	0.113	31	0.226
Living outside U.K.[e,i]	82	0.110	66	0.152	52	0.154	97	0.134	31	0.097
Living in London	82	0.122	66	0.152	52	0.115	97	0.165	31	0.258
Invested in Donation CF[a]	81	1.605	66	1.879	51	1.784	93	1.763	31	1.645
Invested in Reward CF[a,b]	78	2.026	64	2.375	51	2.412	91	2.220	30	2.133
Invested in Equity CF	81	1.741	66	1.727	52	1.788	95	1.716	30	1.833
Invested in Debt CF	77	1.675	62	1.774	50	1.760	90	1.789	29	1.759
Raised on Donation CF	82	1.439	66	1.409	51	1.353	96	1.406	31	1.452
Raised on Reward CF	82	1.512	66	1.545	52	1.442	97	1.526	31	1.387
Raised on Equity CF	82	1.378	66	1.394	52	1.404	97	1.392	31	1.484
Raised on Debt CF	81	1.420	66	1.439	52	1.442	97	1.454	30	1.533

Notes: Difference significant at least at 10% level between:
a. No Experience and Failure w/o Signal
b. No Experience and Failure w/ Signal
c. No Experience and Success w/o Signal
d. No Experience and Success w/ Signal
e. Failure w/o Signal and Failure w/ Signal
f. Failure w/o Signal and Success w/o Signal
g. Failure w/o Signal and Success w/Signal
h. Failure w/ Signal and Success w/o Signal
i. Failure w/ Signal and Success w/ Signal
j. Success w/o Signal and Success w/Signal

Table 5. The Effect of Failure on Investors' Behavior

	Willingness to Invest (w.1)	Willingness to Invest (w.2)	Willingness to Invest (w.3)	Amount Invested (s.1)	Amount Invested (s.2)	Amount Invested (s.3)
Higher quality project	0.578***	0.529***	0.529***	159.6**	128.0*	148.0*
	(0.107)	(0.110)	(0.114)	(57.39)	(59.22)	(59.62)
Past Startup Outcome						
No Experience	-0.0653	-0.106	-0.134	-95.47	-84.78	-62.93
	(0.134)	(0.139)	(0.146)	(77.30)	(80.41)	(78.91)
(b) Fail no Signal	-0.244	-0.368*	-0.391*	-176.5*	-185.0*	-139.2+
	(0.164)	(0.174)	(0.182)	(74.00)	(78.61)	(80.30)
(c) Fail w/ Signal	-0.0181	0.0191	0.0290	12.59	27.65	74.09
	(0.178)	(0.181)	(0.190)	(99.20)	(108.2)	(111.0)
(d) Success w/ Signal	0.00327	-0.0906	-0.0827	60.33	-26.31	-80.24
	(0.199)	(0.196)	(0.192)	(127.6)	(127.5)	(112.5)
Balancing controls included	NO	YES	YES	NO	YES	YES
Further investor controls included	NO	NO	YES	NO	NO	YES
Constant	3.381***	3.195***	3.423***	269.2***	-62.66	-148.0
	(0.119)	(0.294)	(0.324)	(62.64)	(157.9)	(166.4)
Adjusted R^2	0.074	0.095	0.088	0.028	0.027	0.077
N	328	311	293	328	311	293

Notes. Robust standard errors in parentheses. Willingness to invest is an ordered variable ranging from 0 to 5. Amount invested is a winsorized count variable to prevent noise from outliers (upper bound 5%) count variable. Baseline for "Past Startup Outcome" is "Success no Signal", baseline for "Donation CF", "Reward CF", "Equity CF", and "Debt CF" is "No Interest." Significance levels: $+ p<0.1$ $* p<0.05$ $** p<0.01$ $*** p<0.001$

Table 6. The Effect of Failure on Investors' Behavior: Hypothesis Testing

	Willingness to Invest			Amount Invested		
	(w.1)	(w.2)	(w.3)	(s.1)	(s.2)	(s.3)
H1: (a) – (b) > 0						
F statistic	2.23	4.48	4.61	5.69	5.54	3.01
P value (two tailed)	0.137	0.035	0.033	0.018	0.019	0.084
H2: (c) – (b) > 0						
Wald statistic	1.32	3.67	3.85	4.25	4.57	4.34
P value (two tailed)	0.252	0.056	0.051	0.040	0.033	0.038
H3: (c) – (b) – (d) >0						
Wald statistic	0.64	2.92	3.32	0.68	2.18	3.94
P value (two tailed)	0.425	0.088	0.069	0.411	0.141	0.048
H4: (c) – (d)						
Wald statistic	0.01	0.23	0.26	0.12	0.14	1.44
P value (two tailed)	0.925	0.631	0.612	0.793	0.709	0.232

Table 7. Additional Analyses: Hypotheses Testing

	Willingness to Invest			Amount Invested		
	(wr.1)	(wr.2)	(wr.3)	(sr.1)	(sr.2)	(sr.3)
	Empathy	Similarity	Perception	Empathy	Similarity	Perception
H1: (a) – (b) > 0						
F statistic	4.15	2.62	11.54	2.85	4.30	12.08
P value (two tailed)	0.043	0.107	0.001	0.092	0.039	0.001
H2: (c) – (b) > 0						
F statistic	3.13	3.72	6.01	3.85	3.80	6.65
P value (two tailed)	0.078	0.056	0.015	0.051	0.053	0.010
H3: (c) – (b) – (d) >0						
F statistic	2.11	0.66	3.84	4.97	1.79	1.42
P value (two tailed)	0.145	0.417	0.051	0.027	0.182	0.234
H4: (d) – (c) > 0						
F statistic	0.03	0.11	0.07	2.26	0.10	0.04
P value (two tailed)	0.871	0.740	0.787	0.134	0.753	0.843

Figure A1. Example of Business Idea (page 1 of 4)

Introduction

Trickle is monetising a huge and largely untapped market within the restaurant, bar and cafe sector - with a revolutionary approach to efficiency and discounting - by repackaging empty tables and surplus stock from quality businesses as exciting, time-sensitive opportunities for thousands of potential local customers.

It's simple - local businesses reduce the price of their products to reach Trickle customers, who make cut-price last-moment purchases over Trickle in a couple of taps. These customers are provided with location and time-relevant offers from businesses tailored to their preferences - through a variety of channels.

Having proved our market with 440 local businesses signed up across Liverpool and London, and 35,000 downloads, Trickle is now preparing its technology for scalable-launch across the UK. The opportunity is for Trickle to be the comprehensive platform for local businesses to fill capacity, market themselves and get bums on seats.

Figure A2. Example of Team

TEAM

Ellis Turner

Experience

Co-founder and CEO – Trickle, from January 2014 until present

Co-founder and CEO – OtherDining, from February 2011 until December 2013

Senior Analyst – Accenture, from January 2009 until January 2011

Education

University of Liverpool, BA, Business Management – from 2006 to 2009

Abraham Philips

Co-founder and COO – Trickle, from January 2014 until present

Co-founder and COO – OtherDining, from February 2011 until December 2013

IT manager – Tesco, from January 2009 until January 2011

Education

University of Liverpool, BSc, Software Development– from 2004 to 2008

Figure A3. Example of Q&A (Success with no Signal of Skill

Q&A

Investor 1 asked:

How do you plan to expand your employees base?

Ellis replied:

I appreciate this question. At this stage, we are investing in a solid sales force that can reach and deal with restaurants; part of the proceedings will go in that direction. In the future, we plan to involve data scientists for the analytics part of our business model.

Investor 2 asked:

What happened to your early startup?

Ellis replied:

○ Failure
● Success

Thanks for your question. I learned a lot from my past experience with OtherDining. The startup was successfully sold for £ 500,000.

Investor 3 asked:

How will you react in case other players are copying the business model?

Ellis replied:

Thanks for pointing this out. We are offering restaurants special conditions in exchange of exclusive contracts for this specific business model. We also plan to develop loyalty programs to avoid multi-homing. Eventually, selling our business to a larger player like Tripadvisor may be an interesting exit strategy.

Investor 4 asked:

Will you ever develop a version compatible with Google and Windows-powered devices?

Ellis replied:

Thanks for your interest in Trickle and your question about the future of our product. At the moment, rather than designing a browser version, and an Android and a Windows mobile one, we will design the browser version of our app in order to be responsive to a mobile environment.

Appendix Table A1. Additional Analyses.

	Willingness to Invest			Amount Invested		
	(wr.1)	(wr.2)	(wr.3)	(sr.1)	(sr.2)	(sr.3)
	Reciprocity	Similarity	Perception	Reciprocity	Similarity	Perception
Past Startup Outcome						
No Experience	-0.143	0.025	-0.183+	-62.03	-131.7	-110.9+
	(0.149)	(0.145)	(0.101)	(79.95)	(86.99)	(60.34)
(b) Fail no Signal	-0.375*	-0.310	-0.419***	-128.4+	-199.8*	-198.4***
	(0.184)	(0.191)	(0.123)	(75.99)	(96.39)	(57.09)
(c) Fail w/ Signal	-0.002	0.109	-0.026	67.87	18.97	8.294
	(0.196)	(0.199)	(0.137)	(109.1)	(117.9)	(82.75)
(d) Success w/ Signal	-0.040	0.185	-0.082	-116.0	-32.69	34.55
	(0.205)	(0.199)	(0.183)	(104.4)	(145.4)	(120.5)
Donation CF						
-Potential Pledger	0.241			24.22		
	(0.213)			(105.0)		
-Pledger	-0.379			-2.084		
	(0.413)			(139.2)		
-Serial Pledger	-1.811+			1350.3*		
	(1.090)			(524.9)		
Reward CF						
-Potential Pledger	0.084			45.70		
	(0.213)			(94.91)		
-Pledger	0.319			-181.3		
	(0.257)			(125.3)		
-Serial Pledger	-0.245			4.112		
	(0.453)			(382.4)		
Equity CF						
-Potential Pledger	0.0787			22.19		
	(0.198)			(112.3)		
-Pledger	-0.254			449.3		
	(0.482)			(375.6)		
-Serial Pledger	1.156			-353.4		
	(0.887)			(268.3)		
Debt CF						
-Potential Pledger	-0.105			15.10		
	(0.219)			(114.9)		
-Pledger	0.525			560.9		
	(0.374)			(365.3)		
-Serial Pledger	-0.789			881.7***		
	(0.518)			(238.6)		
Same functional background		0.150			241.9**	
		(0.133)			(91.17)	
Team drives investment		0.212			94.49	
		(0.172)			(88.49)	
Same industry background		-0.214			-138.5+	
		(0.200)			(76.69)	
Market drives investment		0.221+			14.61	
		(0.130)			(70.08)	
Constant	3.301***	3.197***	3.462***	-139.5	-116.0	308.9***
	(0.336)	(0.328)	(0.0805)	(159.7)	(176.4)	(46.80)
Controls of Table 6 Model 3	Y	Y	N	Y	Y	N
Adjusted R^2	0.081	0.207	0.099	0.129	0.153	0.026
N	293	253	526	293	253	526

Notes. Robust standard errors in parentheses. Willingness to invest is an ordered variable ranging from 0 to 5. Amount invested is a winsorized count variable to prevent noise from outliers (upper bound 5%) count variable. Baseline for "Past Startup Outcome" is "Success no Signal", baseline for "Donation CF", "Reward CF", "Equity CF", and "Debt CF" is "No Interest." Control of Table X Model 3 include: Age, Male dummy, College or higher education dummy, foreign dummy, London dummy, professional investor dummy, a risk aversion index, a dummy for owning the housing solution, a set of dummy variables for investment behavior with respect to Donation CF, Reward CF. Equity CF, and Debt CF. Significance levels: + $p<0.1$ * $p<0.05$ ** $p<0.01$ *** $p<0.001$.