Entrepreneurial Fundraising Strategies and the Gender Gap: Theory and Evidence from Equity Crowdfunding

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Abstract

Start-ups with female founders typically raise less money than their male counterparts. A prior literature explores investor demand and finds evidence of assortative matching, where investors prefer to invest in entrepreneurs of their own gender. In the context of equity crowdfunding, we examine the supply side of the gender funding gap, asking how female and male founders anticipate different investor demand. We develop an assortative matching theory that generates four benchmark predictions, namely that female founders (i) ask for less funding, (ii) have the same campaign success probability, (iii) receive less funding if successful, and (iv) have the same overfunding ratio, defined as the ratio of funding received over funding requested. Leveraging proprietary data from a UK equity crowdfunding platform thar includes both successful and unsuccessful ventures, the evidence matches the first three predictions, also finding that all-female teams have larger funding gaps than mixed-gender teams. For the overfunding ratio, we find that mixed-gender (all-female) teams have higher (lower) overfunding ratios than the all-male benchmark. We also find that female investors fund mixed-gender teams relatively more, whereas male investors give disproportionately less to all-female teams. Gender gaps increase for more capital-intensive ventures.

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

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1. Introduction

It is well-documented that female-led startups raise less capital than their male counterparts (Coleman and Robb, 2009). However, it remains unclear how much of the gender gap is driven by demand-side investor considerations, versus supply-side entrepreneur considerations. A recent academic literature (discussed below) makes considerable progress in better understanding the investor side. A consistent finding is the prevalence of assortative matching, where female (male) investors are more likely to invest in female (male) entrepreneurs. However, there has been limited progress in understanding how entrepreneurs respond to the gender funding gap. While the literature is careful to control for company characteristics (such as industry) and other founder characteristics (such as prior experience), little is known about the way that female entrepreneurs anticipate their heightened fundraising challenges.

In this paper we specifically focus on the context of equity crowdfunding where demand and supply are more readily observable. We first develop a theoretical benchmark for when to expect gender gaps in a world with assortative matching. In the model the entrepreneurs set funding goals that must be met for the campaign to succeed, otherwise no funding is provided at all. We derive the optimal fundraising strategies of female and male entrepreneurs who face different investor demands. The model generates four benchmark predictions. First, female entrepreneurs have lower funding goals, i.e., the ask for less funding. Second, given their differential asks, the probability of campaign success is the same for female and male entrepreneurs. Third, the amount received in successful campaigns is lower for female entrepreneurs. Fourth, despite different campaign outcomes, female and male entrepreneurs should have the same overfunding ratio, defined as the ratio of funding received over funding asked for. These predictions provide the theoretical framework for our empirical analysis.

Our empirical analysis leverages proprietary data from an equity crowdfunding platform, specifically from SEEDRS, a large UK equity crowdfunding platform.[1] Their data opens up the "black box" of fundraising in the sense we observe how female and male entrepreneurs ask for different amounts of funding, and how female and male investors pledge to support their respective campaigns. Importantly, we observe data the ventures whose campaigns succeed and those who don't. The UK has one of the most developed equity crowdfunding markets, largely because the Financial Conduct

[1] The two leading equity crowdfunding platforms are CrowdCube and SEEDRS. They are similar in size and jointly account for over 80% of the market (Beauhurst 2020).

Authority (the relevant regulator) adopted a laissez-faire approach in the early days of the industry.[2] The recent work of Bernstein et al. (2017) and Ewens and Townsend (2020) demonstrates how equity crowdfunding platforms provide a powerful lens for studying the financing of early-stage ventures. Unlike "low-stakes" rewards-based crowdfunding platforms like Kickstarter, equity crowdfunding involves "high-stakes", where investors make substantial investments and want proper financial returns. To illustrate, Mollick (2014) finds that the average amount of funds raised in a successful Kickstarter campaign is $7,825, whereas in our SEEDRS data we find the average to be £290,001 (≈$433,558), i.e., 55 times larger.

In our data 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 investment pledges. 9% of all campaigns have only female founders, and another 6.6% have mixed-gender founder teams. The average all-male founder team sets an investment goal of £205,330, and the average successful campaign raises £332,881. By comparison, the average all-female (mixed gender) team only asks for £124,734 (£148,789) and, if successful, raises £115,561 (£185,000). This alone suggests large gender differences across founder teams. Furthermore, to illustrate assortative matching we note that 7.3% of investors in all-male teams are female investors. The corresponding numbers are 14.3% in all-female teams and 16.2% in mixed-gender teams.

The first step in our empirical analysis is to examine the relationship between founder gender and the entrepreneur's choices of campaign funding goals. We are careful to distinguish gender effects from other human capital factors such as education and prior experiences. We also control for numerous campaign and company characteristics, not just their industry, but also the type of product and delivery model. We even perform some natural language processing on the company descriptions submitted for the fundraising campaign to assess the growth ambitions and capital intensities of the ventures. Consistent with the first theorical benchmark, we find that females teams have significantly lower fundraising goals, even after controlling for all company characteristics. The effect is statistically significant for all-female as well as mixed-gender teams.

[2] In the US only accredited investors can invest in equity crowdfunding, but UK regulations do not impose such restrictions. According to Beauhurst (2020), at least 40% of early-stage deals in the UK come via equity crowdfunding platforms where the general public (i.e., unaccredited investors, aka the crowd) invest in start-ups in return for equity. 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)).

The second empirical step concerns the relationships between gender and campaign success. Facing lower demand, one might have thought that female teams are less likely to reach their minimum campaign goals. However, our theory benchmark suggests that once we account for female founders setting lower goals there should be no differences in the probability of reaching the funding goal. This is exactly what we find in our empirical analysis.

The third step of the analysis looks at the amounts of funding raised, related to the third and fourth theoretical predictions. We recognize two mechanisms by which gender might affect funding amounts. First there is the 'direct effect' of how founder gender affects investor demand. Second, there is an 'indirect effect' of how founder gender affects the funding goal, which in turn affects the realized funding amount. We call the combination of these two effects the 'total effect.' With this in mind, we distinguish two regression models. In the first model we deliberately omit the funding goal as a control variable. We call this the "total effect" model because the estimated coefficient captures the entire gender effect, i.e., it does not separate out the direct effect from the indirect effect. This regression model tests our third model prediction. We find a strong negative coefficient for all-female teams, although the coefficient for mixed-gender teams is insignificant.

The second model adds funding goal as a control variable. We call this the 'direct effect' model because the added control separates out the indirect effects coming from the initial campaign goal. This model effectively tests the fourth model prediction about the overfunding ratios, i.e., it evaluates the amount of funding received relative to the amount initially asked for. Here our empirical results deviate slightly from the theoretical benchmark. The theory suggest that there should be no gender effects in the overfunding ratio. We do find this to be true on average when looking at a continuous measure of female representation. However, when we specifically distinguish between all-female vs. mixed-gender teams, we find that the all-female coefficient is negative and significant, whereas the mixed-gender coefficient is actually positive and significant. This says that, relative to the benchmark model, the overfunding ratio is too low (high) for all-female (mixed-gender) teams. We also provide a simple model extension, based on differential market depth, that can account for this departure from the benchmark model.

We further disaggregate investor demand into the demand from female and male investors (and also investors of unknown gender). This allows us to take a deeper look into the assortative investment patterns. We find that female investors do not invest significantly more into all-female teams, but we

do find that they invest significantly more into mixed-gender teams. Male investors, by contrast, invest significantly less into all-female teams. They also invest less into mixed-gender teams, although that coefficient becomes insignificant in the direct model. These investment patterns are also consistent with our notion of differential market depth and further help to explain the departures from the fourth benchmark.

We also examine how any gender biases are moderated by industry and company characteristics. The work of Herbert (2023) suggests that gender gaps vary by industry, and that industries with greater female participation exhibit smaller gender gaps. We examine this possibility in our data in two ways, measuring an industry's female share first from the percentage of female founders, and then from the percentage of female investors. For the latter we find no significant interaction effects whatsoever, suggesting that an industry's share of female investors does not affect any results. For the former we find that all interaction effects are negative, but mostly insignificant (with one exception). The industry's share of female founders is thus mostly irrelevant; if anything, it widens, not narrows, the gender gap.

We consider whether gender gaps are moderated by the growth ambitions or capital intensity of ventures. The concern is that estimated gender gaps could be coming from female founders having lower growth ambitions or less capital intensive business models. We find no evidence that growth ambitions change any of the estimated gender gaps, but we do find that gender gaps widen for more capital intensive ventures. Finally, we also consider longer-term funding outcomes beyond the SEEDRS platform. We find that all-female teams raise less external funding, although mixed gender teams actually raise more.

Our paper contributes to several prior literatures. The economics literature on gender differences goes back to the seminal debate between taste-based discrimination (Becker, 1971) versus statistical discrimination (Arrow, 1973). Important elaborations include the recognition of unintentional biases (Bertrand et al., 2005), stereotypes (Bordalo et al., 2016), biased beliefs (Coffman, et al., 2021) and systemic discrimination (Bohren et al., 2024). A large body of experimental evidence also suggests that in general women are more risk-averse than men (Byrnes et al. 1999; Eckel and Grossman 2008; Croson and Gneezy 2009). However, this may not be the case once we consider self-selection, especially in business and finance occupations (Adams and Ragunathan, 2017; Atkinson et al., 2003; Huang and Kisgen, 2013).

In the finance literature, significant gender differences have been found across wide range of financial activities, including trading (Barber and Odean, 2001), credit (Alesina et al., 2013), boards (Adams and Ferreira, 2009), and financial literacy (Lusardi and Tufano, 2015). Not surprisingly, gender differences also affect the financing of startups. Verheul and Thurik (2001), Coleman and Robb (2009), Robb and Coleman (2010), and Hebert (2020) all find that female entrepreneurs raise less money than their male counterparts. Moreover, Klapper and Parker (2011) document gender differences in the founding of new companies, and Fairlie and Robb (2009) document performance differences. While descriptively rich, much of this literature cannot distinguish supply-side entrepreneur factors from demand-side investor factors.

A recent literature on gender differences in venture capital helps to better understand the demand side. Gompers and Wang (2017) document the overall trends of female participation in the venture capital industry. With female participation around 9% and stagnating, they argue that the venture capital industry is lagging behind comparable professions. Gompers et al. (2021) look at the performance of venture capital deals and funds. They find that female partners significantly underperform their male counterparts. However, they suggest that performance differentials can be traced back to the support provided by colleagues.[3] Calder-Wang and Gompers (2021) show that venture capital partners are more likely to hire female partners if they themselves have daughters. Increased gender diversity within venture capital firms also improves investing performance.

Separately, a recent literature studies rewards-based crowdfunding, mostly based on the data from the leading US platform called Kickstarter. Gafni et al. (2021) find that female campaigners set minimum goals that are similar to male campaigners and achieve a higher rate of campaign success. They find strong evidence of assortative matching between campaigners and backers. In a complementary survey, they also find evidence of taste-based discrimination among male backers. Greenberg and Mollick (2017) also find that female campaigners have a higher success rate than their male counterparts. Their evidence for assortative matching suggests "activist homophily" where some female backers are supporting female campaigners as a social cause.[4] Superficially, this literature looks quite similar to the equity crowdfunding literature, because of comparable platform

[3] Using a different study design, Raina (2018) finds that the worst investment performance is achieved by male venture capitalists investing in female ventures.
[4] The work of Lin and Pursiainen (2018) and Xu (2018) further examine some of the learning dynamics on the Kickstarter platform.

technologies. However, the social context and the economic stakes are very different. Kickstarter is about helping friends and strangers whose project have an emotional appeal to the donor. Equity crowdfunding, by contrast, is an investment platform for early-stage investors who want a financial return. As noted above, the investment stakes are also very different.

Turning to the academic literature on equity crowdfunding itself, Vulkan et al. (2016) provides a useful overview of how equity crowdfunding works. Estrin et al. (2017) argues that equity crowdfunding contributes to the aggregate funding of start-ups and does not pose unreasonable risks to investors. McGuire (2016) provides market-level evidence that equity crowdfunding increases overall funding to female entrepreneurs. Bollaet et al (2021) reviews the literature on how Fin Tech generally increases access to early stage finance especially to women.

Several studies leverage the rich deal-level data available on equity crowdfunding platforms. Bernstein et al. (2017) uses AngelList, a prominent US platform, for a randomized field experiment about investor attention. They find that the characteristics of founding teams interest investors more than product or market characteristics. Ewens and Townsend (2020) also use AngelList data and focus their analysis on gender effects. Their central findings resolve around gender biases in the form of assortative matching. Female (male) investors express more interest in female (male) entrepreneurs. Moreover, the male entrepreneurs that male investors were more interested in do, not outperform the female entrepreneurs they were less interested in. Bapna and Ganco (2021) also perform a randomized field study that takes a deeper look into assortative matching. A core finding is that investor experience attenuates gender biases. Two more studies worth mentioning are Horvat and Papamarkou (2017), who also find evidence of assortative matching in terms of same-gender entrepreneur-investor ties; and Mohammadi and Shafi (2018), who find that female investors invest relatively less in younger and higher-tech ventures.[5]

Another literature worth mentioning here studies gender differences at the pitching stage when entrepreneurs seek attention from investors. Brooks et al (2014) use a randomized field trial where pitch decks are randomly associated with different founders whose pictures are included. They find that investors have a bias for “attractive men”. Gornall and Strebulaev (2020) perform a similar

[5] Somewhat unrelated to our main interests here, several equity crowdfunding papers look at the dynamic relationships between investors. Wang et al. (2019) examines the signalling effect that angel investors can have on the crowd. Asterbro et al. (2024) look at herding effects by studying the sequence of bids within campaigns. Finally, Zhao et al. (2020) look at how lead investors moderate the differential campaign successes of female and male entrepreneurs.

exercise without pictures, randomizing founder names. They find that investors express more interest in female than male founders. Finally, Howell and Nanda (2019) use data from in-person pitches and find no bias among the judges. However, they find that female founders are less likely to follow-up with judges after the competition, resulting in fewer network connections.

With the exception of this last paper, almost all of the literature on gender in entrepreneurial finance focuses on the demand-side, thereby providing a deeper understanding of investor preferences and biases. A refreshing aspect of Howell and Nanda (2019) is that it starts to focus on the actions of entrepreneurs, specifically looking at how they form network ties. Our paper differs from the prior literature in terms of focusing on the entrepreneurs' fundraising strategies, asking whether female founders approach fundraising differently. Our key novelty is to first derive a theory model that describes an equilibrium with assortative matching, and then to evaluate the empirical data, showing how much but not all of the evidence conforms to the benchmark predictions. A central finding is that, on the supply side, female entrepreneurs anticipate lower investor demand, and reduce their fundraising targets accordingly.

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 all the empirical analysis. It is followed by a brief conclusion. Finally, there is an Online Appendix that contains empirical robustness results and theoretical proofs.

2. Theoretical Foundations

In this section, we develop a simple theory to anchor our empirical analysis. The purpose of the model is not to provide a comprehensive description of all the complex decision processes but to provide a theoretical benchmark against which to evaluate the empirical evidence. More specifically, the purpose of the theory is (i) to explain the mechanisms of gender assortative matching and how they might impact a fundraising campaign, (ii) to identify the trade-offs faced by the entrepreneur launching an equity fundraising campaign, and (iii) to derive a set of benchmarks concerning the expected equilibrium relationship between gender and campaign outcomes. We can then evaluate the empirical evidence against this benchmark model to detect any remaining

anomalies. The Online Appendix contains all formal derivations, here we limit ourselves to a brief description.

Our model focuses on the amount of money raised in an equity crowdfunding campaign. Denote the amount the venture receives an entrepreneur receives by *y*, a random variable that is defined by the following equation:

$$y = n * \psi * \lambda \quad (1)$$

n is a shift parameter of investor demand. We will use *n* as a parameter that captures differential investor demand for campaigns of male versus female founders. To simplify the exposition, we will refer to *n* as the number of interested investors, but the model is more general.[6] ψ is a "campaign signal" that investors receive from the entrepreneur, and λ is an "external signal" that investors receive about the attractiveness of the venture. Let *g* be the minimum campaign goal set by the entrepreneur at the beginning of the campaign.[7] Using the rules of equity crowdfunding, we denote the amount of funding by 0 if $y < g$ and y if $y \geq g$. That is, the campaign is only successful if the entrepreneur reaches the minimum goal *g*. Otherwise, it fails, and no investments are made.

We now explain the assumptions surrounding the three key variables n, ψ, and λ. For n, we focus on assortative gender matching and ask under what conditions female founders expect fewer interested investors.[8] Let the superscripts $i = F, M$ refer to female and male entrepreneurs, and the subscripts $j = f, m$ to female and male investors. Let Q^F and Q^M be the number of female and male entrepreneurs, and $q = Q^F/Q^M$ the female to male ratio for entrepreneurs. Let P_j^i the number of investors of gender j that invest in entrepreneurs of gender i. P_j $(= P_j^F + P_j^M)$ denotes the total number of investors of gender j. Let $p = P_f/P_m$ be the female to male ratio for investors. Finally, let $\pi_f^F = P_f^F/P_f$ be the assortative ratio for female investors (i.e., the fraction of female investors that invest in female entrepreneurs); similarly, $\pi_m^M = P_m^M/P_m$. It is worth noting that throughout our

[6] For expositional brevity, we describe the model as if each investor only makes one investment. The case where the same investor invests in multiple companies is equivalent: all we need to do is count the same investors multiple times across different companies. Moreover, since *n* is a general shift parameter, we can also interpret it as differences in the average amount investors pledge to male versus female campaigns.

[7] For simplicity, we ignore the choice of valuation here. Empirically we find that campaign goals have high explanatory power, but valuations do not.

[8] For brevity, the theory discussion only focuses on two gender categories: female vs. male teams. In the empirical analysis we will also look at mixed gender teams. While our focus here is on gender, a similar analysis can also be applied to other observable characteristics.

analysis the strength of the assortative matching mechanism, as reflected in π_f^F and π_m^M, can differ for female vs. male matches. The number of investors interested in female and male teams is thus given by $n^F = \frac{P_f^F + P_m^F}{Q^F}$ and $n^M = \frac{P_f^M + P_m^M}{Q^M}$. In the Online Appendix, we show that the condition for female entrepreneurs to expect fewer investors is given by

$$n^F < n^M \Leftrightarrow \frac{\pi_f^F p + (1-\pi_m^M)}{(1-\pi_f^F)p + \pi_m^M} < q \qquad (2)$$

This condition is more likely to be satisfied the smaller p (fewer female investors), the larger q (more female entrepreneurs), the smaller π_f^F (female investors less interested in their own gender), and the larger π_m^M (male investors more interested in their own gender). In the Online Appendix, we exhibit the data needed to estimate the parameters and verify that condition (2) is indeed satisfied in our data. This justifies assuming $n^F < n^M$ throughout our theory, so that female founders expect lower demand from investors than male founders.

Concerning the campaign signal ψ, let us briefly consider the following puzzle. Given the campaign rules, why doesn't every entrepreneur simply ask for a campaign goal close to zero (e.g., g=£0.01)? Clearly, s/he could always achieve that goal and then let the campaign run for as long as s/he wanted to. The reason this is not happening is that investors infer a signal from the entrepreneur's choice of g. Doubtlessly, a goal of g=£0.01 would be viewed as a joke.[9] More generally, a low goal is likely to be interpreted as a signal that the entrepreneur does not want a lot of money. This implies that the entrepreneur must be strategic in setting an appropriate goal. There is a fundamental trade-off here: setting a higher goal signals to the market a desire to raise more money, but this is risky since it also increases the probability of failing to achieve the goal.

We capture this trade-off with the simplest possible signalling model where investment demand y responds to the signal g through some signaling function $\psi(g)$. For tractability, we use a constant elasticity specification $\psi(g) = g^\gamma$, where $\gamma \in (0,1)$ is an exogenous parameter that measures how responsive investments are to campaign goals.

[9] While entrepreneurs can in principle set up whatever goal they want, the advice given by the platforms themselves is that unusual goals are unlikely to be funded. See https://www.seedrs.com/learn/help/how-do-i-value-my-business-2 and https://drop.studio/crowdfunding-academy/how-to-set-up-crowdfunding.

Concerning the external factors that may affect investor demand, we assume that λ is a market signal commonly observed by all investors. At the beginning of the campaign, however, the entrepreneur does not know the realization of λ, only its distribution. For tractability, we assume that λ has a negative exponential distribution with a mean of μ and density $\omega(\lambda)$.

The entrepreneur is assumed to be risk-neutral and chooses the optimal campaign goal g to maximize the expected amount of funds raised. This is denoted by F and is given by

$$F = \int_{y=g}^{y=\infty} y(n, g, \lambda)\omega(\lambda)d\lambda$$

We immediately recognize a risk-return trade-off for setting a campaign goal. A higher value of g increases the expected investments y but also increases the success hurdle, as captured by the lower limit in the above integral. The optimal campaign goal therefore trades off these two marginal effects.

Finally, we denote the probability of campaign success by

$$S = \int_{y=g}^{y=\infty} \omega(\lambda)d\lambda,$$

and we define the overfunding ratio as the ratio of expected fundraising F divided by the campaign goal g. This measures how much companies raise over and above their campaign goal.

In the Online Appendix, we formally derive the equilibrium properties of the model. We summarize them with the following four main propositions.

Proposition 1: The optimal g increasing in n.

The intuition is that an entrepreneur facing a higher demand has more to gain from setting a more aggressive campaign goal. Importantly, if Equation 2 holds, female entrepreneurs expect lower demand. We should then expect them to set lower campaign goals. We will empirically examine this in Table 3.

Proposition 2: The probability of campaign success S is independent of n

In the absence of a theory, it is not immediately obvious how the number of potential investors (or, more generally, ex-ante investment demand) is related to campaign success. However, our simple theory of optimal campaign choices generates a useful theoretical benchmark, namely that campaign success should be independent of the expected number of investors. This is because entrepreneurs adjust their optimal campaign goals in line with the expected demand. Founders anticipate the level of demand they can expect as a function of their gender composition. They compare the marginal return from asking for more funding against the marginal cost of failing to meet the minimum funding goal. What Proposition 2 establishes is that these marginal returns and costs are proportional to n. This is what generates the prediction that female and male entrepreneurs should have equal campaign success rates. We empirically examine this in Table 4.

Proposition 3: The expected amount of funds raised F is increasing in n

Proposition 3 shows that a higher number of interested investors should result in a higher total funding amount. Importantly, if Equation 2 holds, we should expect female entrepreneurs to raise less funding. Empirically, we consider this in the first two columns of Table 5 that look at the "total effect" of gender on fundraising.

Proposition 4: The overfunding ratio is independent of n

Again, without a theoretical foundation, this result is not immediately obvious. Yet, we obtain a simple benchmark prediction that the overfunding ratio should not depend on the expected number of investors (n). Even if Equation 2 holds, the benchmark model predicts no gender differences in the overfunding ratio. Empirically, we consider this in the last two columns of Table 5 that look at the "direct effect" of gender on fundraising.

Our theory is meant not meant to explain all our empirical results, instead it is meant to provide a theoretical benchmark of an equilibrium model with assortative matching. This anchors our empirical analysis and allows us to identify any remaining gender biases.[10]

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.[11]

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

[10] Naturally, there are many ways in which we could augment the theory to make it more realistic. For example, we could use more general functional forms, we could try to fully model all the campaign dynamics, we could broaden the optimization problem to also include valuation, we could assume male and female founders have different degrees of risk aversion, or we could try to fully model the signalling game. While all this would make the theory richer, it would also distract us from our main goal, which is to provide a simple and transparent benchmark to guide our empirical analysis.

[11] Unfortunately, the authors were unable to access SEDRS data after this date.

SEEDRS campaign page. As such, we gathered data on entrepreneurs' education and professional experience, as well as gender.[12]

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, 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 the daily dynamics of investment flows into each campaign. Investor gender data comes directly from SEEDRS. SEEDRS does not directly ask for the gender of investors but instead determines it based on the investor's first name using a statistical algorithm. As a result, an estimate of investor gender is not available for 12% of investors that have gender-ambiguous names. For an additional 7% of investors, gender also is unknown due to missing data.

We structure our data into two 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%.

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.

[12] For prior business education, see the work of Colombo and Grilli 2005; Gimmon and Levie 2010; Kaplan and Stromberg 2004; and Mollick 2014. For prior entrepreneurial experience, see the work of Colombo and Grilli 2005; Hsu 2007; Gimmon and Levie 2010; Gompers et al. 2010.

3.2. Variable Definitions

Throughout the paper, we use the subscript i to denote cross-sectional variation (i.e., across campaigns). We will use the following main variable categories:

- $\boldsymbol{G_i}$ stands for **fundraising strategy** variables, namely funding goal.
- $\boldsymbol{S_i}$ stands for the **campaign success** dummy.
- $\boldsymbol{F_i}$ stands for the **funding amount** variable
- $\boldsymbol{X_i}$ stands for **founder characteristics** variables, namely gender, experience, and education.
- $\boldsymbol{Z_i}$ stands for all **control** variables.

Table 1 provides an overview of all the variables used in the analysis. We now discuss them in greater detail. For this, it is 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.[13] 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 seven days. After seven days, the founders are allowed to close the campaign. In other words, founders can stop the campaign as early as the 8th day after reaching the goal, or they can wait for longer. Each company chooses its own final stopping date.

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 as the company's post-money (or pre-money) valuation, which includes (excludes) the amount of the fundraising goal. Those two measures are mechanically related.[14]

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.

[13] On SEEDRS, entrepreneurs are advised to set funding goal and company valuation to be realistic and comparable to other similar companies. 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.

[14] The key mechanical relationships are: Fundraising Goal = Equity Offered (at fundraising goal) * Post-money Valuation; and Post-money Valuation = Pre-money Valuation + Goal.

Most investors show interest by registering a pledge and then pay the money if the campaign is successful. For the total funding amount (F_i), we sum up all pledges provided they have not been cancelled or rejected.[15]

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, management experience, business education, and most importantly 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 use the same approach of calculating shares and dummies for our experience and education variables. For entrepreneurial experience we ask where founders have experience founding a 'proper' company. By 'proper,' we define any company that has some signs of success: either 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 management experience we look at prior work experience in senior management roles. For business education, we look at whether the founders have an MBA.[16]

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 program (this program is for the first money into very young companies and offers up to 50% tax credits) or under the EIS program (this is for slightly older companies and offers up to 30% tax credits), or no eligibility.[17] Since eligibility is partly related to age, our dummies indirectly proxy for company age (which is not otherwise recorded in the data). From SEEDRS, we also obtain the following sector controls: Clothing and Home, E-Commerce and Marketing, Food and Drink, Games and

[15] We discuss cancelations and rejections in Section 4.6.
[16] In section 4.6 we report several robustness checks about our measurement of experience and education.
[17] 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 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.

Entertainment, Finance, Transport and Travel, and Technology. We also use calendar fixed effects from Q3 of 2012 to Q2 of 2017.

In any cross-sectional gender analysis, it is desirable to control for as many other company characteristics as possible, to account for alternative factors. One can never exclude *all* other factors, but our crowdfunding data provides a unique opportunity to use qualitative data rarely observable in standard company databases. Specifically, we leverage the business descriptions they companies use to describe themselves for their campaigns. SEEDS did not properly keep the description data for unsuccessful campaigns, so we can only use it for successful campaigns. Moreover, 4 successful campaigns did not have proper business descriptions. Any regressions with business descriptions are therefore based on a sample of 329 successful campaigns with proper business descriptions. From the company descriptions, we first identity business models. Specifically, we classify business models into one of three categories: business-to-business (B2B), business-to-consumer (B2C), and mixed models (used as omitted category). Next, we classify the companies' model of delivery into three categories: digital, non-digital, and mixed model (used as omitted category).

To further harvest the richness of the companies' texts published during their SEEDRS campaign, we carried out some Natural Language Processing (NLP) analysis.[18] One of the key concerns might be that female founders ask for less funding because their ventures have lower growth ambitions or lower capital requirement. We therefore use NLP analysis to identify signals about two important company-specific characteristics, namely their growth ambition and their capital intensity. We submitted the text to ChatGPT, using the "gpt-3.5-turbo-0301" version. One inconvenience is that this model has a limit on the number of words one can submit. Even in the paid version this limit is still well below the amount of text we had for all campaigns combined. To deal with that we wrote a script which asks ChatGPT sequentially to score each company's text based on the following instructions:

You are going to reply by giving scores between 0 and 100 in the following format: (1) score (2) score. Don't explain why you are giving those scores. Score the following company pitch in terms of (1)

[18] NLP analysis is fast becoming an important tool in finance, originally used to predict prices or events (e.g., Zadeh et al 2009, Diego et al, 2023), innovation levels (Li et al., 2021), and spreading quickly to many other parts of finance research (see Kang et al., 2020, for a survey).

What potential for growth is there?; and (2) How much investment is needed for this kind of business in its first round of financing?

3.3. Descriptive Statistics

Table 2 reports descriptive statistics for our balanced sample. Panel A provides a breakdown by the gender of the founder teams and reports the significance of difference-of-means tests, with male-only being the default category. Panel B reports the most important pairwise correlations. Panel C provides a two-way decomposition of the gender of founder teams and investors.

We note from Panel A of Table 2 that 16% of founders are female. 9% of all teams are all-female, and another 16% have a 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 gender.

Figure 1, Panel A: Fundraising strategies

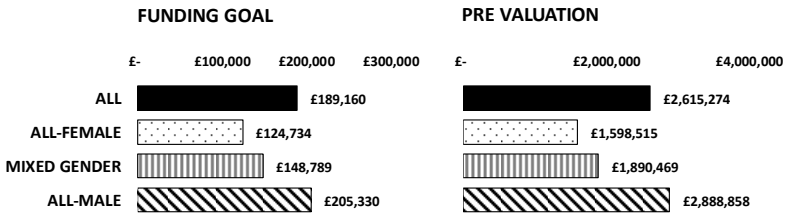
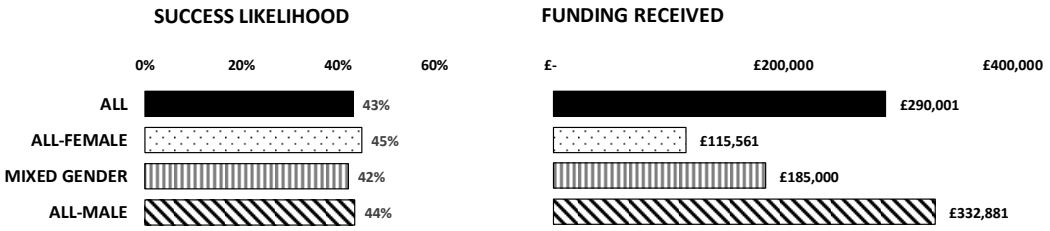


Figure 1, Panel B: Fundraising outcomes



Panel A in Figure 1 shows that the average campaign goal is £189K; the average pre-money valuation is £2.62M. 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 £56K less. They also set considerably lower valuations than all-male teams, with all-female start-ups valuing themselves approximately £1.3M less, and females-mixed start-ups £1M less. Panel B of Figure 1 shows that the average campaign success rate is 43%, with the all-female and females-mixed rations within 2%.[19] Successful teams raise £290K, but females-only teams only raise £115K and females-mixed teams £185K.

These striking differences raise important questions, such as whether all-female teams want less money or whether it is the investors who want to give them less. Naturally, some of this variation could 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.

One more aspect worth considering is the gender of investors and to what extent this can affect the fundraising outcomes from Figure 1. Panel C of Table 2, therefore, provides a two-way gender breakdown. The table also shows the significance levels for difference-of-means tests against the male-only category. The key finding is that the lower funding amounts of females-only and females-mixed teams mainly stems from differences in investments made by male investors. While female investors also invest slightly lower amounts into female founder teams, those differences are not statistically significant. The last row furthermore shows clear evidence of assortative matching: male-only teams receive 7.3% of their funding from female investors, whereas all-female teams receive 14.3%, and female-mixed teams receive even more of their funding from female investors, at 16.2%.

4. Main Empirical Analysis

4.1 Fundraising strategies

To being our empirical analysis, we examine the relationship between founder team characteristics X_i and fundraising strategies G_i. The empirical regression is given by

$$G_i = f_G(X_i, Z_i) + \varepsilon_{G,i} \quad (3)$$

[19] 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.

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. The first two columns use the entire sample and omit the text-based controls (namely the delivery mode, product type, and two GPT variables). The second two columns include those controls and therefore only include successful campaigns. We use two types of measures for founder team characteristics (X_i): continuous shares and dummies. The continuous model in the first and third column regress the fundraising strategy variables G_i on the share of founders that are female. The dummy model in the second and fourth column regress G_i on dummy variables indicating whether the team is all-female, and another whether the team is mixed-gender (the omitted category being male-only teams). Whenever we measure gender with continuous or dummy variables, we also measure all other founder characteristic in the same way.

Table 3 shows that teams that have a higher proportion of female founders ask for significantly less money. This is true after controlling for founder team characteristics (X_i) and the company control variables (Z_i). The dummy specification in the second column lends itself to expressing economic magnitudes.[20] All-female teams ask 23.33% less money, mixed gender teams 24.65% less (the difference between those two coefficients being statistically insignificant). These findings remain valid in the third and fourth column which includes the additional text-based controls. The economic magnitudes are 36.30% less for all-female and 33.77% less for mixed teams.

In terms of control variables, Table 3 finds that teams with more entrepreneurial experience have significantly higher campaign goals. The coefficients are economically large. In the dummy specification of column 2 we find that funding goals increase by 27.76% with entrepreneurial experience, 11.96% with managerial experience, and 48.59% with business education.

Columns 3 and 4 differ from columns 1 and 2 in two important respects: they contain GTP Growth and GPT Capital as additional control variables, and they are not based on the full sample, but the sample of successful campaigns (where the GPT variables can be measured). In the Online Appendix we provide a breakdown of these two effects. Panel A of Table A1 shows that the increase in the absolute size of the coefficients in columns 3 and 4 is driven by the change in sample, not the controls.

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

We also examine the stability of our estimated coefficients, with a view to assessing how likely it is that our results are affected by unobservable information. For this we implement the tests suggested by Oster (2019). We define a base model that includes the fixed effects for SECTORS, QUARTERS , and SEIS/ESI, as well as TEAM SIZE and PRIOR SEEDRS variables. We then augment the model stepwise by first adding founder characteristics (ENT. EXP., MAN. EXP., AND EDUCATION), then adding PRODUCT TYPE and DELIVERY MODE controls, and finally adding the two GPT variables. For each step we calculate the Oster delta relative to the base model. The results are reported in Panel A of Table A1 in the Online Appendix. Our estimated Oster's delta coefficients are greater than 1 (which is the threshold value above which the Oster test rejects the importance of unobserved heterogeneity) in 10 out of 12 cases, and always above 0.9. This suggests that, overall, our results are not particularly sensitive to unobservable information.[21]

Our main focus in this paper is the amount of funding requested and received by founders of different gender. However, the SEEDRS data also contains information on the valuation set by the entrepreneurs, as discussed in section 3.1 and 3.2. We look at the effect of gender both on post-money valuations and investor equity stakes. For this it is useful to recall the simple accounting identify:

*Funding Goal = Valuation * Investor Equity Stake*

We can therefore break out the dependent variable of Table 3 into those two components. To empirically estimate them we recognize their potential interdependence and therefore use seemingly unrelated regressions (aka SUR). Table A3 in the Online Appendix shows that female teams always have negative coefficient for both dependent variables. This suggests that they ask for lower valuations, so their effective cost of capital is higher. It also suggests that they offer smaller equity stakes to investors, i.e., at a higher cost of capital they are more reluctant to part with equity. Note, however, that most of the coefficient in Table A3 are insignificant. This is because as female founders adjust both their valuations and equity stakes, the funding goal coefficient from Table 3 gets split across the two regressions and loses statistical significance.

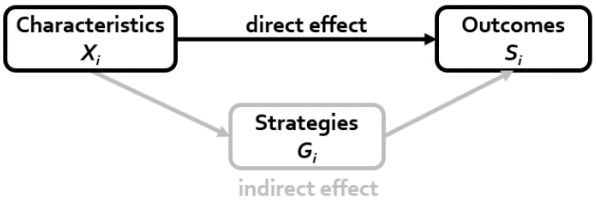
[21] Related to this, Table 3 in the main paper only reports the main control variables. Panel A of Table A2 in the appendix contains an additional table that lists the remaining coefficients not reported in Table 3 (except quarter dummies).

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). Proposition 2 from our theory predicts that there should be no gender differences in the probability of achieving the campaign goals. This is because the founder sets their campaign goal strategically to adjust to their level of expected demand.

To empirically examine this, it is useful to decompose total effects of X_i into direct and indirect effects. The direct effect of founder characteristics X_i on the outcome (S_i for now, others later) 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.[22]

Figure 2: Simple model of mediation



We thus estimate the following equation:

$$S_i = f_S(G_i, X_i, Z_i) + \varepsilon_{S,i} \qquad (4)$$

In the upcoming tables we will make a distinction between the total effects and the direct effect model. For the total effect model we always exclude G_i, but we always include it for the direct effect model.

[22] 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. Chapter 4 of Hayes (2014) contains a detailed explanation of this kind of analysis. In our analysis, we follow Baron and Kenny (1986) and other scholars to examine such mediation effects. The total effect 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.

Table 4 reports the estimation results for campaign success as a dependent variable.[23] We find that, while negative, none of the gender variables are significant. Females face lower investment flows, but they also set lower fundraising goals. Table 4 shows that these two effects balance each other out, leaving female founders with similar probabilities of campaign success, as predicted by our theory.

It is also worth noting that the coefficients for the fundraising goal in columns 3 and 4 is negative and significant. This says that setting higher campaign goals reduces the probability of success in the campaign. Interestingly, the coefficient for Valuation is insignificant, suggesting that the additional breakdown into Valuation and Equity Stakes mentioned in section 4.1 does not provide additional explanatory power in the regressions.

On their own, the results from Table 4 could easily be misinterpreted as suggesting that there are no gender differences. Clearly, this not true because gender differences get reflected in the total amount of funds raised. We now turn our attention to exactly that.

4.3. Fundraising amounts

To examine funding amounts, we estimate the same equation as (2), but with $\log(F_i)$ as the dependent variable. Table 5 reports the result from the cross-sectional regression model. The first two columns estimate the total effect model, the latter two columns the direct effect model. This is where the mediation analysis mentioned above is particularly useful. The total effect model which excludes G_i effectively estimates the effect of founder gender on the total amount of funding received. By contrast, the direct effect model includes G_i. This means that it estimates the effect of founder gender on the overfunding ratio, i.e., how much more (or less) funding female founders receive relative to what they asked for in the first place, as measured by the funding goal G_i.

Columns 1 and 2 of Table 5 show the total effect model. The first column shows that the fraction of female founders has a negative and significant effect on fundraising. This is an important finding, as it shows that even after controlling for numerous other factors, the differences in amounts raised that we first noted in the descriptive statistics of Table 2 continue to persist, especially for all-female teams. This empirical finding is what Proposition 3 predicts, namely that the funding amount is smaller for female teams.

[23] While Table 4 in the main paper reports the main control variables, Panel B of Table A2 in the appendix contains an additional table that lists the remaining coefficients not reported in Table 4 (except quarter dummies).

The second column uses the dummy specification and finds that the negative effect comes mainly from the all-female teams who receive 47.53% less funding. The effect is less pronounced for mixed female teams who receive 27.53% less funding, with the coefficient being statistically insignificant.

Again, we consider the stability of coefficients using the tests suggested by Oster (2019). The results are reported in Panel B of Table A1 in the Online Appendix. Our estimated Oster's delta coefficients are always greater than 1, suggesting that our results are not sensitive to unobservable information.

Columns 3 and 4 of Table 5 pertain to the direct effect model discussed above. This model addresses the prediction of Proposition 4 concerning 'overfunding ratio'. In the third column of Table 5 the female coefficient is statistically insignificant. This is consistent with the benchmark of Proposition 4 where after controlling for campaign goals, there should be no gender effect on the overfunding ratio. Importantly, the coefficient on Goal is highly significant at the 1% level. The coefficient β_G is very close to one (statistically, the difference to one is insignificant). This suggests that on average, companies get one pound for every additional pound they ask for, provided the campaign succeeds. This last qualifier matters since we know from Table 4 that higher goals reduce the likelihood of campaign success. This reflects the risk-return trade-off that is embedded in our theoretical model.[24] We also note that, similar to Table 4, the valuation coefficient is not statistically significant, suggesting once more that it is the funding goal, but not the valuation, that influences campaign outcomes.

While column 3 suggest no departure from the theoretical benchmark model, column 4 reveals some interesting departures concerning the distinction between all-females and mixed-gender teams. Specifically, we find that the all-female coefficient is negative and statistically significant at the 5% level. Even after controlling their lower goals, all-female teams have an overfunding ration that is 17.22% smaller. By contrast, we find that the mixed-gender coefficient is positive and statistically significant at the 10% level. In fact, after controlling their lower goals, mixed-gender teams have an overfunding ratio that is 10.08% larger.

[24] Proposition 4 controls for the campaign goal in a specific way, namely by focusing on the overfunding ratio F_i/G_i. In Table 5 the dependent variable is $\log(F_i)$, and we include the campaign goal $\log(G_i)$ as an independent variable. An equivalent empirical specification is to directly use the overfunding ratio $\log(F_i/G_i)$ as the dependent variable. It is easy to verify that the only difference in that specification is that the coefficient β_G^{Over} of $\log(G_i)$ is given by $\beta_G - 1$. Moreover, we already noted above that β_G is not significantly different from 1. As a consequence, β_G^{Over} is not significantly different from 0.

The results in column 4 deviate from the theoretical benchmark. The departure pertains to the overfunding ratio, which measures how far into the right tail of the distribution funding amounts reach. In the Online Appendix we briefly outline a simple model extension that can readily explain this departure. It is based on the notion that all-female and mixed-gender teams may face differential 'market depth.' By this we mean that they face the same optimization problem for the optimal funding goal, which concerns the left tail of the funding distribution. However, they may have slightly different right tails, i.e., different investor demand after the funding goal has been reached. The theory extension predicts that if all-female (mixed-gender) teams have less (more) market depth, their overfunding is below (above) that of all-male teams. This is precisely what we find in Table 5. [25]

The interesting question naturally becomes where such differences in market depth might be coming from. This brings us to the analysis of investor gender, where we will find some differences in investor demand for all-female vs. mixed-gender teams.

4.4. Investor gender

In this section we take the additional step of disaggregating investor demand by investor gender. As described in Section 3.1, our data classifies investors into female, male, and unknown categories. We rerun the regressions from Table 5 in the two subsamples of female and male investments. The results are reported in Panels A and B of Table 6.[26]

Panel A looks at the funding from female investors. The first two columns show statistically insignificant effects, suggesting that female investors provide the same total funding to all types of teams. The third column, however, shows a positive and statistically significant effect for female founders, suggesting that after controlling for their lower goals, female investors invest more in female teams. Column 4 further unpacks this effect by showing that this stems from investing more in mixed-gender teams. Their coefficient is highly significant at 1%, suggesting that female investors invest 153.70% more. The coefficient for all-female teams suggests that female investors invest 42.90% more, but remains statistically insignificant. These results help to explain some of the results about the overfunding ratio from the fourth column of Table 5. Consistent with the notion of adding

[25] Naturally we cannot exclude the possibility of alternative explanations to the results of Table 5, that may be related to other aspects not captured by our theory.
[26] In Table A4 of the Online Appendix, we also estimate the model for investors with unknown gender. We find no significant gender effects there.

market depth, mixed-funding teams receive more overfunding than predicted by the theoretical benchmark of Proposition 4. To further explain why all-female teams have lower overfunding ratios than the benchmark, we turn to Panel B.

Panel B of Table 6 looks at investments from male investors and presents a very different picture. Indeed, in the first and third column, we find a negative and highly significant coefficient for the proportion of female founders. In the second column, we find a negative and highly significant coefficient for both all-female teams (suggesting 59.91% less funding) and mixed-gender teams (suggesting 38.43% less funding). Of particular interest are the results about the overfunding ratio in the fourth column of Table 6B. We find that the coefficient for mixed-gender teams is statistically insignificant (indicating 9.15% lower funding), but the coefficient for all-female teams is statistically significant at the 5% level, indicating 38.06% less funding. This last result is consistent with the notion that all-female teams have lower market depth. Overall, we note that the analysis of investor gender helps to better understand the departures from the benchmark model noted in the previous section. Specifically, the lower overfunding ratio of all-female teams is related to a lack of funding from male investors, whereas the higher overfunding ratio of mixed-gender teams is related to extra funding by female investors.

4.5. Interaction effects

So far, our regressions control for a large vector of founder and company characteristics. However, one may also ask if gender effects are moderated by these characteristics. For example, the work of Hebert (2020) suggests that the funding gap for female entrepreneurs is more pronounced in male-dominated industries, but sometimes reverses in female-dominated industries. We therefore begin by asking whether our gender effects follow a similar pattern.

In our data we can construct two measures for the share of females in different industries. The first concerns the fraction of female founders across different industries, the second the fraction of female investors across different industries. Specifically, we calculated the share of female entrepreneurs/investors for each campaign and then average these shares by industry. We are mainly interested in the interaction effects, i.e., how the gender coefficients are moderated by our measure of industries' female share.

Panel A of Table 7 reports the results for female founder shares, Panel B for female investor shares. The first two columns replicate the regressions from columns 3 and 4 of Table 3, the remaining two columns replicate the total effect from columns 1 and 2 of Table 5. Throughout we find that the main coefficients from Table 3 and 5 remain very similar. Our main interest are the interaction variables. We find that almost all interaction variables are negative and insignificant with one interesting exception, namely the coefficient for 'Females x Female founder share' in column 3 of Panel A, which is negative significant at the 10% level. [27] These results do not suggest strong effects, but the one negative significant interaction coefficients points in a different direction than what Hebert (2020) found. It suggests that, if anything, the gender gaps becomes larger, not smaller, in industries with more female founders. We interpret this as more competition for funding in those industries, where a larger number of female founders are competing for a limited supply of funding that disproportionately comes from female investors.

There are many other characteristics that could moderate the strength of the gender effects. One frequent concern is that female founders may be more risk-averse (although our literature discussion also casts some doubt on this assertion, given the self-selected nature of who becomes an entrepreneurs). If so, we may ask whether they are more conversative in their growth ambitions? And following a similar logic, whether they prefer to select into less capital intensive ventures?

We first examine these claims by looking at the correlations reported in Table 2, using our Growth GPT and Capital GPT variables. For Growth GPT we indeed find negative correlations, although the coefficient is always below 0.1; significant at 10% for the continuous female measure, and insignificant for the two female dummies. For Capital GPT all correlations are positive but below 0.05 and all insignificant. This evidence does not necessarily support the notion that female entrepreneurs avoid more capital intensive opportunities.

Still, we ask whether the gender effect are moderated by the growth ambitions and capital intensity as measured by our GPT variables. The results are reported in Table 8, which has the analogous structure to Table 7. Panel A considers the interaction effects with Growth GPT. We find that all the interaction effects are insignificant. Panel B considers the interaction effects with Capital GPT. There we find negative and significant effects in all four columns. This suggests that as capital intensity

[27] Another less interesting exception is the positive but insignificant coefficient for 'All-female x Female investor share' in column 2 of Panel B.

increases, funding goals and funding amounts received for female founders all become relatively smaller. This suggests that gender gaps increase with the capital intensity of the underlying venture.[28] It thus appears that differences in investor demand vary according the capital intensity of the underlying venture, an effect that may be related to the types of investors willing and able to fund such ventures.

4.6. Longer-term fundraising outcomes

The core of our analysis concerns the fundraising strategies and outcomes on the SEEDRS platform itself. Naturally, one may also be interested in the longer-term outcomes for these companies. We focus on two standard performance indicators concerning subsequent fundraising and exit (see Da Rin et al., 2013).

After SEEDRS, companies may go on and raise further external funding from other equity investors such as venture capitalists or corporate investors. One would expect a funding gap for female founders, especially since the venture capital industry is known to have particularly few female investors (see Calder-Wang and Gompers, 2021, and Gompers et al., 2021). To verify this, we obtained data in December 2024 for our sample companies, gathering equity financing and exit data from Crunchbase, and further augmenting it with exit data from Google searches. We examine three post-SEEDRS outcome variables, namely (i) whether the company raised any external funding, (ii) the amount of external funding raised, and (iii) whether the company had any exit (defined as an acquisition or an IPO). In Table A6 we run linear regression models in the sample of companies that had successful SEEDRS campaigns. We examine three sets of models: the total effect model (similar to columns 1 and 2 of Table 5), the direct effect model (similar to columns 3 and 4 of Table 5), and alternative direct effect models that further includes as a control FUNDING RECEIVED (SEEDRS), which is the total amount of funding received on SEEDRS across all campaigns.

We do not find any significant effect for the probability of exit, possibly because the overall exit rate in the sample remains low (i.e., between 10% to 12%). However, we find a negative and significant relationship between the percentage of female founders and external funding, both in the probability

[28] In Table A5 of the Online Appendix we further consider interaction effects with other founder characteristics. Perhaps surprisingly, we find that the interaction of all-female teams with more entrepreneurial experience is negative, suggesting that more experienced all-female teams ask and receive relatively less funding. We find no interaction effects with managerial experience or education.

regressions of Panel D, and the amount regressions of Panel E. When breaking the effect into all-female vs. mixed-gender teams, we find negative significant coefficients for all-female teams, but positive significant coefficients for mixed-gender teams.

These findings confirm the conjecture that female founders continue to raise less equity after SEEDRS. Maybe the most interesting insight from Table A6 is that the gender effect persists in the two direct effect models, so even after we control for the total amount of funding received on SEEDRS. Recall that our theory explains how female founders set lower fundraising goals because they anticipate lower investor demand. The theory focuses on behaviours within the campaign, not beyond. We should therefore not expect Proposition 4 to hold beyond the campaign itself. Indeed, this is what we find, namely that the gender gap remains significant in both of the direct effect models.[29]

The analysis of external funding suggests that the fundamentals of gender gaps and assortative matching apply well beyond equity crowdfunding. What remains unique to our context is the fact that companies must stipulate upfront the minimum amount of funding they seek. This feature allows us to study how founder anticipate investor demand, which is at the core of our theory and empirical analysis.

4.7. Robustness analysis

In this section, we consider further empirical robustness checks and model extensions that speak to the representativeness of the results. The Online Appendix contains all the tables related to the discussion in this section.

Our fundraising analysis naturally focuses on the total amount of funds raised. In our theory, we simplified our exposition by focusing on the number of interested female and male investors, assuming they always invest the same amount. This raises an interesting empirical question to what extent the gender gap we found in this paper stems from female founders finding fewer interested investors versus receiving smaller average investment amounts from their investors. In the Online Appendix, we therefore break out total funding amounts into (i) the number of investors as reported in Table A7, and (ii) the average investment amounts as reported in Table A8. Both Table A7 and A8

[29] The gender patterns in external funding are also related to our discussion at the end of section 4.3., where we introduced the notion of differential market depth. The findings here are very similar: all-female teams face lower investor demand, whereas mixed-gender teams face higher demand –here even higher than all-male teams.

contain three panels, Panel A for all investors, Panel B for female investors, and Panel C for male investors. The main results are as follows. Table A7 considers the number of investors. We find negative significant effects for the continuous female variable as well as the all-female dummy, both in the overall sample and in the male investor subsample. We find no significant effect in the female investor subsample. Table A8 considers the average investment amount per investor. We find no significant effects in the full sample. In the female investor subsample we a positive effect for mixed gender (which is significant in the direct effect model). In the female investor subsample we negative gender effects in the total effect model.

This paper shows that all-female teams obtain less funding than their all-male counterparts. There is also the possibility of raising more money across multiple campaigns. One may thus wonder if the lower funding amounts for female teams are due to female founders choosing a different fundraising approach of raising money through a larger number of smaller campaigns. Under this conjecture, female founders may not mind raising less money in a given campaign because they plan to come back for more in a subsequent campaign. Our data allow us to examine this conjecture within the SEEDRS data, where we can observe multiple campaigns by the same company. Table A9 in the Online Appendix estimates a cross-sectional model where the dependent variable is a dummy variable of whether a company launches a second campaign. The sample here is thus restricted to each company's first campaign. The gender coefficients are either insignificant or negative significant, which is contrary to the conjecture above. Thus, there is no evidence that the underfunding of female founders can be explained by female founders returning faster to investors to ask for more.

While on the topic of repeat campaigns, we note that our main analysis controls for having a past SEEDRS campaign (approximately 25% of the sample do). As robustness, Table A10 in the Online Appendix reruns the regressions from Tables 3, 4 and 5, but dropping all repeat campaigns. This does not change the main results, apart from some loss of statistical significance due to the lower number of observations.

We performed some robustness analysis on our measure of experience, reported in Table A11 of the Online Appendix. Our base measure is based on whether founders have prior founding experiences. 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 with a start-up. As a robustness we broader this definition by including results for being a founder OR having prior success with a start-up. We find that this does not substantially change any of our results.

Our base measure for education is whether founders have an MBA. For robustness, Table A12 of the Online Appendix considers an alternative measure of higher education that includes any post-graduate education. We find that the main pattern of results remains, although the effect of post-graduate education on campaign amounts is weaker and, in some cases, even negative.

We use ChatGPT for the NLP analysis of the companies' SEEDRS text. ChatGPT is increasingly being used in Finance and Management research.[30] We perform two types of robustness checks for our variables of GPT Growth and GPT Capital. First, we originally asked ChatGPT to just give us numerical values, without explaining why. To make sure that the instruction not to provide explanations does not impact the results, we went back to ChatGPT and asked it again to rank the companies but allowed it to explain why. This generated a ranking along with ample text justifications. We report the results of using the alternative measures GPT Growth and GPT Capital in Table A13. We find that they are highly correlated with our main GPT variables, and that using them does not affect any results.

For the second robustness check we consider an older but popular NLP tool called "Bag-of-word" (BOW henceforth). This model uses a representation of text as an unordered collection of words. It disregards word order but captures multiplicity.[31] We rerun our core analysis replacing the ChatGPT variables with BOW variables.[32] Table A14 shows the results. Again, we find a very similar pattern to our main results.

[30] See Chen and Chan (2024), Niu et al. (2024), and Yoganarasimhan and Iakovetskaia (2024). Lo and Singh (2023) provide an overview and short history of the use of NLP models in finance.
[31] While the model is simple, it is remarkably robust. It has previously been used in finance (Garcia et al., 2023, Niu et al., 2024; see also Lo and Singh, 2023), in accounting (Mawlood et al., 2021), and many AI applications.
[32] Since the campaign texts are relatively short, using too few words would create many "ties" between different start-ups. We therefore chose a relatively large number of words. Specifically, we used the following words {growth, ambitious, global, aggressive, big plater, dominance, become large player, scale, determined, aspiring} for identifying growth ambitions; and {large capital, finance rounds, need money, production, financing, funds} for capital intensity. We also checked that our choice is robust by making sure that the rankings do not change significantly by the removal of any one or two words from the above lists.

Most of our companies are located in the UK. For robustness, we control for whether campaigns are denominated in Pounds or Euros, indicating whether the company is operating mainly in the UK or not. The results are reported in Table A15 of the Online Appendix. We find that this currency choice has no material effect on our results.

We briefly mentioned in Section 3.2 that investors are 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. In our main analysis we exclude such pledges that were cancelled or left unpaid so as to focus on realized investment amounts. An analysis of strategic investor behavior is outside the scope of this paper, but the work by Åstebro et al. (2019) 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 that entrepreneurs reject are very small. In our main analysis we also exclude these rejected pledges. Lastly, we also exclude pledges that were rejected by SEEDRS due to concerns about money fraud or due to investors' input errors. As a robustness check we add all these rejected amounts back into our measure of funding received and rerun the analysis of Table 5. Table A16 in the Online Appendix shows that our empirical results are not affected by including those rejected pledges.

A common tool for the analysis of gender gaps is to perform the so-called Blinder-Oaxaca decomposition (see Fairlie and Robb, 2009). We report our results in Table A17 of the Online Appendix. The first column compares both all-female and mixed-gender teams to all-male teams, the second column all-female teams to all-male teams, and the third column mixed-gender teams to all-male teams. To get statistical convergence of the model we need to use year fixed effects instead of quarter fixed effects. The Blinder-Oaxaca decomposition begins by stating the male/female gap for the dependent variable $\log(F_i)$, which ranges from 0.37 to 0.72. It then asks what explanatory variables can account for these differences. The campaign goal $\log(G_i)$ is by far the most important factor. The only other significant variable is team size.

5. Conclusion

In this paper we use equity crowdfunding data to study gender differences in start-up finance. We first develop four theoretical benchmark predictions based on a simple assortative matching logic.

We then empirically examine the fundraising strategies and outcomes. We find that female teams ask for less money, have the same probability of campaign success, but end up raising less money. One interesting departure from the benchmark model concerns the overfunding ratio, where we find that all-female teams have lower ratios but mixed-gender teams higher ratios than the all-male benchmark. We also find that all gender gaps increase for more capital intensive ventures.

Naturally, we recognize some limitations of our analysis. To begin with, our data only allows us to identify gender effects in the cross-section. Even though we include a large number of controls, and perform some sensitivity analysis, one can never fully exclude the possibility of some remaining unobserved heterogeneity. Moreover, we consider a sample of companies that launch campaigns on an equity crowdfunding platform. An interesting open research question remains to what extent female entrepreneurs seek or avoid equity crowdfunding in the first place (see also Ahlers et al. (2015) and Löher (2017). Another interesting question concerns the dynamics across multiple fundraising events. For example, future research might examine how founders adjust their campaigns based on the underlying business developments in their companies. Finally, there is always the question of external validity. There is ample room for future research on gender effects in other fundraising contexts, such as venture capital, corporate investing, and angel financing.

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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.

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.
TOTAL FEMALE INVESTMENT		Total amount invested in campaign from female investors, as natural log.
TOTAL MALE INVESTMENT		Total amount invested in campaign from male investors, as natural log.
REPEAT CAMPAIGN		Dummy variable = 1 if there is a second SEEDRS campaign.
Founder characteristics		
FEMALES (%)	X_i	Share of female founders in the company's founding team
ALL-FEMALE (D)	X_i	Dummy variable = 1 if FEMALE (%) =1; 0 otherwise.
MIXED-GENDER (D)	X_i	Dummy variable = 1 if 0 < FEMALE (%) < 1; 0 otherwise.
ENTREPRENEURIAL EXP. (%)	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.
ENTREPRENEURIAL EXP. (D)	X_i	Dummy variable = 1 if ENT. EXP. (%) > 0; 0 otherwise.
MANAGEMENT EXP. (%)	X_i	Share of founders in the company's founding team with prior experience in senior management.
MANAGEMENT EXP. (D)	X_i	Dummy variable = 1 if MAN. EXP (%) > 0; 0 otherwise.
EDUCATION (%)	X_i	Share of founders in the company's founding team with an MBA
EDUCATION (D)	X_i	Dummy variable = 1 if EDUCATION (%) > 0; 0 otherwise
Control variables		
GROWTH GPT	Z_i	GPT score from 0 to 100 for how ambitious in terms of growth a campaign claimed to be.
CAPITAL GPT	Z_i	GPT score from 0 to 100 for how capital intensive a campaign claimed to be.
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.
PRODUCT TYPE	Z_i	Dummy variables for whether the campaign's product is B2B, B2C or a mixed type. In all regressions the omitted category is mixed type.
DELIVERY MODE	Z_i	Dummy variables for the mode of delivery of the campaign's product. Categories include digital, non-digital or mixed. In all regressions the omitted category is mixed mode of delivery.
SEIS	Z_i	Dummy whether the campaign is eligible for the Seed Enterprise Investment Scheme (SEIS) tax break.

Variable	Category	Description
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).
QUARTER	Z_i	A series of dummy variables denoting the quarter of campaign start, for the period Q2 2012 to Q2 2017.

Table 2 Panel A. Summary Statistics

This table shows mean values for $G_i, S_i, F_i, X_i, and\ Z_i$ variables in the cross-section, overall and distinguishing based on the team gender dummy, and tests for statistically significantly different means based on team gender using a two-sided t-test. The stars, when present for all-female and mixed-gender groups, indicate statistically significantly different mean against the all-male group with p-value < 0.1 (*), <0.05 (**), and <0.01 (***).

		Average			
Variable	Category	ALL	ALL-MALE	ALL-FEMALE	MIXED-GENDER
Sample of All Campaigns:		*N=767*	*N=577*	*N=69*	*N=121*
FUNDING GOAL	G_i	11.5	11.6	11.2**	11.3**
VALUATION	G_i	14	14	13.8	14
EQUITY OFFERED	G_i	9.75	9.96	9.51	8.92
CAMPAIGN SUCCESS	S_i	.434	.435	.449	.421
FEMALES (%)	X_i	.156	0	1	.417***
ALL-FEMALE (D)	X_i	.09	0	1	0
MIXED-GENDER (D)	X_i	.158	0	0	1
ENTREPRENEURIAL EXP. (%)	X_i	.184	.205	.152	.105***
ENTREPRENEURIAL EXP. (D)	X_i	.259	.282	.159**	.207*
MANAGEMENT EXP. (%)	X_i	.661	.684	.667	.55***
MANAGEMENT EXP. (D)	X_i	.761	.773	.696	.744
EDUCATION (%)	X_i	.087	.089	.0797	.082
EDUCATION (D)	X_i	.129	.13	.116	.132
TEAM SIZE	Z_i	1.9	1.81	1.25***	2.69***
PRIOR SEEDRS	Z_i	.257	.248	.246	.306
SEIS	Z_i	.46	.449	.449	.521
EIS	Z_i	.441	.444	.507	.388
PRODUCT TYPE: B2B	Z_i	.138	.146	.058**	.149
PRODUCT TYPE: B2C	Z_i	.205	.21	.217	.174
PRODUCT TYPE: MIXED	Z_i	.179	.17	.217	.198
PRODUCT TYPE: UNKNOWN	Z_i	.478	.475	.507	.479
DELIVERY MODE: DIGITAL	Z_i	.31	.308	.203*	.38
DELIVERY MODE: NON-DIGITAL	Z_i	.123	.114	.232***	.0992
DELIVERY MODE: MIXED	Z_i	.218	.22	.203	.215
DELIVERY MODE: UNKNOWN	Z_i	.349	.357	.362	.306
SECTOR: Clothing, Home	Z_i	.155	.132	.333***	.165
SECTOR: E-Commerce, Marketing	Z_i	.164	.18	.0725**	.14
SECTOR: Finance	Z_i	.136	.135	.188	.107
SECTOR: Food, Drink	Z_i	.116	.116	.087	.132
SECTOR: Games, Entertainment	Z_i	.103	.0988	.101	.124
SECTOR: Technology	Z_i	.179	.194	.087**	.157
SECTOR: Transport, Travel	Z_i	.147	.144	.13	.174
Sample of Successful Campaigns:		*N=333*	*N=251*	*N=31*	*N=51*
FUNDING AMOUNT	F_i	11.6	11.8	11***	11.4*
CAPITAL GPT	Z_i	62.7	62.4	64	62.9
GROWTH GPT	Z_i	73.6	73.9	71.6	73.1
Sample of First Campaigns:		*N=570*	*N=434*	*N=52*	*N=84*
REPEAT CAMPAIGN		.228	.221	.212	.274

Table 2 Panel B. Key pairwise correlations

This table shows the pairwise correlations and their statistical significance for the variable categories G_i, F_i, X_i, and select Z_i in the sample of successful campaigns. Stars indicate statistically significant correlation with p-value <0.1 (*), <0.05 (**), and <0.01 (***).

	No.		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
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																	
FUNDING FEMALE INV.	5		0.631***	0.299***	0.148**	0.663***	1																
FUNDING MALE INV.	6		0.878***	0.444***	0.275***	0.912***	0.650***	1															
FEMALES (%)	7	X_i	-0.162**	-0.067	-0.05	-0.162**	-0.031	-0.209***	1														
ALL-FEMALE (D)	8	X_i	-0.118**	-0.057	-0.02	-0.131**	-0.071	-0.157**	0.875***	1													
MIXED-GENDER (D)	9	X_i	-0.084	-0.012	-0.067	-0.072	0.082	-0.129**	0.336***	-0.136**	1												
ENT. EXP (%)	10	X_i	0.113**	0.138**	-0.018	0.101*	-0.026	0.130**	-0.103*	-0.041	-0.141**	1											
ENT. EXP (D)	11	X_i	0.140**	0.130**	-0.002	0.122**	-0.037	0.138**	-0.124**	-0.078	-0.102*	0.905***	1										
MAN. EXP. (%)	12	X_i	0.056	0.04	0.054	0.053	0.031	0.071	-0.062	0.032	-0.173**	0.276***	0.250***	1									
MAN. EXP. (D)	13	X_i	0.125**	0.104*	0.027	0.126**	0.092*	0.113**	-0.085	-0.042	-0.059	0.205***	0.221***	0.844***	1								
EDUCATION (%)	14	X_i	0.137**	0.155**	-0.042	0.141**	0.160**	0.102*	-0.019	-0.032	-0.001	-0.143**	-0.112**	0.136**	0.104*	1							
EDUCATION (D)	15	X_i	0.155**	0.175**	-0.043	0.154**	0.160**	0.108**	-0.018	-0.033	0.006	-0.132**	-0.086	0.124**	0.087	0.926***	1						
GROWTH GPT	16	Z_i	0.256***	0.175**	0.043	0.269***	0.193***	0.284***	-0.093*	-0.084	-0.024	0.014	0.032	0.05	0.073	0.117**	0.135**	1					
CAPITAL GPT	17	Z_i	0.153**	0.173**	0.002	0.136**	0.076	0.116**	0.049	0.041	0.011	0.007	0.015	-0.047	-0.06	0.04	0.055	0.238***	1				
TEAM SIZE	18	Z_i	0.086	0.084	-0.005	0.067	0.102*	0.029	-0.094*	-0.263***	0.441***	-0.219***	-0.045	-0.169**	0.05	-0.051	0.041	0.098*	-0.004	1			
PRIOR SEEDRS	19	Z_i	-0.301***	0.047	-0.271***	-0.290***	-0.259***	-0.297***	-0.032	-0.016	-0.011	0.074	0.035	0.044	0.03	-0.054	-0.063	-0.127**	-0.085	-0.039	1		
SEIS	20	Z_i	-0.353***	-0.537***	0.108**	-0.358***	-0.169**	-0.304***	0.009	-0.041	0.110**	-0.186***	-0.177**	-0.051	-0.055	-0.094*	-0.108**	-0.160**	-0.094*	0.002	-0.098*	1	
EIS	21	Z_i	0.329***	0.557***	-0.165**	0.341***	0.131**	0.293***	-0.004	0.039	-0.087	0.165**	0.153**	0.02	0.018	0.027	0.048	0.165**	0.09	0.005	0.112**	-0.878***	1

Table 2 Panel C. Fundraising Amounts by Gender of Team and Investor

This table shows mean values for funding received (F_i) by team gender and investor gender, and tests for statistically significant differences in means based on team gender with a two-sided t-test. The stars, when present for all-female and mixed-gender groups, indicate a statistically significantly different mean against the all-male group with p-value < 0.1 (*), <0.05 (**), and <0.01 (***). P-values for the t-test are reported in parentheses.

		Average Funding Received			
		ALL N=333	ALL-MALE N=251	ALL-FEMALE N=31	FEMALES MIXED N=51
From All Investors	(£)	290,001	332,881	115,561** (0.039)	185,000* (0.075)
By Investor Gender:					
From Females	(£)	25,503	25,856	18,246 (0.536)	28,180 (0.818)
From Males	(£)	201,963	238,976	70,407** (0.035)	99,767** (0.027)
From Unknown Gender	(£)	62,535	68,049	26,909 (0.229)	57,053 (0.691)
Fraction From Female Investors	(%)	9.31	7.3	14.3*** (0.001)	16.2*** (0)

Table 3. Determinants of Funding Goals

This table reports OLS regressions for campaign goal 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, with stars indicating p-value <0.1 (*), <0.05 (**), and <0.01 (***). Standard errors are clustered at the company-level.

		Funding Goal			
		Continuous model	Dummy model	Continuous model	Dummy model
FEMALES	(%)	-0.347**		-0.614**	
		(-2.53)		(-2.81)	
ALL-FEMALE	(D)		-0.266*		-0.451*
			(-1.72)		(-1.82)
MIXED-GENDER	(D)		-0.283**		-0.412*
			(-2.12)		(-1.65)
ENT. EXP.	(%, D)	0.245*	0.156	0.485**	0.339**
		(1.86)	(1.60)	(2.40)	(2.17)
MAN. EXP.	(%, D)	0.113	0.159	0.026	0.261
		(1.09)	(1.60)	(0.13)	(1.15)
EDUCATION	(%, D)	0.396**	0.286**	0.495	0.363*
		(2.35)	(2.43)	(1.59)	(1.79)
TEAM SIZE		0.124**	0.120**	0.170**	0.172**
		(2.92)	(2.51)	(2.25)	(1.99)
PRIOR SEEDRS		-0.921***	-0.910***	-0.912***	-0.910***
		(-9.26)	(-9.25)	(-6.87)	(-6.78)
GPT GROWTH				0.022**	0.021**
				(2.18)	(1.98)
GPT CAPITAL				0.011	0.011
				(1.63)	(1.60)
DELIVERY MODE	Fixed effects	No	No	Yes	Yes
PRODUCT TYPE	Fixed effects	No	No	Yes	Yes
SEIS/EIS	Fixed effects	Yes	Yes	Yes	Yes
SECTOR	Fixed effects	Yes	Yes	Yes	Yes
QUARTER	Fixed effects	Yes	Yes	Yes	Yes
N		767	767	329	329
Adjusted R-squared		0.344	0.346	0.334	0.338

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 strategies (G_i). All variables are described in Table 1. T-statistics are in parentheses, with stars indicating p-value <0.1 (*), <0.05 (**), and <0.01 (***). Standard errors are clustered at the company-level.

		Campaign success			
		Total effect		Direct effect	
		Continuous model	Dummy model	Continuous model	Dummy model
FEMALES	(%)	-0.152		-0.221	
		(-0.89)		(-1.30)	
ALL-FEMALE	(D)		-0.135		-0.181
			(-0.71)		(-0.95)
MIXED-GENDER	(D)		-0.080		-0.146
			(-0.52)		(-0.93)
ENT. EXP.	(%, D)	0.063	0.012	0.114	0.043
		(0.36)	(0.09)	(0.65)	(0.32)
MAN. EXP.	(%, D)	0.588***	0.577***	0.632***	0.630***
		(4.49)	(4.47)	(4.72)	(4.68)
EDUCATION	(%, D)	-0.059	-0.106	0.039	-0.034
		(-0.25)	(-0.64)	(0.17)	(-0.20)
TEAM SIZE		0.041	0.001	0.072	0.029
		(0.62)	(0.01)	(1.07)	(0.39)
PRIOR SEEDRS		1.054***	1.061***	0.925***	0.935***
		(8.67)	(8.61)	(6.90)	(6.88)
GOAL				-0.174**	-0.173**
				(-2.78)	(-2.74)
VALUATION				-0.067	-0.066
				(-1.02)	(-0.98)
DELIVERY MODE	Fixed effects	No	No	No	No
PRODUCT TYPE	Fixed effects	No	No	No	No
SEIS/EIS	Fixed Effects	Yes	Yes	Yes	Yes
SECTOR	Fixed effects	Yes	Yes	Yes	Yes
QUARTER	Fixed effects	Yes	Yes	Yes	Yes
N		767	767	767	767
Pseudo R-squared		0.200	0.198	0.213	0.212

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 strategies (G_i). All variables are described in Table 1. T-statistics are in parentheses, with stars indicating p-value <0.1 (*), <0.05 (**), and <0.01 (***). Standard errors are clustered at the company-level.

		Funding Received			
		Total effect		Direct effect	
		Continuous model	Dummy model	Continuous model	Dummy model
FEMALES	(%)	-0.713**		-0.090	
		(-3.22)		(-1.48)	
ALL-FEMALE	(D)		-0.645**		-0.186**
			(-2.62)		(-3.02)
MIXED-GENDER	(D)		-0.322		0.096*
			(-1.21)		(1.73)
ENT. EXP.	(%, D)	0.447**	0.281*	-0.047	-0.064
		(2.00)	(1.66)	(-0.85)	(-1.43)
MAN. EXP.	(%, D)	0.024	0.309	-0.002	0.043
		(0.10)	(1.23)	(-0.03)	(0.80)
EDUCATION	(%, D)	0.547	0.373*	0.038	0.000
		(1.61)	(1.71)	(0.49)	(0.00)
TEAM SIZE		0.147*	0.118	0.085	-0.057**
		(1.90)	(1.30)	(1.25)	(-2.61)
PRIOR SEEDRS		-0.878***	-0.881***	0.084	0.043
		(-6.26)	(-6.25)	(1.28)	(1.08)
GPT GROWTH		0.027**	0.026**	0.005*	0.005*
		(2.59)	(2.37)	(1.77)	(1.72)
GPT CAPITAL		0.010	0.010	-0.002	-0.002
		(1.40)	(1.39)	(-0.88)	(-0.81)
GOAL				1.011***	1.014***
				(62.42)	(58.35)
VALUATION				0.011	0.009
				(0.60)	(0.54)
DELIVERY MODE	Fixed effects	Yes	Yes	Yes	Yes
PRODUCT TYPE	Fixed effects	Yes	Yes	Yes	Yes
SEIS/EIS	Fixed effects	Yes	Yes	Yes	Yes
SECTOR	Fixed effects	Yes	Yes	Yes	Yes
QUARTER	Fixed effects	Yes	Yes	Yes	Yes
N		329	329	329	329
Adjusted R-squared		0.333	0.335	0.952	0.953

Table 6: Total Investment by Gender

This table reports OLS regressions for total investments from female investors in Panel A and from male investors in Panel B, as two separate regressions. The explanatory variables are founder team characteristics (X_i) and control variables (Z_i). The direct effect regressions further include fundraising strategies (G_i). All variables are described in Table 1. T-statistics are in parentheses, with stars indicating p-value <0.1 (*), <0.05 (**), and <0.01 (***). Standard errors are clustered at company level to take into account repeat campaigns.

Table 6 Panel A. Total Investment from Female Investors

		Total Investment from Female Investors			
		Total effect		Direct effect	
		Continuous model	Dummy model	Continuous model	Dummy model
FEMALES	(%)	-0.005		0.757**	
		(-0.01)		(2.12)	
ALL-FEMALE	(D)		-0.217		0.357
			(-0.39)		(0.87)
MIXED-GENDER	(D)		0.420		0.931**
			(0.75)		(2.41)
GOAL				1.202***	1.226***
				(8.88)	(8.85)
VALUATION				0.107	0.099
				(0.71)	(0.69)
ALL OTHER CONTROLS		Yes	Yes	Yes	Yes
N		329	329	329	329
Adjusted R-squared		0.145	0.150	0.439	0.453

Table 6 Panel B. Total Investment from Male Investors

		Total Investment from Male Investors			
		Total effect		Direct effect	
		Continuous model	Dummy model	Continuous model	Dummy model
FEMALES	(%)	-0.983***		-0.400**	
		(-4.07)		(-2.74)	
ALL-FEMALE	(D)		-0.914***		-0.479**
			(-3.60)		(-2.94)
MIXED-GENDER	(D)		-0.485*		-0.096
			(-1.78)		(-0.72)
GOAL				0.930***	0.937***
				(26.23)	(25.82)
VALUATION				0.057	0.060
				(1.16)	(1.20)
ALL OTHER CONTROLS		Yes	Yes	Yes	Yes
N		329	329	329	329
Adjusted R-squared		0.292	0.288	0.790	0.791

Table 7. Interactions with Industry Gender Characteristics

This table reports OLS regressions for the number of days until a campaign was stopped. Panel A reports interactions with the proportion of female founders at the industry level, and Panel B with the proportion of female investors at the industry level. The explanatory variables are founder team characteristics (X_i) and control variables (Z_i). The direct effect regressions further include fundraising strategies (G_i). Explanatory and female share variables are standardised All variables are described in Table 1. T-statistics are in parentheses, with stars indicating p-value <0.1 (*), <0.05 (**), and <0.01 (***). Standard errors are clustered at company level to take into account repeat campaigns.

Table 7 Panel A. Interaction with Female Founder Share

		Funding goal		Funding received	
		Continuous model	Dummy model	Continuous model	Dummy model
FEMALES	(%)	-0.137**		-0.150**	
		(-2.07)		(-2.28)	
ALL-FEMALE	(D)		-0.424		-0.596**
			(-1.62)		(-2.33)
MIXED-GENDER	(D)		-0.354*		-0.254
			(-1.70)		(-1.18)
FEMALES X FEMALE FOUNDER SHARE		-0.108		-0.143*	
		(-1.38)		(-1.79)	
ALL-FEMALE X FEMALE FOUNDER SHARE			-0.175		-0.232
			(-0.80)		(-1.06)
MIXED-GENDER X FEMALE FOUNDER SHARE			-0.475		-0.550
			(-1.43)		(-1.55)
ALL OTHER CONTROLS		Yes	Yes	Yes	Yes
N		329	329	329	329
Adjusted R-Squared		0.338	0.348	0.340	0.348

Table 7 Panel B. Interaction with Female Investor Share

		Funding goal		Funding received	
		Continuous model	Dummy model	Continuous model	Dummy model
FEMALES	(%)	-0.186**		-0.207**	
		(-2.75)		(-3.06)	
ALL-FEMALE	(D)		-0.460*		-0.637**
			(-1.82)		(-2.55)
MIXED-GENDER	(D)		-0.389		-0.274
			(-1.63)		(-1.09)
FEMALES X FEMALE INVESTOR SHARE		-0.027		-0.091	
		(-0.42)		(-1.34)	
ALL-FEMALE X FEMALE INVESTOR SHARE			0.082		-0.065
			(0.40)		(-0.31)
MIXED-GENDER X FEMALE INVESTOR SHARE			-0.126		-0.255
			(-0.81)		(-1.55)
ALL OTHER CONTROLS		Yes	Yes	Yes	Yes
N		329	329	329	329
Adjusted R-Squared		0.332	0.335	0.334	0.334

Table 8. Interactions with growth ambitions and capital intensity

This table reports OLS regressions for the campaigns' funding goals and funding received. Panel A reports interactions with our GPT score for growth, Panel B with our GPT score for capital. The explanatory variables are founder team characteristics (X_i) and control variables (Z_i). The direct effect regressions further include fundraising strategies (G_i). Explanatory and GPT variables are standardised. All variables are described in Table 1. T-statistics are in parentheses, with stars indicating p-value <0.1 (*), <0.05 (**), and <0.01 (***). Standard errors are clustered at company level to take into account repeat campaigns.

Table 8 Panel A. Interactions with Growth GPT

		Funding goal		Funding received	
		Continuous model	Dummy model	Continuous model	Dummy model
FEMALES	(%)	-0.205**		-0.235**	
		(-2.95)		(-3.31)	
ALL-FEMALE	(D)		-0.509**		-0.692**
			(-2.09)		(-2.80)
MIXED-GENDER	(D)		-0.411		-0.331
			(-1.64)		(-1.25)
GROWTH GPT		0.175**	0.214**	0.213**	0.263**
		(2.51)	(2.76)	(2.91)	(3.26)
FEMALES X GROWTH GPT		-0.091		-0.086	
		(-1.26)		(-1.15)	
ALL-FEMALE X GROWTH GPT			-0.281		-0.230
			(-1.16)		(-0.90)
MIXED-GENDER X GROWTH GPT			-0.164		-0.316
			(-0.79)		(-1.40)
ALL OTHER CONTROLS		Yes	Yes	Yes	Yes
N		329	329	329	329
Adjusted R-Squared		0.337	0.339	0.335	0.337

Table 8 Panel B. Interactions with Capital GPT

	Funding goal		Funding received	
	Continuous model	Dummy model	Continuous model	Dummy model
FEMALES (%)	-0.172**		-0.205**	
	(-2.49)		(-2.94)	
ALL-FEMALE (D)		-0.393		-0.597**
		(-1.58)		(-2.41)
MIXED-GENDER (D)		-0.429*		-0.336
		(-1.73)		(-1.27)
CAPITAL GPT	0.090	0.242**	0.079	0.213**
	(1.35)	(3.15)	(1.12)	(2.65)
FEMALES X CAPITAL GPT	-0.267***		-0.230***	
	(-4.06)		(-3.39)	
ALL-FEMALE X CAPITAL GPT		-0.904***		-0.775**
		(-3.92)		(-3.23)
MIXED-GENDER X CAPITAL GPT		-0.425**		-0.374**
		(-2.97)		(-2.63)
ALL OTHER CONTROLS	Yes	Yes	Yes	Yes
N	329	329	329	329
Adjusted R-Squared	0.362	0.369	0.351	0.354