Be careful what you ask for:
Fundraising strategies in equity crowdfunding

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Abstract

A fundamental question in entrepreneurial finance is what determines the amount of money raised. This paper uses the context of equity crowdfunding to ask how amounts raised can be broken down into what the entrepreneurs ask for, versus what the investors want to give. The empirical analysis exploits unique features of equity crowdfunding campaigns, where entrepreneurs not only set investment goals, but also determine when to close successful campaigns. We find that more experienced and more educated founder teams ask for more money. Their campaigns are more likely to succeed, and they raise more money. Female teams ask for less, their campaigns are equally successful, yet they raise significantly less money (especially all-female teams). Female teams face lower investment flows but hold out for longer at the end of fundraising campaigns to raise more money. Overall the analysis shows that fundraising outcomes are deeply influenced by how much money entrepreneurs ask for.

Keywords: Entrepreneurial finance, Equity crowdfunding, Start-ups, Fundraising, Gender

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1. Introduction

The so-called "FinTech revolution" is beginning to have a significant impact on the way new companies are financed. In the UK alone, it is estimated that at least 40% of early stage financing is now received via Equity Crowdfunding platforms, where the public (i.e., unaccredited investors, aka the crowd) invest in start-ups in return for equity. The UK is widely acknowledged as the most developed market, largely because the Financial Conduct Authority (the relevant regulator) adopted a laissez-faire approach in the early days of the industry. A 2017 report estimated over 300 successful investment campaigns in 2017, making crowdfunding the second largest investor category in the UK (by number of companies), after venture capital, but ahead of corporate investors or angel networks (see Halmari, et al. (2017)). Equity crowdfunding platforms are increasingly favoured by angel investors who contribute a substantial fraction of investments (Wang, et al. 2019). Many regulators around the world are now following the FCA model, and equity crowdfunding is growing fast in much of the developed world.

This is good news not only for start-ups, but also for finance researchers. These electronic platforms provide a window on the process of how entrepreneurs raise money from investors, revealing details that are difficult to observe in more traditional offline settings. In particular we can observe the fundraising strategies pursued by entrepreneurs, and how the investors react. This allows us to address some long-standing fundamental questions about the entrepreneurial fundraising process.

Our central research question is what determines fundraising campaign outcomes? We are not just interested in whether campaigns succeed or not, but how much money entrepreneurs actually raise for their ventures. A central theme is to distinguish whether certain entrepreneurs want to raise less money, a choice made by the entrepreneur, versus receive less money, a choice made collectively by the investors. The unique strength of our data is that in addition to the usual information about the amounts actually raised, we also observe specific choices made by the entrepreneur. First, at the beginning of the campaign, the entrepreneur sets a campaign goal, which is a signal of what s/he wants. S/he also specifies how much equity is issued in return. Second, at the end of a successful campaign that has met its campaign goal, the entrepreneur decides when to close the campaign. This decision reveals further information about the amount of money the entrepreneur truly wants, beyond what s/he asked for at the start. Our research therefore speaks to the importance of how entrepreneurs set their fundraising goals.

In order to analyse entrepreneurial fundraising strategies, we look for meaningful variation across start-ups. A prior literature, including the influential work of Bernstein et al. (2017), suggests that the most important characteristics of early stage ventures revolve around founder teams. We focus on three important dimensions of founders: their prior entrepreneurial experience (Colombo and Grilli 2005; Hsu 2007; Gimmon and Levie 2010; Gompers, et al. 2010) their prior business education (Colombo and Grilli 2005; Gimmon and Levie 2010; Kaplan and Stromberg 2004; Mollick 2014), and their gender (Ewens and Townsend 2019; Bapna and Ganco 2018; Marom, Robb and Sade 2016).

In the UK the two leading equity crowdfunding platforms are CrowdCube and SEEDRS. They are similar in size and jointly account for over 80% of the market. We obtained the proprietary data from SEEDRS. Our dataset encompasses all campaigns on SEEDRS for the period July 2012 (when SEEDRS started) to June 2017. To obtain further information on founder characteristics we augment the data with information available online on Linked-In. We have complete information on 767 campaigns, of which 333 (43%) were successful. These campaigns involve 576 distinct companies and comprise 18,955 investors making a total of 45,952 pledges. Among the successful campaigns, the average goal is £189K, and the average amount eventually raised is £291K. Across all campaigns, 26% of all founder teams have at least one founder with prior entrepreneurial experience, and 13% with prior business education. Moreover, 9% of all campaigns only have female founders, and another 16% have founder teams of mixed gender.

Our empirical analysis proceeds in four steps. In the first step we examine the relationships between founder characteristics and the choice of campaign parameters. In particular we look at how different start-ups choose different campaign goals and different valuations (i.e., how much equity they are giving up). Our regressions control for numerous other company characteristics and timing. The second step looks at campaign success, which means that within 60 days the company receives enough investment pledges to meet its campaign goal. If the goal is not met, the campaign fails and none of the pledges are converted into investment. However, if the goal is met, the company is allowed to keep the campaign going.

The third step of our analysis looks at the final amount of money raised, thus answering our main research question about the determinants of fundraising amounts. Our analysis distinguishes between direct versus total effects. A company characteristic, such as experience of the founders, can have a direct effect on campaign success, as well as an indirect effect through the campaign choices, namely the goal and the valuation. The total effect is then the sum of the direct and indirect effect (Hayes 2014). We also examine daily funding flows as a measure of investor interest, and its relationship with founder characteristics.

The final fourth step further exploits the richness of our data, leveraging the dynamics in the daily investment data. Of particular interest to us is the entrepreneur's decision when to stop the campaign. This reveals information about how much money the entrepreneur actually wants, over and beyond what they asked for at the beginning when formulating their investment goal. Specifically, we estimate a dynamic panel model with two equations. The first equation measures investor demand, as a function of company characteristics and other intervening events. The second equation estimates the entrepreneur's decisions to close their campaign. This optimal stopping decision takes into account the endogenous investment flows which are estimated in the first equation.

Our main findings across the four steps are as follows. Teams with more entrepreneurial experience ask for more money upfront, have a higher probability of success, end up raising more money. Interestingly, the additional funding amount is fully reflected in the higher campaign goals, so once we control for goals, there is no more significant experience effect. This suggests that experienced entrepreneurs fully take their strengths into account when setting their investment goals. As far as business education, we measure it by whether founders have an MBA, although the results are very similar using other measures of business education. We find that teams with more business education ask for more money and higher valuations. Their success probability is the same, but the total amount of funding raised is significantly higher. Again, we find that this higher amount is fully reflected in their higher initial fundraising goals.

Concerning gender effects, the fraction of females in the team is associated with lower fundraising goals and lower valuations. This effect is driven by both female-only and mixed gender teams. We find that gender does not have a significant effect on campaign success. However, the amounts of money eventually raised are significantly lower for female teams. Even after we account for their lower investment goals and lower valuations, all-female and mixed gender teams still raise less money.

In a panel model based on daily investment flows, we jointly estimate investors' investment and entrepreneurs' stopping decisions, to further explain this last finding. We find that all-female start-ups attract lower daily investment flows, both before and after reaching their targets. Importantly, we find that female teams hold out for longer, i.e., they prolong their campaigns to raise additional money. While the evidence for this last finding is statistically not very strong, it hints at the possibility that even though female founders ask for less, they actually do want more funding. Overall, we note that it matters what entrepreneurs ask for, since the final amount of money raised is largely determined by their initial ask. Hence the title of the paper: "Be careful what you ask for, as you may get it."

While we believe that our joint analysis of founder characteristics, campaign choices, investor behaviour, and campaign outcomes breaks new ground, and sheds new light on the question of what determines fundraising amounts, we also recognize some limitations of our analysis. First, we can control for selection effects within the population of companies that start campaigns on SEEDRS, but we are unable to control for the self-selection of companies into SEEDRS in the first place. This does not bias our results, because our model estimates well-defined effects within a well-defined population. However, it leaves open an interesting research question about what kind of entrepreneurs seek equity crowdfunding in the first place, such as the work by Ahlers, et al. (2015) and Loher (2017). Second, our data does not allow us to observe the gender of investors. A recent literature suggests that investors tend to invest in entrepreneurs of the same gender. This is consistent with the lower investment flows identified in our data. The novelty of our contribution is to show how female teams respond to lower investor demand, both in terms of setting lower goals at the beginning of campaigns and delaying the final stopping decisions at the end of campaigns. Third, our analysis of gender effects looks at the impact of gender but cannot uncover the origins of why female entrepreneurs behave differently, or why investors seems to treat female teams differently. This last question is clearly a much larger challenge for the entire literature on gender and finance.

The literature on crowdfunding is growing fast. Most of that literature focuses on rewards-based crowdfunding platforms (Mollick 2014; Mollick and Nanda 2016; Xu 2017), or lending platforms (Havrylchyk and Verdier 2018; Mohammadi and Shafi 2016). However, we would expect equity crowdfunding to be somewhat different. Compared to rewards-based platforms, the investment amounts are significantly larger. An average campaign on Kickstarter, a leading rewards-based platform, raises \$23K, compared to about £292K on SEEDRS. Compared to lending platforms, the risks are much higher given that equity crowdfunding platforms target start-ups whereas lending platforms target established businesses.

The literature about equity crowdfunding focuses mostly on investor behaviour. One central question is the wisdom of the crowd: is there herd behaviour, and is that behaviour rational? Estrin and Khavul (2015) examine this question with UK data from CrowdCube, whereas Åstebro et al. (2017) approach this question using SEEDRS data. This paper changes the perspective by focusing on the strategies of the entrepreneurs, asking how their choices affect campaign outcomes. This paper takes a deeper look into the question of how much money entrepreneur actually raise, and what founder characteristics and choices affect these outcomes.

Our paper also contributes to the broader literature on gender and finance. Experimental evidence suggests that women are in general more risk-averse than men (Eckel and Grossman 2008; Croson and Gneezy 2009). However, this may not be the case once we consider self-selection into the occupation in business and finance (Adams and Ferreira, 2009; Adams and Ragunathan, 2017; Atkinson et al., 2003; Huang and Kisgen, 2013). In entrepreneurial finance, Verheul and Thurik (2001), Coleman and Robb (2009), and Robb and Coleman (2010) find that female entrepreneurs raise a smaller amount of start-up capital. These factors may explain why female-owned businesses are less successful than male-owned businesses (Fairlie and Robb 2009). Perhaps closer still to our study, Marom, Robb and Sade (2016) show that on Kickstarter men seek significantly higher levels of capital than women for their projects and raise more funds than women. Moreover, Bapna and Ganco (2018) report the results from a randomized field experiment on a US equity crowdfunding platform. Their main finding is that female investors are significantly less interested in male founder teams, although there are no significant effects for male investors in their study. In a related vein, Ewens and Townsend (2019) consider data from AngelList. They find that male investors are less interested in female-led ventures, even though the male-led ventures they prefer end up performing worse.

The remainder of this paper is structured as follows. Section 2 provides some theoretical foundations. Section 3 describes the data, explains the variables, and provides descriptive statistics. Section 4 contains the main empirical analysis. Section 5 looks at the robustness and extensions. It is followed by a brief conclusion.

2. Theoretical Foundations

Central to our analysis is the entrepreneur's decision to set the fundraising goal, which has to be met for the campaign to succeed. In this section we provide some theoretical foundations on how to think about this choice.

It is useful to start with a puzzle. Why doesn't the entrepreneur ask for £1 only? Clearly s/he could always achieve that goal and then let the campaign run for as long as s/he wanted to. The problem is that investors will infer information from the entrepreneur's choice of fundraising goal. A goal of £1 would probably be viewed as a joke. More generally, a low goal is likely to be interpreted as a signal that the entrepreneur doesn't want or need a lot of money. Consequently, it is likely that investors will respond accordingly and limit their investment pledges. This in turn implies that the entrepreneur has to be strategic in terms of setting an appropriate goal. The basic trade-off is that setting a higher goal signals to the market a desire to raise more money. At the same time, it is riskier, since it increases the probability of not hitting the goal.

To provide some theoretical clarity on how entrepreneurs strategically chose their fundraising goals, we introduce a highly stylized and minimalistic model. The purpose of the model is not to provide a realistic description of the more complex decision processes at work in reality, but to illustrate how optimal choices are likely to be influenced by simple model parameters about founder abilities and preferences. The appendix contains all of the formal derivations, here we limit ourselves to a brief description.

In our model the crowd observes various start-up characteristics, including founder team experience, education and gender. The aggregate amount of funding available is denoted by ϕ. The entrepreneur doesn't know this parameter, his/her guess is characterized by a normal distribution with mean μ and variance σ. Based on that, the entrepreneur choses a campaign goal γ. If $\phi < \gamma$, the campaign fails, and no investment takes place. If $\phi > \gamma$, the campaign succeeds. To model the signalling role of γ, we assume that maximum funding provided by investors is $\lambda\gamma$, where $\lambda>1$ is some fixed parameter. This simply says that crowd investors take the fundraising goal γ into account and limit the maximum investment amounts accordingly. This assumption is not meant to be a realistic description of investment behaviour, instead it is meant to capture the simple notion that investors interpret fundraising goals as a signal of the company's funding need.

This simple model generates an easily tractable analytical solution of optimal fundraising goals. In the appendix we derive three main results.

1. Entrepreneurs ask for less than what they expect is available on average, i.e., $\gamma < \mu$. After they reached their goal, they take more funding (up to ϕ).
2. Entrepreneurs with better signals (lower σ) ask for more (γ higher), i.e., an amount closer to their expected amount (γ closer to μ).
3. Entrepreneurs who are more risk-averse ask for less funding (γ lower).

The first result provides a simple characterization of optimal fundraising goals. Entrepreneurs are strategic and trade off the signalling benefit of a higher goal against the higher risk of campaign failure. The optimal choice (γ) is always below the expected available amount (μ).

The second result suggests that entrepreneurs who have a better estimate of the expected value (lower σ) set higher goals (higher γ). This is because they are more confident in their ability to read the market, and thus set a reachable goal. In our empirical analysis we can think of entrepreneurial experience and business education as proxies for the ability to better predict investor demand (i.e., lower σ).

The third result suggests that risk aversion affects the optimal goal choice. There is a large prior literature that suggests that females are more risk averse than males. There are many nuances and controversies around this (see Kaplan and Walley 2016). Relevant to us, it is not clear that this result also applies to the entrepreneurs that self-selected to seek funding on SEEDRS. Notwithstanding this, the model predicts that *if* female entrepreneurs are more risk-averse, *then* they would ask for less funding at the start. For a given investor demand ϕ, this also implies that they would continue accepting more funding at the end of the campaign.

3. Data

3.1. Data Sources

We use three main data sources: (i) proprietary data from SEEDRS, a UK based equity crowdfunding platform; (ii) publicly available LinkedIn profiles of entrepreneurs; and (iii) other publicly available data.

SEEDRS provided us with the data for the period 2012-2017, which covers 1,125 campaigns, with 135,053 investments made by 39,555 investors. We exclude 55 fund campaigns and convertible campaigns, 25 campaigns that were still ongoing in June 2017 and 1 campaign that was missing valuation data. The first equity crowdfunding campaign in our sample received its first investment on July 4th, 2012 and the last campaign closed on June 3rd, 2017.

The SEEDRS data includes identifying information about the founders (entrepreneurs) that were running these crowdfunding campaigns. This includes company name, names of entrepreneurs, their titles and roles in the start-up, and their equity shares. We use this information to manually identify the founders (entrepreneurs). We define a founder as an individual with a management role and an equity stake that exceeds 5%. We do not count non-executive directors, entrepreneurs with advisory roles, or entrepreneurs with a small equity stake as part of the founding team. Since most of these are British companies, we manually check this by looking up their Companies House UK incorporation records and first annual return, where available.

For each founder of a company that ran a SEEDRS equity crowdfunding campaign, we hand-collected information about their educational and professional background from their publicly available LinkedIn profiles. We also used the information about the team that was included on the SEEDRS campaign page. As such, we gathered data on entrepreneurs' education and professional experience, as well as gender. The professional experiences include both the current company of the SEEDRS crowdfunding campaign, as well as other employment, prior, concurrent, and possibly after the campaign. We gathered and coded this data for 1,425 entrepreneurs from 792 companies; for 35 companies, none of the founders had LinkedIn or any information on their SEEDRS profile. Our 1,425 entrepreneurs ran 1,007 SEEDRS campaigns.

From SEEDRS we obtain data on campaign goals, valuation, equity offered, and all investment pledges associated with the campaign. It should be noted that relative to traditional databases of entrepreneurial finance (such as Thomson One for venture capital deals), the quality of the SEEDRS data is clearly superior. Valuation data, for example, is notoriously hard to obtain in these traditional databases. Moreover, our pledge-level investment data is very granular, allowing us to look at daily dynamics of investment flows into each campaign.

We structure our data into four samples. The first is the sample of all crowdfunding campaigns where the analysis is cross-sectional in nature. The second is the sample of all successful crowdfunding campaigns, which is again cross-sectional in nature. A campaign is successful when it raises enough money to satisfy the campaign goal. SEEDRS average campaign success rate is approximately 35%. The third sample is a panel of daily events about their campaign, including investment flows. Specifically, the third sample considers the panel of all campaigns from the day of first investment, until either reaching goal (for successful campaigns) or the day of last investment (for unsuccessful campaigns). The fourth sample focuses only on successful campaigns and adds campaign stopping decisions, made by entrepreneur, in response to observed daily investment flows. This fourth sample is a panel that follows successful campaigns from the first day that they can stop (which is one week after reaching the goal), until the day the campaign is ended.

We use a balanced data sample where none of the dependent or explanatory variables relevant for our analysis are missing. For the cross-sectional data our balanced sample of 767 campaigns includes 333 successful campaigns and 434 unsuccessful campaigns. The panel data for the third sample consist of 45,952 observations for the 767 campaigns. Successful campaigns take an average of 31 days to reach their goal, and a further 30 days to close. For the fourth sample, we have 7,814 observations in the balanced data from 321 successful campaigns that stopped on or after the 7th day of reaching their campaign goals.[1]

3.2. Variable Definitions

Throughout the paper we use the subscript i to denote cross-sectional variation (i.e., across campaigns), and the subscript t to denoted time variation in panel date (i.e., varying daily). For our empirical analysis it is useful to introduce variable categories. For the cross-sectional analysis of campaigns, we use the following variable categories:

- We denote by $\boldsymbol{G_i}$ the **fundraising strategy** variables, namely funding goal and equity offered.
- We denote by $\boldsymbol{S_i}$ the **campaign success** dummy.
- We denote by $\boldsymbol{F_i}$ the **funding amount** variable.
- We denote by $\boldsymbol{X_i}$ the **founder characteristics** variables, namely entrepreneurial experience, business education, and gender.
- We denote by $\boldsymbol{Z_i}$ the **control** variables, namely founder team size, prior SEEDRS campaigns, tax breaks, sector dummies, and quarter fixed effects.
- We denote by $\boldsymbol{M_i}$ the **momentum** variables, which are proxies for investor demand. They are measured during the first week of the campaign and include number (#) and strengths ($) of competing campaigns, tax credit deadlines, Google trends, rain, and temperatures.

For the daily panels we further use the following variable categories:

- We denote by $\boldsymbol{Stop_{i,t}}$ the **campaign stopping** variable, measured daily.
- We denote by $\boldsymbol{Inv_{i,t}}$ the daily **investment flow** variable, measured daily.
- We denote by $\boldsymbol{M_{i,t}}$ the **momentum** variables, namely number (#) and strengths (£) of competing campaigns, tax credit deadlines, Google trends, rain, and temperatures, all measured daily.
- We denote by $\boldsymbol{P_{i,t}}$ the **panel** variables, namely the time trend, day-of-week and holidays, measured daily, and cooling off amounts, measured during the mandatory cooling off period (the first week after reaching the goal).

Table 1 provides an overview of all the variables used in the analysis. We now discuss them in greater detail. For this, it useful to briefly explain the campaign process. Prior to the launch of the campaign the company defines its fundraising strategy (G_i). It sets the all-important fundraising goal which is the minimum amount of money that needs to be raised for the campaign to succeed. Whether a campaign reaches its goal or not is the basis for the campaign success variable (S_i). Specifically, if after 60 days the campaign has not received enough investment pledges to cover the fundraising goal, the campaign fails and no investment takes place. However, if the goal is reached within this time frame, then the campaign continues. There is a mandatory cooling off period that lasts 7 days. After 7 days the founders are allowed to close the campaign. In other words, founders can stop the campaign as early as the 8th

[1] For 15 campaigns, it appears that they stopped during the cooling off period, so these are excluded from this analysis.

day after reaching the goal, or they can wait for longer. Each company choses its own final stopping date ($Stop_{i,t}$).

Another component of the fundraising strategy (G_i) is what investors receive in return for the funds invested. This can be expressed equivalently as the amount of equity offered (at the fundraising goal), or the company pre-money valuation. Those two measures are mechanically related.[2] We provide some descriptive statics on both measures and Table 4 contains regression for both. In the subsequent analysis, however, we can only use one of them as dependent variables.[3]

Next let us explain how investment pledges work on the SEEDRS platform, and how we use the pledge-level investment data to calculate the amounts of funds raised every day by each campaign. Most investors show an interest by registering a pledge, and then pay the money if the campaign is successful. However, investors are also allowed to either cancel the investment (at any time) or to leave the investment unpaid once the campaign is successful. Thus, a small number of investors cancel pledges or don't pay them. We exclude such pledges that were cancelled or left unpaid, so as to focus on realized investment amounts. An analysis of strategic investor behaviour is outside the scope of this paper, but the work by Åstebro et al. (2017) uses the same dataset to examine exactly that.

After founders close their campaigns, they can also reject some of the funding. In the data, this is common but the amounts the entrepreneurs reject are very small. We exclude the rejected pledges from the analysis. Lastly, we also exclude pledges that were rejected by SEEDRS due to concerns about money fraud, or due to investors' input errors. Summing up, we use the universe of non-cancelled and non-rejected investment pledges to calculate daily investment flows into each campaign ($Inv_{i,t}$) and the total funding amount (F_i).

For the founder characteristics variables (X_i), we aggregate founder-level variables into campaign-level data. We focus on team averages and dummy variables that measure the presence of entrepreneurial experience, business education, and gender. For gender we distinguish three categories of companies: all-male, all-female, and mixed gender. We also calculate the share of founders that are female. We similarly calculate our main measures of entrepreneurial experience and business education. Specifically, we calculate shares and dummies for whether any founders have experience founding a 'proper' company. We define 'proper' any company that has some signs of success, defined as an IPO, acquisition, private investment, or (self-reported) business growth. This definition helps us to weed out founders of trivial companies (e.g., personal consulting) or tax shelters. For business education we look at whether founders have MBA. Section 5 reports several robustness checks about our measurement of experience and education.

For the control variables (Z_i), we include the size of the founder team. Since companies can come back to SEEDRS to run additional campaigns, we control for whether the company had a prior SEEDRS campaign. In the UK, there are tax breaks for investors that differ by the type of company. We distinguish between campaigns where the company has eligibility under the SEIS programme (this is for the first money into very young companies and offers up to 50% tax credits), or under the EIS programme (this is for slightly older companies and offers up to 30% tax credits), or no eligibility.[4]

[2] The key mechanical relationship is given by Equity Offered * Goal = Post-money valuation = Pre-money Valuation + Goal. This can be solved for Equity Offered = Goal / (Goal + Pre-money Valuation), and it can also be solved for Pre-money Valuation = Goal*((1 - Equity Offered) / Equity Offered).

[3] Note that entrepreneurs are advised to set funding goal and company valuation to be realistic and comparable to other similar companies. This is the advice from CrowdCube (2018) and similar advice is given by SEEDRS. We think of entrepreneurs setting the goal and equity offered as the result of an optimization problem that is a function of how much funding they need and what they think they can get, subject to the signalling considerations discussed in Section 2.

[4] To be more specific, investors in the UK can receive initial tax relief of 50% on investments up to £100,000. Additionally, investors in SEIS eligible companies receive a 50% Capital Gains Tax (CGT) exemption on gains

Since eligibility is partly related to age, our dummies indirectly proxy for company age (which is not otherwise recoded in the data). From SEEDRS we also obtain the following sector controls: Clothing and Home, E-Commerce and Marketing, Food and Drink, Games and Entertainment, Finance, Transport and Travel, and Technology. We also use calendar fixed effects from Q3 of 2012 to Q2 of 2017.

We also include momentum variables (M_i and $M_{i,t}$) as measures of external investor demand, both at the daily level (used in panel analysis), and as an average during the first week of campaign (used in cross-sectional analysis). The first category of momentum variables relates to competition on the SEEDRS platform, which we measure with the number (#) and fundraising strength ($) of competing campaigns. The second category relates to investor behaviour at the end of the tax year that is potentially induced by tax breaks for investors described earlier. We interact tax credit incentives with the applicable deadline for determining the investment portfolio and filing UK income taxes, which is typically in the first week of April each year. We also consider the number of searches for "equity crowdfunding" on Google in the UK as a measure of popularity for this alternative asset class in general, partially due to media coverage. Note that we are not considering searches specific to the SEEDRS platform because we do not want to capture individuals who search for the key word "SEEDRS" just to get to the SEEDRS site. As a last category of the momentum variables we consider the weather – the amount of rainfall and the temperature in London, which is the most frequent location o investors and founders on the platform.

We also include additional controls, denoted by $P_{i,t}$, that are specific to panel analysis. Most of these variables are daily and related to time -- the time trend, fixed effects for the day-of-week as well as for long weekend or a week of public holidays. For the fourth sample, which starts after the cooling off period (the first week after reaching the goal), we also include the amount of funds raised during this mandatory cooling off period as an additional control in the panel setting.

3.3. Descriptive Statistics

Table 2 reports descriptive statistics for our balanced sample. Panel A focused on the cross-section of campaigns, Panel B on the panel data. Panel C reports some of the most important pairwise correlations for the cross-sectional sample. We note from Panel A of Table 2 that the fraction of founders with prior entrepreneurial experience is 18%, and that 26% of all teams have at least one founder with such experience in the balanced sample. Similarly, 9% of founders have prior business education, and 13% of all teams have at least one founder with business education in the balanced sample. In terms of gender mix, we find that 16% of founders are female. 9% of all teams are all-female, and another 16% have mixed gender team in the balanced sample. By means of comparison, a report by Atomico (2017) finds that 5% of start-up founders are all-female. This suggests that SEEDRS attracts slightly more female founders than the general population.

Figure 1 illustrates the heterogeneity in fundraising strategies and outcomes by experience, education, and gender, in the balanced sample.

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which are invested in SEIS shares. To qualify for SEIS, the company must be new, broadly speaking: less than two years old, have fewer than 25 employees, and gross assets of less than £200,000. For older companies, and for a larger investment level, there is EIS: investors can invest up to £1,000,000 in unlisted qualifying later-stage qualifying companies in any tax year, and receive 30% tax relief.

Figure 1, Panel A: Fundraising strategies

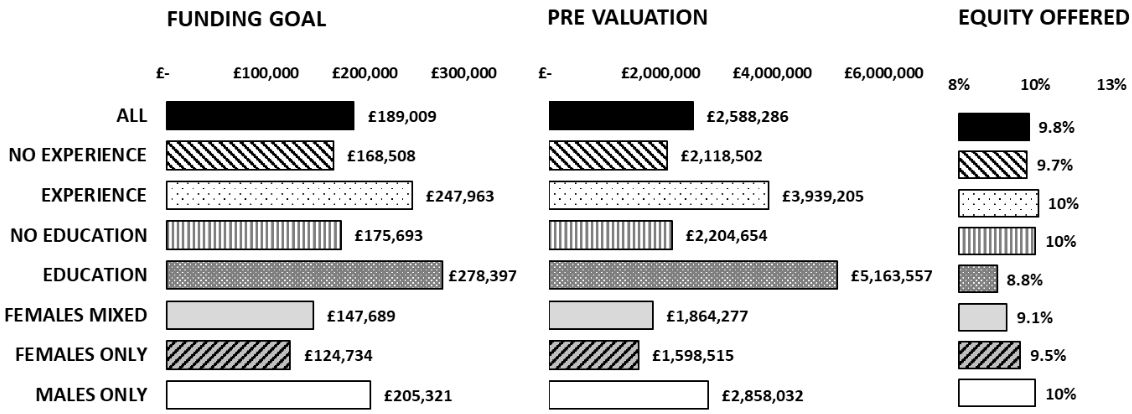
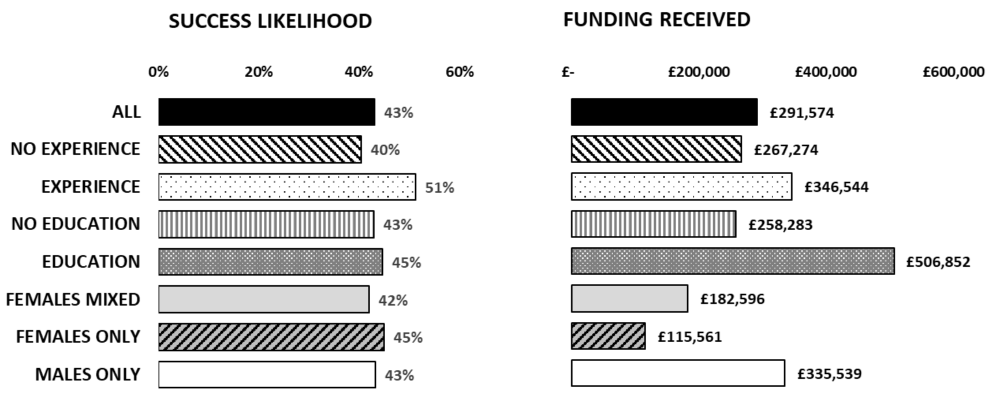


Figure 1, Panel B: Fundraising outcomes



Panel A in Figure 1 shows that the average campaign goal is £189K, the average pre-money valuation is £2.58M, with 10% equity offered at goal. Panel B of Figure 1 shows that the average campaign success rate is 43%.[5] Successful teams raise £292K.

Experienced teams set higher goals and company valuations relative to inexperienced teams, but they offer a very similar share of equity. Specifically, a team that has at least one experienced founder has an average goal of £248K and an average valuation of £3.9M. A team of inexperienced founders asks for £79K less in terms of fundraising goal and has on average a valuation that is £1.9M less. For business education, where the few teams with MBAs set an £100K higher goal and value themselves approximately £3M more, on average, relative to numerous teams without any founds that have an MBA. In terms of gender, we note that female teams set lower fundraising goals: all-female teams ask for £80K less than all-male teams, mixed-gender teams ask for £58K less. They also set lower valuations than all-male teams. All-female start-ups value themselves approximately £1.3M less, mixed gender one £1M less.

[5] This is marginally higher than the platform-wide campaign success rate of 35% due to the fact that entrepreneurs that ran unsuccessful campaigns had less information listed on their LinkedIn profiles and were more likely to be excluded from the balanced data sample. Unsuccessful campaigns are also associated with unknown sector (industry) of the company more frequently, which also led to exclusion.

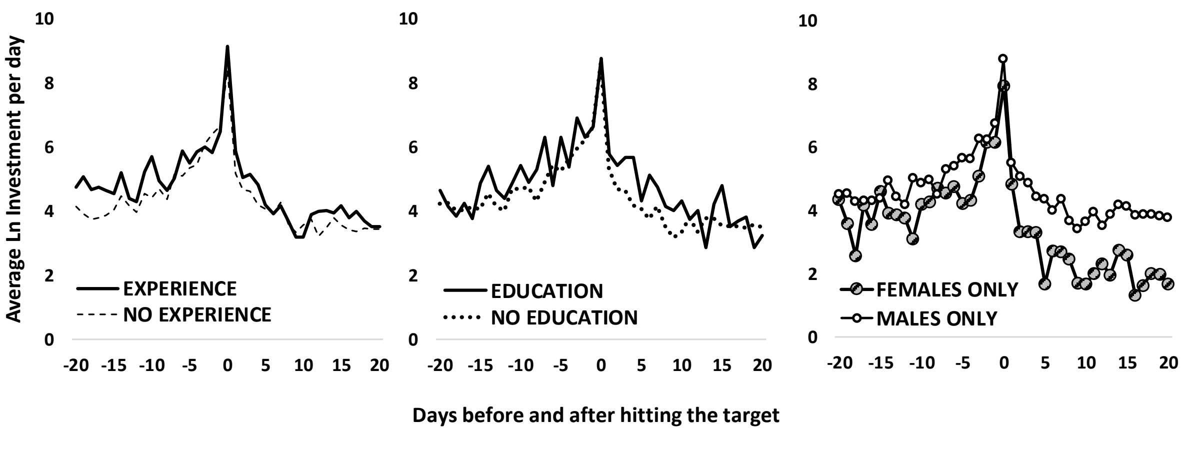
These descriptive statistics already suggest that experienced teams pursue more aggressive fundraising strategies, whereas female teams pursue safer fundraising strategies. Some of this variation could naturally be because these teams are running equity crowdfunding campaigns in different sectors, or because all-male teams might have different levels of experience or education, etc. We explore this more deeply in our formal regression analysis.

There are no substantial differences in the likelihood of success by gender and education, although there are some differences by experience. Experienced teams reach the goal 51% of the time on average, as compared to 40% for inexperienced teams. Experienced teams also raise more money: a team that has at least one experienced founder raises £79K more than a team with inexperienced founders. This comparison is in a sample of successful campaigns, since campaigns that do not reach their goal target and that are therefore unsuccessful do not raise any money at all. Teams with at least one MBA founder have similar success rates as teams without MBA founders, but the successful ones raise £250K more on average.

While female teams have similar prospects for campaign success, they raise considerably less money. All-female teams raise £116K on average, which is a little over a third of the money raised by all-male teams. Mixed gender teams raise £183K on average, which is a little over half of the money raised by all-male teams. These striking differences raise important questions that our formal regression analysis aims to address. In particular, the descriptive evidence that all-female teams pursue safer fundraising strategies and raise less money, does not yet tell us whether all-female teams want less money, or whether it is the investors who want to give them less.

Figure 1, Panel C finally looks at daily investment data of successful campaigns, around the time of reaching the target goal. While there are no notable differences due to experience or education, we note lower investment flows to teams composed of female founders only, especially after reaching the goal. Our panel analysis will take a deeper look at these investment dynamics.

Figure 1, Panel C: Daily Investment Flows



4. Empirical Results

Our empirical analysis is comprised of four parts. First, we examine how founder team characteristics relate to fundraising strategies. Second, we examine how founder team characteristics and fundraising strategies affect the likelihood of campaign success. Third, we examine the determinants of fundraising outcomes. Fourth, we analyse the choice to stop campaigns, which also requires modelling daily investment flows.

4.1. Fundraising Strategies

We start off by modelling the relationship between founder team characteristics X_i and fundraising strategies G_i. The empirical regression is given by

$$G_i = f_G(X_i, Z_i) + \varepsilon_{G,i} \tag{1}$$

Recall that the subscript i indicates that variation is cross-sectional across campaigns. The standard errors $\varepsilon_{G,i}$ are clustered at the company level, to account for repeat campaigns of the same company. We estimate the model using OLS regressions. Table 3 reports the results for three fundraising strategies: funding goal, the valuation, and the equity offered.[6]

We use two types of measures for founder team characteristics X_i: continuous shares and dummies. The continuous model regresses the fundraising strategy variables G_i on the share of founders that are experienced, that have business education, and that are female. The dummy model regresses G_i on dummy variables indicating whether the team has at least one experienced founder, at least one founder with business education, whether the team is female-only, and whether the team is mixed-gender.

Table 3 finds that experienced teams have significantly higher campaign goals. The coefficients are economically large. In the dummy specification of column 2, for example, having a founder with prior entrepreneurial experience increases the funding goal by 22%.[7] The effects of experience on valuation and equity offered, however, are not statistically significant. Teams with prior business education also have higher funding goals, the effect is statistically significant, and the magnitude of the effect is large. Column 2, for example, suggests having a founder with an MBA increases the funding goal by 36%. Teams with prior business experience also ask for higher valuations. The presence of an MBA increases valuations by 50%. When it comes to the equity offered, the effects of higher valuations and larger funding goals wash out each other, and the coefficient is insignificant.

Table 3 shows that teams that have a higher proportion of female founders ask for significantly less money and set significantly lower valuations. These effects wash out each other for the equity offered. The lower funding goals and lower valuation are important finding by themselves, especially since our regressions already control for founder team experience and education, not to mention all the control variables in X_i. The dummy specifications in Table 3 reveal some important additional insights about the differences between mixed-gender versus all-female teams. All-female teams ask for 23% less money and mixed-gender teams ask for 25% less money.[8] The all-female coefficient for the pre-money valuation is also almost significant, with a P-value of 0.114.

4.2. Campaign Success

We now turn to the question of how founder team characteristics (X_i) and fundraising strategies (G_i) affect campaign outcomes. In this subsection we focus on campaign success (S_i), in the next on funding amounts (F_i). It is useful to decompose total effects of X_i on S_i into direct and indirect effects (the same logic will also apply to F_i). The direct effect of founder characteristics X_i on outcome S_i is the effect after accounting for all other factors, specifically the fundraising strategy G_i and the controls Z_i. The indirect effect recognizes that founder characteristics X_i affect the fundraising strategy G_i, which in turn influences the outcome S_i. This decomposition of total effect into direct effect and indirect effect is visually illustrated in Figure 2. Chapter 4 of Hayes (2014) contains a detailed explanation of this kind

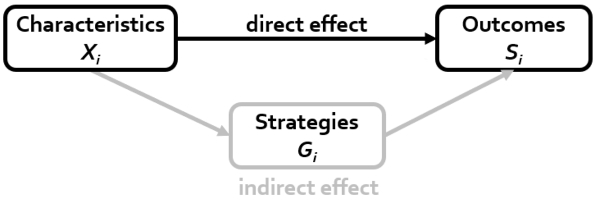
[6] Given the simultaneity of choice, we also re-estimated Table 3 using SUR models with any two of the three equations. We found that the results were always very similar. We thus conclude that the correlation of residuals in these regression models is not a concern.

[7] Regression output is $\ln(Goal) = a + \hat{b}X + e$, thus we use $\exp(\hat{b})$ when interpreting coefficients.

[8] Note that the P-value is 0.086 for all-female teams and 0.033 for mixed-gender teams.

of analysis.[9] It is natural to interpret indirect effects as entrepreneurs' strategic choices, and direct effects as investor preferences. At the same time, we remember that the entrepreneurs' strategic choices themselves are influenced by their expectations of investor demand, as discussed in section 2.

Figure 2: Simple model of mediation



The empirical model we want to estimate is given by

$$S_i = f_S(G_i, X_i, Z_i) + \varepsilon_{S,i} \tag{2}$$

For the direct effect model, we include G_i, and for the total effect model we exclude it. Control variables Z_i are always included and capture team age, prior SEEDRS campaign, presence of tax breaks and company age, as well as the sector and calendar fixed effects.

As noted in Section 3.2, three variables describe the fundraising strategy G_i: fundraising goal, valuation, and equity offered. However, there are only two choices, because valuation and equity offered are mechanically related. To reduce multi-collinearity with the funding goal variable, we drop the valuation variable and focus on the equity offered variable (see Panel C of Table 2). For robustness we verify that using valuation instead of equity offered yields very similar results.[10]

The first two columns of Table 4 report the total effects, deliberately omitting the fundraising strategy variables (G_i). The last two columns add the strategy variables and therefore estimate the direct effect. Probably the most important finding of Table 4 is that the funding goal variable is highly significant and negative. This provides clear evidence that companies face a fundamental trade-off. A higher funding goal promises larger funding amounts in case of success (a result we will confirm in Table 5). However, setting a higher goal is risky, because it meeting the goal becomes more difficult. Table 4 also shows that most founder team characteristics are insignificant. The main exception is experience which is positive and significant in the continuous model for the direct effect.

4.3. Fundraising Amounts

Beyond the question of whether a campaign succeeds or not, our core research question focuses on the amount of money actually raised. For this we turn to funding amount (F_i) as our dependent variable, transformed with natural log. As with campaign success, we exclude G_i for the total effect model and include it for the direct effect model. The control variables Z_i are always included.

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[9] The typical method to distinguish between direct and indirect relationships is to run regressions with and without the mediator variable G. This is formally called mediation analysis in the statistics literature. In our analysis, we follow Baron and Kenny (1986) and other scholars to examine such mediation effects. The total effects is a coefficient δ in regression $S = \delta_c + \delta X + \epsilon_x$. The direct effect is the coefficient α in regression $S = \alpha_c + \alpha X + \alpha_g G + \epsilon_{x,g}$. If all the relationships are linear, the indirect effect can be estimated as the product $\beta \times \theta$, where β and θ are the coefficients from two regressions, $G = \beta_c + \beta X + \psi_x$ and $S = \theta_c + \theta G + \psi_g$. Thus, the indirect effect is $\delta - \alpha$, i.e. the difference between the total effect and the direct effect.

[10] Results are qualitatively similar when the equity variable is replaced by (i) the valuation variable, (ii) the residual valuation variable (obtained by regressing valuation on goal, in line with the sequential regression approach to dealing with multicollinearity), or (iii) when the equity variable is excluded from the specification (which is another approach to dealing with multicollinearity). See Dormann et al. (2013) for a review of these methods.

Table 5 shows how the key variables of interest—founder characteristics X_i, fundraising strategy G_i, and control variables Z_i—relate to funding amount F_i. The total effects of experience and business education are positive and significant. For example, teams with at least one experienced founder raise 39% more than inexperienced teams.[11] However, the direct effort model shows insignificant coefficients for experience and education. This suggests that their effect is fully explained by the indirect effect. That is, teams with more experience or more education raise more money because they set higher fundraising goals. Once this is accounted for, there no residual direct effect left.

In the total effect model all-female teams raise 47% less than all-male teams. When we decompose this total effect, both the direct and indirect effect of gender are negative. The indirect effect comes from the lower campaign goals chosen by all-female teams, and account for 31% of the effect. After controlling for fundraising strategy (goal and equity offered), the direct effect is that all-female teams still raise 16% lower amounts. This suggests that all-female teams choosing a safer fundraising strategy is one part of what explains why female teams raise less money. The other part of the explanation is the direct effect, which suggests that investors provide less funding to all-female teams, even after controlling for all these other factors, including the choices of funding goals and equity offered.

The results for mixed-gender teams are subtly different. Such teams raise 28% less than all-male teams. However, their direct effect is positive: after controlling for fundraising strategy, mixed-gender teams raise 10% more than all-male counterparts. Yet it is the indirect effect of a much lower goal that accounts for why mixed-gender teams raise less than all-male teams. That is, mixed teams raise 38% less funding due to setting a lower goal (the indirect effect).

In the direct effect model the coefficient on campaign goal is highly significant. Interestingly, it not statistically different from 1. This suggests that there is a one-to-one relationship between campaign goal and investment raised for successful campaigns, justifying the title "be careful what you ask for, as you might get it!"

One natural concern is that funding amount F_i is only observed for successful campaigns. We might worry about how founder characteristics influence selection into success and bias our results when we only consider the sample of successful campaigns. The result that most founder team characteristics are insignificant in explaining campaign success (as in Table 4) provides first indication that the sample of successful campaigns is largely representative. We performed alternative analyses, discussed and reported in the appendix, that formally account for potential selection bias by adding a selection equation to the model. We find that this selection correct never materially affects any of our results.

4.4 Daily Investment Flows

Our analysis so far examines the effects of founder characteristics and fundraising strategies on campaign outcomes. We now exploit some of the richness of the crowdfunding data, which allows us to observe the dynamics of the fundraising process. In particular we consider the daily investment flows and their determinants.

Table 6 reports the results from a random effect panel regression of daily investment flows ($Inv_{i,t}$) as a function of campaign characteristics (G_i, X_i, Z_i). Due to the dynamic nature of the sample we further add momentum variables ($M_{i,t}$), described in Section 3.2, that capture time-varying factors that may influence investor demand. A prior crowdfunding literature shows that campaign momentum can have an important effect on outcomes (see especially Mollick 2014, Vulkan et al. 2015; Åstebro et al. 2018). The additional time-varying variables that we include pertain to weather, competition on the platform, and the broader popularity of equity crowdfunding. Specifically we include exogenous (and possibly

[11] Regression output is ln(Funding)=a+bhatX+E, thus we use exp(bhat) when interpreting coefficients.

non-linear) variation in weather which influences internet usage, similar to Cardona et al. (2013), Gilchrist and Sands (2016), or Xu (2017). In addition, we also consider exogenous activity on the SEEDRS platform. This includes how many competing campaigns there are on the platform, and how strong they are in terms of attracting investments flows. Additionally, we measure time-varying investor interest, through Google searches for the term "equity crowdfunding", and through the timing of investor tax-incentives at the end of the tax year. Finally, we introduce additional panel variables that serve as controls, $P_{i,t}$. As discussed in Section 3.2, these variables are related to time and include the time trend, fixed effects for the day-of-week, and fixed effects for long weekend or a week of public holidays.

The relevant sample for daily investment flows is from initial investment until either the day the campaign reaches its goal (if successful), until the day of last investment (if unsuccessful). What happens to successful campaigns after the campaign reaches its goal is something that we analyse separately in the next section. Therefore, we estimate the following equation for daily investment flows across all campaigns. As before, we exclude G_i for the total effect model and include it for the direct effect model:

$$Inv_{i,t} = f_{Inv}(G_i, X_i, Z_i, P_{i,t}, M_{i,t}) + \varepsilon_{i,t}^{Inv}$$

The results we report in Table 6 show that the momentum variables ($M_{i,t}$) are generally statistically significant determinants of daily investment flows. As expected, investor demand tapers off during holidays and at the end of the tax year for campaigns that do not have tax break incentives. On the other hand, investor demand picks up on cold and rainy days, likely reflecting investor's greater online presence. Additionally, prior campaign success is a strong determinant of daily investment flows, as is the length of time that has passed since the first investment.

As far as the entrepreneur characteristics, we find that female entrepreneurs face lower daily investment flows than male counterparts even after accounting for the amounts that female entrepreneurs set as their campaign goals. This suggests that female entrepreneurs both ask for less money and also face lower investment flows for a given level of the ask. These two factors together explain why campaigns led by female entrepreneurs raise less money.

4.5. Stopping the Campaign

Our analysis so far shows that daily investment flows and the funding goal (what the entrepreneurs ask for) are the two key dimensions that determine fundraising outcomes. Still, we are left with an interesting question whether the amount of money that the entrepreneur asks for reflects what s/he really wants? We already saw in our theory discussion of section 2 that entrepreneurs optimally ask for less than what they think they can get on average (i.e., $\gamma < \mu$). We now ask how much additional money different types of entrepreneurs want. To examine this empirically we exploit a unique feature of our data, namely the entrepreneurs' decision when to stop their campaigns.

Consider a simple analogy of the decision to turn off a tap of water that is filling a bucket. Clearly you need to turn off the tap sometime, to take the bucket elsewhere and make use of the water. One reason to stop the tap is that the bucket is full, i.e., you don't any more water. Another reason to stop is that even though water is still flowing, the flow rate is so low that it isn't worth your time anymore. Either way, the more water you need, the longer you will wait before switching off the tap. The decision when to turn off the tap therefore reveals something about how much you want the water. We now apply the same logic to the stopping decision in equity crowdfunding.

The entrepreneur takes the decision to stop the campaign ($Stop_{i,t+1}$). This decision depends on the flow rate of investments ($Inv_{i,t}$), as well as all the campaign characteristics (G_i, X_i, Z_i). The investment flow rate is a function of the entrepreneurs' company characteristics, reflecting investor interests. In order to model the entrepreneurs' stopping decision we thus need a system of two equations, one for the entrepreneurs' stopping decision itself, and one for investors' endogenous investment decisions. Having these two equations helps us to distinguish whether a late stopping decision is due to a high level of investor interest, or due to a high demand for additional funds by the company.

To model the stopping decision, the panel sample starts the days after the mandatory cooling off period and ends when the campaign stops. The decision to stop at date $t+1$ ($Stop_{i,t+1}$) is a function of the state of the company at date t. The panel analysis also uses additional panel controls, denoted by $P_{i,t}$. We write

$$Inv_{i,t} = f_{Inv}\left(G_i, X_i, Z_i, P_i, M_{i,t}\right) + \varepsilon_{i,t}^{Inv} \tag{4}$$

$$Stop_{i,t+1} = f_{Stop}\left(G_i, X_i, Z_i, P_i, Inv_{i,t}\right) + \varepsilon_{i,t}^{Stop} \tag{5}$$

The first stage is to estimate the investment flow ($Inv_{i,t}$), using the panel version of the momentum variables. The second step is to use the instrumented investment flows in the stopping equation. To estimate this two-equation model we use a two-stage GLS random effects estimator. In all regression results throughout the paper, we also cluster the standard errors at company level to take into account repeat campaigns.

The identifying assumption is that $M_{i,t}$ are the instruments for $Inv_{i,t}$. They directly affect investor interest but only affect the entrepreneur's stopping decision indirectly, through the effect of $Inv_{i,t}$. While the exclusion restriction can never be proven directly, we believe that it is a reasonable assumption in our context. Deadlines for tax credits, for example, are relevant to investors, but not the entrepreneurs. The number and strengths of competing fundraising campaigns don't matter directly to the entrepreneur who isn't investing, but matter indirectly in terms of affecting investor interests which may wander between the entrepreneur's campaign and other competing campaigns. Furthermore, Google searches for "equity crowdfunding" in UK are representative of changes in investor interest, potentially due to media and marketing, but they should not affect the entrepreneur's stopping decision directly. Moreover, we would argue that the behavioural effects of weather conditions are more likely to apply to investors than entrepreneurs.[12]

To test our identification approach, we use the standard test for instrument informativeness in the first stage. Since the number of instruments exceeds the number of endogenous variables and our IV model is overidentified, we also test whether the excluded instruments are independent of the error process and conclude that overidentifying restrictions (and thus the instruments) are valid.[13] We also test for the informativeness of the instruments ($M_{i,t}$) and find that the daily tax credit incentives and deadlines, competition on the platform, Google search trends, and weather, are all jointly strongly associated with the investment flows.[14] This suggests that the instrumental variables are not correlated with the residual term in the second stage, and that the model is not mis-specified. One may also be concerned about any survivorship bias within the sample, along the lines discussed at the end of section 4.3. As discussed in the appendix, we find that selection effects are not a concern in this particular system of equations. Table 7 thus present the results from instrumental variable regressions without the selection correction.

The first two columns of Table 7 show the results for the investment flow model ($Inv_{i,t}$). While there are no significant effects for experience or education, there is a negative effect for female entrepreneurs.

[12] This last argument strikes us as plausible, but it is not strictly needed. In particular we reran our model allowing weather variables to affect both the investment and the stopping decision, finding that none of our results depend on this.
[13] With a P-value of 0.7 for the Sargan-Hansen test, we do not reject the null hypothesis that overidentifying restrictions are valid.
[14] With a P-value of 0.002 for the Sanderson-Windmeijer F test, we reject the null hypothesis that all the daily momentum variables ($M_{i,t}$) have a coefficient of zero.

Specifically, all-female teams attract a lower flow rate of investments that is statistically significant. Together with the finding from Section 4.4, this evidence suggests that investor have less interest in all-female companies, both before and after they reach the campaign goal. Note also that in column 1 the proportion of females has a negative coefficient with a P-value of 0.156.

Table 6 only shows direct effect, which already control for Funding Goal, as well as the Cooling Off amount. Both of these variables are positive and significant. We also find that the number of competing SEEDRS campaigns, tax incentives, and Google trends all predict investment flows.

The third and fourth column of Table 6 show the results for the stopping model ($Stop_{i,t+1}$). Technically this is the second-stage equation of an instrumental variable regression. A first important result in columns 3 and 4 is that the endogenous investment variable ($Inv_{i,t}$) has a negative coefficient that is highly significant. This suggests that stopping decisions of entrepreneurs are sensitive to the flow of money from the investors, as predicted in our water tap analogy. Next we note that neither entrepreneurial experience nor business education are significant. This suggests that after reaching their goal, there are no significant differences in the preferences for additional funds along these dimensions.

Table 6 reveals some interesting gender effects. In the third column we find a negative and significant effect for the fraction of female founders. This says that teams with more female founders hold out for longer, i.e., they want more money and are willing to wait longer to get it. In the fourth column the gender coefficients are also negative albeit not statistically significant. The P-value on the all-female coefficient is 0.162. We would consider this evidence indicative albeit not conclusive. It suggests that while all-female teams ask for less funding at the beginning, and receive less funding during the process, at the end of the campaign it appears that they actually want more money.

It is worth noting that this pattern is consistent with the model predictions about risk-aversion discussed in section 2. Unfortunately, our data does not contain a direct measure of risk-aversion, so there may well be other factors that also explain this observed pattern. Still, this finding is important, because it is hard to reconcile with the alternative hypothesis that female-led companies simply have lower capital requirements. If that were the case, then there is no reason to believe that female-led ventures would hold out for longer to raise more money at the end of campaigns. Our key contribution is thus to identify a pattern of behaviours that suggests that female-led teams have higher unmet funding needs.

5. Robustness and Extensions

In this section we consider many empirical robustness checks and models extensions that speak to the representativeness of the results presented in Section 4.

The analysis presented earlier includes all founder team characteristics jointly. Including multiple characteristics together allows us to separate effects, for example separate the effect of gender from the effect of experience. As a robustness we check that the results are qualitatively similar when team characteristics are included one-by-one.

We performed considerable robustness analysis on our measure of experience. Our base measure is based on whether founders have prior founding experiences. For the robustness we further consider whether their prior founding experience was successful or not. Moreover, we also ask whether founders have prior experience working in a (successful or unsuccessful) start-up as a non-founder. This gives us a 2x2 matrix to work with, distinguishing successful vs. unsuccessful experiences in one dimension, and founders vs. non-founders in the second dimension. In our base model we presented results for being a founder AND having prior success. This left out founders with no identifiable success, and people that worked in a successful start-up but were not start-up founders. We find that adding either or both categories does not substantially change our main results. We also considered the importance of founders having sector-specific experience but did not find that this mattered.

As an alternative measure of fundraising outcomes, we also consider the likelihood that teams raise much more than the original goal. For this one can use many thresholds, we focus here on whether companies go 25% over goal. About 40% of all successful campaigns pass this threshold of overfunding, suggesting this is not a rare event. Moreover, the results are qualitatively similar for other funding-to-goal thresholds such as 15% over or even 50% over. We find that experienced teams and all-female teams are less likely to overfund, consistent with our main results. Moreover, we find again that fundraising outcomes are deeply influenced by how much money entrepreneurs ask for. Specifically, we find that there is a positive and statistically significant relationship between campaign goal and likelihood to overfund for successful campaigns.

One concern is that there could be confounding characteristics besides entrepreneurial experience, business education, and gender. We investigated various other aspects of founder's work experience and education, including non-business education, type of work experience and positions, and so forth, but found that they were not significant. Most of our companies are located in the UK. For robustness we add some simple geographic controls for whether companies are located inside or outside UK but find that this has no material effect on our results. We also test whether being inside or outside of greater London matters and again find no significant differences.

Another concern is that our industry controls are not sufficient for capturing heterogenous capital intensity. We therefore consider additional data that measure the companies' business models (distinguishing B2B vs. B2C vs. mixed models) and the companies' model of delivery (digital, non-digital, or mixed model). This data is incomplete for unsuccessful campaigns, so we can only use it for successful campaigns. Adding it as controls there does not affect any of our main results.

We also consider several interaction effects. One question is whether the role of the goal is different across gender categories, but we find that these interaction effects are not significant. Another question concerns the interaction of gender and experience, but again we find that these interaction effects are not significant.

Finally, there is the question of repeat campaigns. Our main analysis controls for having a past SEEDRS campaign (approximately 25% of the sample do) but makes no distinction whether they were successful or not. As a robustness we therefore look at the number of successful and unsuccessful campaigns of SEEDRS. We find that both types of prior campaigns positively predict current campaign success.

6. Conclusion

Equity Crowdfunding is becoming a more important way for new businesses to raise funds. However, as the industry matures questions are being asked about the overall effectiveness of this new medium. A recent 156-page document from the FCA identifies a number of problems and proposes solutions to lessons being learned from the last 6 years.[15] The report recognizes the importance of entrepreneurs being able to raising money on such platforms.

In this paper we use equity crowdfunding data to consider the relationship between founder team characteristics, fundraising strategies, and fundraising outcomes. We leverage the fact that the entrepreneurs' choices are observable in crowdfunding campaigns, and therefore allow us to distinguish between what the entrepreneurs ask for, versus what the investors want to give. We find that founder teams with more entrepreneurial experience and more business education ask for more money, often at higher valuations. Experienced teams are more likely to succeed in their campaigns, and end up raising more money, as do the teams with more business education. Female teams ask for less money, have the same probability of campaign success, but end up raising less money. Interestingly, they also hold out for money longer before closing their campaigns. This suggests that even if they ask for less, they

[15] See https://www.fca.org.uk/news/press-releases/fca-proposes-changes-rules-crowdfunding-platforms for a short summary.

actually may want more funding. Overall, the analysis points to the importance of entrepreneur's fundraising strategies, and in particular the setting of the fundraising goal. On of the strongest results in the paper is that while setting a higher goal reduces the probability of success, it also helps companies to raise more money: "Be careful what you ask for, as you might actually get it."

Our findings raise important questions about the underlying reasons as to why different entrepreneurs chose different fundraising strategies. One important question for future research concerns the question of how entrepreneurs determine their fundraising goals. Of particular interest is why female founder teams ask for less money: is this mainly driven by expectations of what they think they can get (rightly or wrongly), or do other factors also influence this behaviour?

Another interesting question concerns the dynamics across multiple fundraising events. Our current analysis focuses on individual fundraising campaigns as a unit of analysis. Future research might investigate how entrepreneurs dynamically adjust their fundraising strategies across multiple campaigns, and how they adjust based on the underlying business developments in their start-up companies. Finally, there is always the question of how fundraising strategies are related to the ultimate success of the company in terms of exit and returns.

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Table 1: Description of variables

This table lists all of the variable names with their descriptions. It also lists their variable categories, where the index i indicates cross-sectional variation across campaigns, and the index t indicates temporal variation in the daily panel.

Variable	Category	Description
Dependent variables		
FUNDING GOAL	G_i	Desired campaign investment amount, as natural log.
VALUATION	G_i	Pre-money valuation of the company, as natural log.
EQUITY OFFERED	G_i	Equity offered, as FUNDING GOAL / (FUNDING GOAL + VALUATION); in percent.
CAMPAIGN SUCCESS	S_i	Dummy variable = 1 if campaign successfully reaches goal; 0 otherwise.
FUNDING AMOUNT	F_i	Total amount invested in campaign, as natural log.
INVESTMENT FLOW	$Inv_{i,t}$	Daily campaign investment flow, as natural log.
STOP	$Stop_{i,t}$	Daily dummy whether the founder has stopped the campaign, once allowed to do so after the cooling off period.
Founder characteristics		
EXPERIENCE (%)	X_i	Share of founders in the company's founding team with prior entrepreneurial experience in a start-up that experienced an IPO, acquisition, private investment rounds, or business growth.
EXPERIENCE (D)	X_i	Dummy variables = 1 if ENTEXP(%) > 0; 0 otherwise
EDUCATION (%)	X_i	Share of founders in the company's founding team with an MBA
EDUCATION (D)	X_i	Dummy variables = 1 if BUSEDU(%) > 0; 0 otherwise
FEMALES (%)	X_i	Share of female founders in the company's founding team
FEMALES ONLY (D)	X_i	Dummy variables = 1 if FEMALE(%) =1; 0 otherwise
FEMALES MIXED (D)	X_i	Dummy variables = 1 if 0 < FEMALE(%) < 1; 0 otherwise
Control variables		
PRIOR SEEDRS	Z_i	Dummy variable indicating whether the company had already raised some equity from SEEDRS.
TEAM SIZE	Z_i	The number of company founders at the time of the SEEDRS campaign.
SEIS	Z_i	Dummy whether the campaign is eligible for the Seed Enterprise Investment Scheme (SEIS) tax break.
EIS	Z_i	Dummy whether the campaign is eligible for the Enterprise Investment Scheme (EIS) tax break.
SECTOR	Z_i	A series of dummy variables for: Clothing and Home (Clothing & Accessories, Home & Personal, Healthcare); E-Commerce and Marketing (Advertising & Marketing, Data & Analytics, Content & Information); Finance (Finance & payments, Recruitment & Procurement, Property); Food and Drink (Food & Beverage); Games and Entertainment (Entertainment, Games); Technology (Programming & Security, SaaS/PaaS); Transport and Travel (Automotive & Transport, Travel, Leisure & Sport, Energy).

Variable	Category	Description
QUARTER	Z_i	A series of dummy variables denoting the quarter of campaign start, for the period Q2 2012 to Q2 2017.
Momentum variables		
COMPETITION (#)	$M_{i,t}$ or M_i	The number of other competing open campaigns on SEEDRS; daily or average over first week of campaign.
COMPETITION (£)	$M_{i,t}$ or M_i	The average flow to other competing open campaigns on the platform, as natural log; daily or average over first week of campaign.
DEADLINE*EIS	$M_{i,t}$ or M_i	Last three weeks of the tax year and SEIS eligibility, daily or any time during the first week of campaign.
DEADLINE*SEIS	$M_{i,t}$ or M_i	Last three weeks of the tax year and EIS eligibility, daily or any time during the first week of campaign.
DEADLINE*NONE	$M_{i,t}$ or M_i	Last three weeks of the tax year and neither SEIS nor EIS eligibility, daily or any time during the first week of campaign.
GOOGLE TRENDS	$M_{i,t}$ or M_i	The number of searches for "equity crowdfunding" on Google in UK; daily or total over first week of campaign.
RAIN	$M_{i,t}$ or M_i	Average daily rainfall in London, as natural log; daily or average over first week of campaign.
TEMP	$M_{i,t}$ or M_i	Average daily temperature in London, as dummies in 5°C increments; daily or average over first week of campaign.
Additional panel variables		
WEEK-DAY	$P_{i,t}$	A series of dummy variables denoting the day of the week.
TIME TREND	$P_{i,t}$	Time trend.
HOLIDAYS	$P_{i,t}$	Long weekend or week of public holidays, according to the calendar of UK Bank Holidays.
COOLING OFF	P_i	Investment top-up amount (in addition to the funding goal) received during the campaign's cooling off period, as natural log.

Table 2: Panel A: Summary statistics for cross-sectional variables

This table shows descriptive statistics for the variable categories G_i, S_i, F_i, X_i, Z_i and M_i in the cross-section of all campaigns.

Variable	Category	Mean	Standard Deviation	Minimum	Maximum	N
FUNDING GOAL	G_i	11.51	1.2	6.53	14.73	767
VALUATION	G_i	14.01	1.15	4.38	18.32	767
EQUITY OFFERED	G_i	9.75	6.88	0.04	99.98	767
CAMPAIGN SUCCESS	S_i	0.43	0.496	0	1	767
FUNDING AMOUNT	F_i	11.64	1.47	6.57	15.29	333
EXPERIENCE (%)	X_i	0.18	0.34	0	1	767
EXPERIENCE (D)	X_i	0.26	0.44	0	1	767
EDUCATION (%)	X_i	0.09	0.25	0	1	767
EDUCATION (D)	X_i	0.13	0.34	0	1	767
FEMALES (%)	X_i	0.16	0.31	0	1	767
FEMALES ONLY (D)	X_i	0.09	0.29	0	1	767
FEMALES MIXED (D)	X_i	0.16	0.36	0	1	767
TEAM SIZE	Z_i	1.897	0.88	1	5	767
PRIOR SEEDRS	Z_i	0.26	0.44	0	1	767
SEIS	Z_i	0.46	0.499	0	1	767
EIS	Z_i	0.44	0.497	0	1	767
SECTOR: Clothing, Home	Z_i	0.16	0.36	0	1	767
SECTOR: E-Commerce, Marketing	Z_i	0.16	0.37	0	1	767
SECTOR: Finance	Z_i	0.14	0.34	0	1	767
SECTOR: Food, Drink	Z_i	0.12	0.32	0	1	767
SECTOR: Games, Entertainment	Z_i	0.103	0.304	0	1	767
SECTOR: Technology	Z_i	0.18	0.38	0	1	767
SECTOR: Transport, Travel	Z_i	0.15	0.35	0	1	767
COMPETITION (#)	M_i	37.79	14.52	8.43	65.29	767
COMPETITION (£)	M_i	6.56	1.32	1.47	10.83	767
DEADLINE*SEIS	M_i	0.02	0.16	0	1	767
DEADLINE*EIS	M_i	0.03	0.18	0	1	767
DEADLINE*NONE	M_i	0.001	0.04	0	1	767
GOOGLE TRENDS	M_i	181.59	111.78	0	445	767
RAIN	M_i	-0.03	1.24	-2.3	2.59	767
TEMP <5C	M_i	0.099	0.299	0	1	767
TEMP 5C-10C	M_i	0.28	0.45	0	1	767
TEMP 10C-15C	M_i	0.35	0.48	0	1	767
TEMP 15C-20C	M_i	0.24	0.43	0	1	767
TEMP >20C	M_i	0.03	0.18	0	1	767

Table 2: Panel B: Summary statistics for daily panel variables

This table shows descriptive statistics for the variable categories $Inv_{i,t}$, $Stop_{i,t}$, $M_{i,t}$, $P_{i,t}$ and P_i in the overall daily panel sample, which includes both unsuccessful and successful campaigns (before and after reaching goal).

Variable	Category	Mean	Standard Deviation	Minimum	Maximum	N
INVESTMENT FLOW	$Inv_{i,t}$	2.29	3.27	0	14.74	45952
STOP	$Stop_{i,t}$	0.02	0.13	0	1	20559
COMPETITION (#)	$M_{i,t}$	38.87	13.99	1	67	45952
COMPETITION (£)	$M_{i,t}$	6.69	1.55	0	12.49	45952
DEADLINE*SEIS	$M_{i,t}$	0.02	0.14	0	1	45952
DEADLINE*EIS	$M_{i,t}$	0.02	0.15	0	1	45952
DEADLINE*NONE	$M_{i,t}$	0.01	0.07	0	1	45952
GOOGLE TRENDS	$M_{i,t}$	26.88	20.26	0	100	45952
RAIN	$M_{i,t}$	-0.82	1.65	-2.3	3.87	45952
TEMP <5C	$M_{i,t}$	0.11	0.32	0	1	45952
TEMP 5C-10C	$M_{i,t}$	0.28	0.45	0	1	45952
TEMP 10C-15C	$M_{i,t}$	0.33	0.47	0	1	45952
TEMP 15C-20C	$M_{i,t}$	0.23	0.42	0	1	45952
TEMP 20C-25C	$M_{i,t}$	0.04	0.2	0	1	45952
TEMP >25C	$M_{i,t}$	0.002	0.05	0	1	45952
TIME TREND	$P_{i,t}$	42.53	34.9	1	331	45952
HOLIDAYS	$P_{i,t}$	0.06	0.23	0	1	45952
COOLING OFF	P_i	0.09	0.17	0	1.29	20559

Table 2: Panel C: Key pairwise correlations

This table shows the pairwise correlations for the variable categories G_i, S_i, F_i, X_i, and select Z_i in the sample of successful campaigns

Variable	No.	Category	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
FUNDING GOAL	1	G_i	1														
VALUATION	2	G_i	0.494***	1													
EQUITY OFFERED	3	G_i	0.339***	-0.509***	1												
FUNDING AMOUNT	4	F_i	0.974***	0.500***	0.295***	1											
EXPERIENCE (%)	5	X_i	0.113*	0.138*	-0.0180	0.101	1										
EXPERIENCE (D)	6	X_i	0.140*	0.130*	-0.00167	0.122*	0.905***	1									
EDUCATION (%)	7	X_i	0.137*	0.155**	-0.0418	0.141**	-0.143**	-0.112*	1								
EDUCATION (D)	8	X_i	0.155**	0.175**	-0.0432	0.154**	-0.132*	-0.0861	0.926***	1							
FEMALES (%)	9	X_i	-0.162**	-0.0671	-0.0495	-0.162**	-0.103	-0.124*	-0.0193	-0.0176	1						
FEMALES ONLY (D)	10	X_i	-0.118*	-0.0566	-0.0200	-0.131*	-0.0406	-0.0784	-0.0319	-0.0335	0.875***	1					
FEMALES MIXED (D)	11	X_i	-0.0839	-0.0116	-0.0670	-0.0719	-0.141*	-0.102	-0.00147	0.00643	0.336***	-0.136*	1				
TEAM SIZE	12	Z_i	0.0859	0.0836	-0.00514	0.0675	-0.219***	-0.0446	-0.0513	0.0414	-0.0936	-0.263***	0.441***	1			
PRIOR SEEDRS	13	Z_i	-0.301***	0.0465	-0.271***	-0.290***	0.0740	0.0350	-0.0536	-0.0635	-0.0322	-0.0162	-0.0112	-0.0386	1		
SEIS	14	Z_i	-0.353***	-0.537***	0.108*	-0.358***	-0.186***	-0.177**	-0.0936	-0.108*	0.00900	-0.0407	0.110*	0.00205	-0.0980	1	
EIS	15	Z_i	0.329***	0.557***	-0.165**	0.341***	0.165**	0.153**	0.0271	0.0479	-0.00418	0.0389	-0.0869	0.00455	0.112*	-0.878***	1

Table 3: Determinants of fundraising strategies

This table reports OLS regressions for the campaign goal, valuation, and equity offered, in the cross-sectional sample of all campaigns. The explanatory variables include all founder team characteristics (X_i), and control variables (Z_i). All variables are described in Table 1. T-statistics are in parentheses and standard errors are clustered at the company-level to take into account repeat campaigns.

		Funding Goal		Pre-money Valuation		Equity Offered	
		Continuous model	Dummy model	Continuous model	Dummy model	Continuous model	Dummy model
EXPERIENCE	(%, D)	0.287**	0.197**	0.153	0.071	0.888	0.722
		(2.23)	(2.06)	(1.25)	(0.76)	(1.20)	(1.26)
EDUCATION	(%, D)	0.420**	0.309**	0.480***	0.399***	-1.098	-0.935
		(2.55)	(2.64)	(3.38)	(3.52)	(-1.24)	(-1.34)
FEMALES	(%)	-0.353**		-0.164*		-0.442	
		(-2.57)		(-1.77)		(-0.58)	
FEMALES ONLY	(D)		-0.267*		-0.153		-0.153
			(-1.72)		(-1.58)		(-0.18)
FEMALES MIXED	(D)		-0.293**		-0.060		-1.037
			(-2.14)		(-0.67)		(-1.50)
TEAM SIZE		0.122**	0.130**	0.095**	0.073	0.069	0.217
		(2.88)	(2.70)	(2.47)	(1.62)	(0.25)	(0.72)
PRIOR SEEDRS		-0.914***	-0.885***	-0.080	-0.079	-3.677***	-3.584***
		(-9.27)	(-9.01)	(-1.21)	(-1.17)	(-7.27)	(-7.04)
SEIS		-0.677***	-0.676***	-0.687***	-0.698***	-0.262	-0.212
		(-4.61)	(-4.68)	(-3.64)	(-3.76)	(-0.20)	(-0.16)
EIS		0.233	0.216	0.372*	0.363*	-0.822	-0.841
		(1.54)	(1.45)	(1.84)	(1.82)	(-0.60)	(-0.61)
SECTOR	Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
QUARTER	Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N		767	767	767	767	767	767
Adjusted R-squared		0.343	0.346	0.107	0.107	0.107	0.107

Table 4: Determinants of campaign success

This table reports Probit regressions for campaign success (S_i) in the cross-sectional sample of all campaigns. The explanatory variables include all founder team characteristics (X_i), and control variables (Z_i). The direct effect regressions further include fundraising campaigns (G_i). All variables are described in Table 1. T-statistics are in parentheses and standard errors are clustered at the company-level to take into account repeat campaigns.

		Campaign Success			
		Total effect		Direct effect	
		Continuous model	Dummy model	Continuous model	Dummy model
EXPERIENCE	(%, D)	0.270	0.150	0.327*	0.186
		(1.61)	(1.18)	(1.95)	(1.45)
EDUCATION	(%, D)	0.062	-0.034	0.152	0.029
		(0.25)	(-0.20)	(0.63)	(0.17)
FEMALES	(%)	-0.184		-0.248	
		(-1.09)		(-1.48)	
FEMALES ONLY	(D)		-0.131		-0.173
			(-0.70)		(-0.94)
FEMALES MIXED	(D)		-0.121		-0.179
			(-0.80)		(-1.17)
FUNDING GOAL				-0.201***	-0.194**
				(-3.36)	(-3.25)
EQUITY OFFERED				0.007	0.007
				(0.83)	(0.76)
TEAM SIZE		0.030	0.032	0.055	0.058
		(0.44)	(0.43)	(0.82)	(0.79)
PRIOR SEEDRS		1.066***	1.079***	0.941***	0.961***
		(8.78)	(8.81)	(7.12)	(7.19)
SEIS		0.410**	0.391*	0.284	0.268
		(2.02)	(1.93)	(1.39)	(1.32)
EIS		0.680***	0.666***	0.756***	0.735***
		(3.49)	(3.43)	(4.02)	(3.94)
SECTOR	Fixed effects	Yes	Yes	Yes	Yes
QUARTER	Fixed effects	Yes	Yes	Yes	Yes
N		767	767	767	767
Pseudo R-squared		0.199	0.198	0.211	0.209

Table 5: Determinants of funding amount

This table reports OLS regressions for the funding amount (F_i) in the cross-sectional sample of all successful campaigns. The explanatory variables include all founder team characteristics (X_i), and control variables (Z_i). The direct effect regressions further include fundraising campaigns (G_i). All variables are described in Table 1. T-statistics are in parentheses and standard errors are clustered at the company-level to take into account repeat campaigns.

		Funding Received			
		Total effect		Direct effect	
		Continuous model	Dummy model	Continuous model	Dummy model
EXPERIENCE	(%, D)	0.439*	0.329*	-0.053	-0.060
		(1.92)	(1.82)	(-1.00)	(-1.47)
EDUCATION	(%, D)	0.644*	0.486**	0.014	-0.010
		(1.86)	(2.18)	(0.19)	(-0.19)
FEMALES	(%)	-0.686**		-0.083	
		(-3.15)		(-1.26)	
FEMALES ONLY	(D)		-0.628**		-0.179**
			(-2.49)		(-2.57)
FEMALES MIXED	(D)		-0.333		0.092*
			(-1.22)		(1.72)
FUNDING GOAL				1.032***	1.035***
				(60.37)	(56.89)
EQUITY OFFERED				-0.006*	-0.005*
				(-1.88)	(-1.86)
TEAM SIZE		0.120	0.101	-0.029	-0.057**
		(1.63)	(1.11)	(-1.47)	(-2.73)
PRIOR SEEDRS		-1.000***	-0.984***	0.015	0.017
		(-7.33)	(-7.27)	(0.39)	(0.44)
SEIS		-0.531	-0.531	0.091	0.078
		(-1.43)	(-1.44)	(1.29)	(1.15)
EIS		0.365	0.355	0.084	0.087
		(0.98)	(0.97)	(1.28)	(1.36)
SECTOR	Fixed effects	Yes	Yes	Yes	Yes
QUARTER	Fixed effects	Yes	Yes	Yes	Yes
N total		333	333	333	333
R squared		0.316	0.314	0.952	0.954

Table 6: Determinants of daily investment flows

This table reports random effects panel regressions for daily investment flows ($Inv_{i,t}$). The sample includes all campaigns and includes investment from the start of campaign to reaching goal (for successful campaigns) or last investment (for unsuccessful campaigns). The explanatory variables are founder team characteristics (X_i), control variables (Z_i), fundraising campaigns (G_i), and panel variables ($P_{i,t}$). The explanatory variables further include daily momentum variables ($M_{i,t}$). All variables are described in Table 1. T-statistics are in parentheses and are clustered at company level to take into account repeat campaigns.

		Investment Flow			
		Total effect		Direct effect	
		Continuous model	Dummy model	Continuous model	Dummy model
EXPERIENCE	(%, D)	0.488	0.245	0.396	0.177
		(1.45)	(0.92)	(1.17)	(0.67)
EDUCATION	(%, D)	0.471	0.116	0.420	0.077
		(0.94)	(0.32)	(0.86)	(0.21)
FEMALES	(%)	-0.812**		-0.736**	
		(-2.61)		(-2.38)	
FEMALES ONLY	(D)		-0.818**		-0.756**
			(-2.41)		(-2.22)
FEMALES MIXED	(D)		-0.201		-0.124
			(-0.69)		(-0.43)
FUNDING GOAL				0.240**	0.262**
				(2.04)	(2.20)
EQUITY OFFERED				0.033	0.031
				(1.40)	(1.34)
TEAM SIZE		-0.002	-0.039	-0.037	-0.078
		(-0.02)	(-0.25)	(-0.26)	(-0.50)
PRIOR SEEDRS		1.254***	1.269***	1.573***	1.598***
		(4.79)	(4.82)	(5.48)	(5.54)
SEIS		0.371	0.313	0.546*	0.504
		(1.17)	(1.01)	(1.72)	(1.60)
EIS		1.261***	1.237***	1.223***	1.197***
		(3.92)	(3.93)	(4.14)	(4.11)
HOLIDAYS		-0.349***	-0.350***	-0.349***	-0.349***
		(-4.95)	(-4.95)	(-4.95)	(-4.95)

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		Investment Flow			
		Total effect		Direct effect	
		Continuous model	Dummy model	Continuous model	Dummy model
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COMPETITION (#)		-0.010	-0.010	-0.010	-0.010
		(-1.45)	(-1.45)	(-1.45)	(-1.45)
COMPETITION (£)		0.021	0.021	0.021	0.021
		(1.43)	(1.43)	(1.44)	(1.44)
DEADLINE*SEIS		-0.043	-0.042	-0.044	-0.044
		(-0.28)	(-0.28)	(-0.29)	(-0.29)
DEADLINE*EIS		0.204	0.205	0.203	0.204
		(1.01)	(1.01)	(1.01)	(1.01)
DEADLINE*NONE		-0.677*	-0.678*	-0.678*	-0.679*
		(-1.84)	(-1.84)	(-1.84)	(-1.84)
GOOGLE TRENDS		0.002	0.002	0.002	0.002
		(1.41)	(1.41)	(1.42)	(1.42)
RAIN		0.014*	0.014*	0.014*	0.014*
		(1.72)	(1.71)	(1.72)	(1.72)
TEMP: <5C		0.129*	0.129*	0.129*	0.129*
		(1.74)	(1.74)	(1.73)	(1.73)
TEMP: 5C to 10C		0.039	0.039	0.038	0.039
		(0.60)	(0.61)	(0.60)	(0.61)
TEMP: 15C to 20C		-0.004	-0.003	-0.004	-0.003
		(-0.06)	(-0.05)	(-0.06)	(-0.05)
TEMP: >20C		-0.086	-0.086	-0.086	-0.086
		(-0.88)	(-0.87)	(-0.87)	(-0.87)
TIME TREND		-0.006***	-0.006***	-0.006***	-0.006***
		(-3.45)	(-3.45)	(-3.46)	(-3.46)
SECTOR	Fixed effects	Yes	Yes	Yes	Yes
QUARTER	Fixed effects	Yes	Yes	Yes	Yes
WEEK-DAY	Fixed effects	Yes	Yes	Yes	Yes
N		35035	35035	35035	35035
N campaigns		719	719	719	719
Overall R squared		0.081	0.080	0.081	0.082

Table 7: Determinants of campaign stopping decisions

This table reports two-stage GLS (random effects with IV) panel regression for the stopping dummy ($Stop_{i,t+1}$) with instrumented lagged daily investment flows. The sample includes only successful campaigns, and starts after the cooling off period. The explanatory variables in the (2nd stage) stopping regression include the lagged daily investment flows ($Inv_{i,t}$), founder team characteristics (X_i), control variables (Z_i), fundraising campaigns (G_i), and panel variables ($P_{i,t}$). Daily investment flows ($Inv_{i,t}$) are instrumented with a (1st stage) regression that includes all variables from the 2nd stage, as well as the daily momentum variables ($M_{i,t}$). All variables are described in Table 1. T-statistics are in parentheses and are clustered at company level to take into account repeat campaigns.

		Flow (1st stage) direct effect		Stop (2nd stage) direct effect	
		Continuous model	Dummy model	Continuous model	Dummy model
INSTRUMENTED FLOW				-0.037***	-0.037***
				(-3.57)	(-3.60)
EXPERIENCE	(%, D)	0.095	-0.176	0.042	0.025
		(0.26)	(-0.60)	(1.39)	(0.91)
EDUCATION	(%, D)	0.028	-0.358	-0.012	-0.023
		(0.07)	(-1.18)	(-0.37)	(-0.89)
FEMALES	(%)	-0.514		-0.058*	
		(-1.42)		(-1.80)	
FEMALES ONLY	(D)		-0.979**		-0.052
			(-2.58)		(-1.40)
FEMALES MIXED	(D)		0.361		-0.028
			(1.04)		(-0.83)
FUNDING GOAL		0.771***	0.805***	-0.001	0.001
		(6.71)	(7.14)	(-0.04)	(0.06)
EQUITY OFFERED		0.003	0.002	0.001	0.001
		(0.20)	(0.15)	(0.89)	(0.86)
COOLING OFF		1.529**	1.369*	0.170**	0.171**
		(2.01)	(1.84)	(2.50)	(2.50)
TEAM SIZE		-0.157	-0.297**	-0.014	-0.014
		(-1.20)	(-2.10)	(-1.07)	(-1.00)
PRIOR SEEDRS		-0.171	-0.160	0.012	0.014
		(-0.60)	(-0.56)	(0.47)	(0.53)
SEIS		0.364	0.213	0.037	0.035
		(0.83)	(0.50)	(0.78)	(0.72)
EIS		0.113	0.089	-0.038	-0.039
		(0.27)	(-0.21)	(-0.78)	(-0.80)
HOLIDAYS		-0.285*	-0.285*	-0.028**	-0.028**
		(1.74)	(1.74)	(-3.02)	(-3.03)
MOMENTUM VARIABLES		Yes	Yes		
TIME TREND		Yes	Yes	Yes	Yes
SECTOR	Fixed effects	Yes	Yes	Yes	Yes
QUARTER	Fixed effects	Yes	Yes	Yes	Yes
WEEK-DAY	Fixed effects	Yes	Yes	Yes	Yes
N		7814	7814	7814	7814
N successful		321	321	321	321
Between R-squared				0.154	0.152
Sargan-Hansen overidentification test				0.703	0.71
Sanderson-Windmeijer F informativeness test				0.002	0.002