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Gender differences in reward-based crowdfunding☆

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ABSTRACT

We document several gender differences in reward-based crowdfunding by analyzing a large sample of Kickstarter campaigns. We argue that these differences are most plausibly explained by male entrepreneurs' relative over-optimism. Suggesting a tendency to overestimate the demand for their products, we find that male entrepreneurs set higher goal amounts, resulting in more frequent campaign failures. In successive campaigns, male entrepreneurs' goal amounts and success rates converge toward those of female entrepreneurs, consistent with entrepreneurial experience mitigating the behavioral bias. Our findings suggest that entrepreneurs learn from experience, and that female first-time entrepreneurs may have more realistic expectations of the demand for their products, increasing their success rates in crowdfunding. Moreover, although serial entrepreneurs exhibit better performance already in their first campaigns, they still improve over successive campaigns, further highlighting the importance of entrepreneurial learning.

1. Introduction

Recent literature has shown that female entrepreneurs face tighter financial constraints than their male counterparts (e.g., Dupas and Robinson, 2013; Blattman et al., 2014; Faccio et al., 2016; Gottlieb et al., 2022). They also tend to encounter gender-specific barriers in accessing services and credit, such as discriminatory social norms (e.g., Dean and Jayachandran, 2019; Naaraayanan, 2019; Jayachandran, 2021) and investor biases (e.g., Ewens and Townsend, 2020). The rise of financial technology (fintech) has the potential to shrink the gender gap in entrepreneurship caused by the documented hurdles. In particular, crowdfunding via fintech platforms provides entrepreneurs with alternative venues to raise funds directly from a large number of individuals, mitigating the dependence on traditional financial intermediaries. Hence, crowdfunding is part of the broader emergence of non-intermediated financing (Thakor, 2020) and can be viewed as a hybrid of formal and informal financing (Allen et al., 2019).

In this paper, we examine gender differences in behavior and performance in reward-based crowdfunding, in which individuals (the backers) commit funds in exchange for the promise of a reward. This is typically the product planned to be manufactured or the service to be provided by the project once the campaign is successfully funded. This allows prospective entrepreneurs to learn about the potential demand for their products and provides a source of funds complementary to more traditional forms of venture financing (e.g., Chemla and Tinn, 2018; Xu, 2018). Mollick (2016) finds evidence of Kickstarter projects having directly generated a significant number of jobs and patents, suggesting an increasing impact of reward-based crowdfunding on the real economy and as a new source of finance.

In these types of crowdfunding campaigns, the entrepreneur does not know the potential demand for her product ex ante. She has to set the campaign goal amount before launching the campaign and, therefore, faces a trade-off. She only receives the funds if the amount pledged reaches the goal and nothing otherwise. Hence, a higher goal amount makes success less likely. On the other hand, a higher goal amount secures a higher share of the potential after-market demand for her product. As shown by Strausz (2017), due to moral hazard, it

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is generally optimal for campaign backers to pledge funds only up to the goal amount and satisfy further demand in the after-market. The entrepreneur's assessment of expected demand is, therefore, a crucial determinant of the campaign goal amount, which affects the likelihood of campaign success.

We use a large dataset of crowdfunding campaigns on Kickstarter launched by U.S. entrepreneurs to document a number of gender differences in reward-based crowdfunding. While there are well-documented differences in economic decisions by men and women (Eckel and Grossman, 2008), the gender gap in labor market participation in general (Goldin, 2006), and in many high-wage professions in particular (see, e.g., Gompers and Calder-Wang, 2017), has substantially decreased in the last decades. Similarly, Agarwal et al. (2018) show that the gender bias in high-stakes economic decisions has decreased, as evidenced by mortgage signing order. However, the same is not true for growth entrepreneurship. Gompers and Calder-Wang (2017) estimate that only approximately 10% of new entrepreneurs and 9% of venture capitalists are women—and that these shares have not changed much over time. As reward-based crowdfunding represents a relatively new complementary source of venture financing, it is important to understand its potential implications for the gender dynamics in entrepreneurship and entrepreneurial finance.

We begin with a thorough analysis of gender differences in crowdfunding, while much of the existing literature is based on small and possibly non-representative samples. We then argue that male entrepreneurs' relative over-optimism is the most plausible explanation for the higher failure rate of male entrepreneurs in fundraising. If men systematically overestimate the demand for their products, they will set higher campaign goal amounts, pursue lower marginal quality projects, and fail more frequently. Moreover, the existing literature also suggests that behavioral biases, such as over-optimism, can be mitigated by the decision-maker's experience (Gervais and Odean 2001, Statman et al. 2006, Forbes 2005, Chen et al. 2018), meaning that the effects of over-optimism should decrease or disappear over successive campaigns by the same entrepreneur.

The results support our prediction that over-optimism leads to male entrepreneurs setting higher goals. Women's goal amounts are 9% lower than those of men after controlling for a large number of campaign and creator characteristics. This finding is both statistically and economically significant. In contrast, women receive 61% more in pledged funds, independent of the campaign goal. These results suggest that male entrepreneurs systematically overestimate the demand for and quality of their projects relative to female entrepreneurs. This is also consistent with the framework of Coval and Thakor (2005), who suggest that financial intermediaries act as a bridge between optimistic entrepreneurs and pessimistic investors. Correspondingly, we find that female entrepreneurs significantly outperform male entrepreneurs on both the likelihood of campaign success and the amount pledged relative to the goal amount. Controlling for other factors, women are seven percentage points more likely to succeed than men and achieve 15% higher pledged/goal ratios.

Prior studies suggest that the dynamics of teams may also differ depending on gender composition (Gerhards and Kosfeld, 2020). As our data allow us to identify campaigns launched by teams of entrepreneurs, we also perform the same analyses including such teams of multiple entrepreneurs. We find that teams generally set larger goal amounts than individual entrepreneurs, regardless of gender. They also achieve higher pledged amounts. Interestingly, the gender dynamics within teams look very similar to those of individual entrepreneurs. Female teams set lower goals than male teams but achieve higher pledged amounts and campaign proceeds. Mixed teams rank between female and male teams on all of these measures. On the likelihood of success or pledged/goal ratios, male teams appear no different from individual male entrepreneurs, while female teams outperform individual females and other teams. Again, mixed teams rank between male and female teams.

The evidence on the performance of successive campaigns by the same entrepreneurs also supports the over-optimism argument. If relative over-optimism is the driver of male underperformance, this effect should be mitigated in successive campaigns, as the entrepreneurs have the opportunity to learn from experience (Seru et al., 2010; Xu, 2018; Chen et al., 2018; Botsch and Vanasco, 2019). We thus hypothesize that the goal amounts and outcomes of male entrepreneurs' campaigns should converge toward those of females in successive campaigns. We test this hypothesis by including campaign number dummies and their interaction terms with gender in our regression analyses. In support of our hypothesis, we find that men begin with significantly higher goals but lower success rates and pledged/goal ratios in the first campaigns relative to women. However, the differences decrease in the subsequent campaigns. This finding is robust to further controlling for entrepreneur fixed effects and consistent with men exhibiting relative over-optimism in their first campaigns and then "learning away" the over-optimism through campaign experience. Importantly, campaign performance generally improves for both genders in successive campaigns. This is consistent with entrepreneurial learning from past campaign experience.

Existing studies show that overconfident or over-optimistic managers adversely affect corporate decisions, overestimating returns and underestimating downside risks from investment and M&A (e.g., Hirshleifer and Luo, 2001; Malmendier and Tate, 2005, 2008; Gervais et al., 2011). Similarly, overconfident retail investors appear to lose money across different financial markets (e.g., Odean, 1998, 1999; Barber and Odean, 2001). Hence, understanding whether the gender differences in crowdfunding are attributable to the over-optimism of male entrepreneurs has important real-world implications. If over-optimistic male entrepreneurs overestimate the demand for their product and service, they tend to set the campaign goal too high, resulting in more frequent campaign failures. That can potentially lead to welfare losses for both entrepreneurs and backers, as the existing demand and supply cannot be matched, and the resources devoted to the campaign are wasted as well.

We are not the first to study gender differences in crowdfunding. However, the prior evidence is mixed and based on small samples. Gafni et al. (2021) find that female entrepreneurs are more likely to succeed, while Elitzur and Solodoh (2021) find the opposite using a sample from a different platform. We provide the most extensive analysis to date, with a large representative sample including individual entrepreneurs as well as teams. We also provide a novel explanation, i.e. over-optimism, for why men have lower success rates. Our analysis of successive campaigns reveals new striking patterns in gender dynamics in reward-based crowdfunding. While there is earlier evidence that women exhibit higher success rates generally (Gafni et al., 2021), our results showing the convergence of campaign goal amounts and success rates in subsequent campaigns are novel.

More generally, our findings suggest that entrepreneurs learn from past campaign experience. Several existing studies on entrepreneurial learning suggest frameworks where entrepreneurs dynamically learn from experience (e.g., Minniti and Bygrave, 2001; Politis, 2005). Crowdfunding provides a rare setting where we can observe successive ventures by the same entrepreneur and hence observe such learning empirically. Consistent with the framework of Cope (2011), our findings suggest that the outcome of previous campaigns affects the following campaigns. Our findings are also consistent with and complementary to those of Xu (2018), who shows that the feedback obtained from failed crowdfunding campaigns affects entrepreneurs' subsequent decisions to commercialize their products.

Our results are consistent with male entrepreneurs learning away relative over-optimism, which can explain the convergence of goal amounts and success rates over successive campaigns. Female entrepreneurs appear to adjust less amid experience because their room for learning to overcome over-optimism is smaller. We find that the adjustments based on previous campaign outcomes do not differ significantly by gender, and the different dynamics appear driven by different starting points instead of different learning mechanisms. We thus complement studies on learning in other domains, including stock trading (Seru et al., 2010), index trading (Kuo et al., 2015), and lending (Botsch and Vanasco, 2019). There are also interesting parallels to the learning documented by Seru et al. (2010), who find that some investors improve over time, while others stop trading after realizing they lack the skill. In our data, the serial entrepreneurs that launch multiple campaigns exhibit better performance already in their first campaigns but still improve over successive campaigns.

2. Literature review and hypothesis development

2.1. The economics of crowdfunding

Reward-based crowdfunding allows the entrepreneur to not only raise financing for her venture but also to learn about potential demand before committing to production (e.g., Chemla and Tinn, 2018). The entrepreneur sets the campaign goal amount before launching the campaign, and in the event that the pledged funds reach this goal amount, the campaign is deemed successful. At the end of a successful campaign, the pledged funds are transferred to the entrepreneur, who then has to deliver the promised rewards to the campaign backers. If the campaign is not successful, the entrepreneur receives no funds and has no obligation to deliver rewards.

Hence, the choice of a goal amount represents a trade-off. Since the entrepreneur does not know the demand ex ante, a higher goal amount makes success less likely. This fundamental relationship between goal amount and likelihood of success is intuitive and consistent with a number of theoretical models, including Strausz (2017), Ellman and Hurkens (2019), and Schwienbacher (2018). On the other hand, a higher goal amount secures a higher share of the potential after-market demand. Schwienbacher (2018) shows that a high project cost uncertainty and a high risk of idea-stealing (i.e., high incentives to capture a part of the potential after-market demand at an early stage) incentivize the entrepreneur to set a higher goal amount. The entrepreneur's assessment of the expected demand is, therefore, a crucial determinant of the campaign goal amount, which affects the likelihood of campaign success.

2.2. Gender, over-optimism, and crowdfunding campaigns

De Bondt and Thaler (1995) argue that general overconfidence is "perhaps the most robust finding in the psychology of judgment". As observed by Grinblatt and Keloharju (2009), overconfidence entails two different biases: the "better-than-average effect", an irrational shift in the perceived mean, and "miscalibration", an irrational shift in perceived variance. The first effect is often referred to as "optimism" in the literature. We use the term *over-optimism* to denote the entrepreneur's tendency to systematically overestimate the potential demand for her product. When discussing the literature, we use the terms overconfidence and over-optimism interchangeably, as there is little consistency in the terminology used across different studies.

Prior literature shows that manager overconfidence/over-optimism has significant implications for companies.[2] In some cases, overconfident managers may be optimal for shareholders, as overconfidence mitigates risk aversion and may result in lower variable-compensation requirements or induce greater commitments from their firms' stakeholders.[3] However, most of these studies use option exercise behavior to define whether a CEO is overconfident or not. Once a CEO is defined as overconfident, such categorization remains for the entire sample period. Hence, this literature is silent about whether learning-by-doing could mitigate managerial overconfidence.

Most studies on gender differences suggest that men tend to be more overconfident than women. Huang and Kisgen (2013) find evidence that male executives are overconfident relative to female executives, as demonstrated by higher acquisition and debt issue volumes and lower announcement returns around these events. Levi et al. (2014) find that female directors exhibit a lower likelihood of making acquisitions and argue that this is consistent with bidder female directors having relatively lower overconfidence in the precision of their estimates and in their expected value of an acquisition. Barber and Odean (2001) and Grinblatt and Keloharju (2009) find that men trade significantly more than women and generate lower returns as a result. Estes and Hosseini (1988) find that men are significantly more confident than women in making financial decisions. Biais et al. (2005) find, in an experimental setting, that while women are equally likely to hold miscalibrated beliefs, they are significantly less likely to act on such miscalibrated beliefs. They further find that IQ does not improve the performance of men, while it does improve that of women. Coval and Thakor (2005) propose a framework in which financial intermediaries act as a bridge between optimistic entrepreneurs and pessimistic investors.

In the context of reward-based crowdfunding, there are at least two ways in which over-optimism can reduce an entrepreneur's likelihood of success. First, over-optimism may lead the entrepreneur to pursue lower quality projects, due to biased estimates of project potential, which could result in lower success rates for male entrepreneurs. This would also be consistent with the empirical and survey results of Kuppuswamy and Mollick (2016), who find that male entrepreneurs are more likely to attempt a campaign in the face of low-quality opportunities. Second, as campaign goal decisions are substantially driven by the entrepreneur's prior assessment of product demand, this is the metric that should be most prone to be affected by over-optimism. If male entrepreneurs systematically overestimate the demand for their products, they will set higher goal amounts and experience lower success rates.

Based on these arguments, and given the substantial amount of evidence of men exhibiting higher levels of over-optimism than females, we propose our first hypothesis:

Hypothesis 1. *Male entrepreneurs' crowdfunding campaigns are less likely to succeed than female entrepreneurs' crowdfunding campaigns due to over-optimism, as reflected in higher campaign goal amounts*

2.3. Experience as a mitigator of over-optimism

The literature suggests that over-optimism is mitigated by experience. Gervais and Odean (2001) show how a trader's bias in learning about his own ability can create overconfident traders. They also show how a trader's level of overconfidence changes dynamically with successes and failures. As a result, a trader's expected level of overconfidence is highest in the early stages of his career and tends to decrease as he develops a more realistic assessment of his abilities. Statman et al. (2006) find empirical support for such a learning effect in overconfidence. In the context of entrepreneurship, Forbes (2005) finds evidence that older entrepreneurs tend to be less overconfident.

On Kickstarter, a substantial number of entrepreneurs return after their first campaign to launch a second campaign, and in some cases

[2] Over-optimistic managers overinvest when they have abundant internal funds and undertake value-destroying mergers and acquisitions (Malmendier and Tate, 2005, 2008; Galasso and Simcoe, 2011), use less external finance and, conditional on accessing external capital, issue less equity (Malmendier et al., 2011; Ben-David et al., 2013; Deshmukh et al., 2013). They also prefer shorter-maturity debt (Landier and Thesmar, 2009). Optimistic bank CEOs create more liquidity (Huang et al., 2018).

[3] See, e.g., Goel and Thakor (2008), Gervais et al. (2011), Campbell et al. (2011), Otto (2014), Humphery-Jenner et al. (2016), and Phua et al. (2018).

many more. This allows us to study the dynamics of campaign performance. When the same entrepreneur launches multiple successive campaigns, she can learn from the prior experience and adjust the successive campaign's parameters accordingly. Kuppuswamy and Mollick (2016) study such serial campaign creators and find evidence of gender differences in the propensity to attempt a second campaign, with women being significantly less likely to attempt a second campaign than men when they have succeeded or failed by large margins.

If male entrepreneurs set higher goal amounts and are less likely to succeed due to their over-optimism, we would expect this effect to decline in subsequent campaigns, as male entrepreneurs have more room to update their miscalibrated demand expectations through campaign experience. Kuhnen (2015) provides evidence that people learn differently from positive and negative experiences, which leads individuals to form overly pessimistic beliefs about available investment options. If men face more negative outcomes than women in their crowdfunding campaigns, their beliefs about future campaigns should thus become more pessimistic at a faster rate than those of women.

This should mitigate the initial relative over-optimism, leading to male entrepreneurs' campaign goals being adjusted closer to those set by female entrepreneurs in successive campaigns. Consequently, male entrepreneurs' campaign success rates should also converge toward those of female entrepreneurs.

Based on this reasoning, we propose our second hypothesis:

Hypothesis 2. *For entrepreneurs with multiple projects, the goal amounts and campaign performance of male entrepreneurs converge toward those of female entrepreneurs in successive crowdfunding campaigns, as male entrepreneurs' over-optimism is mitigated by campaign experience*

However, if male managers suffer from a particular type of attribution bias, i.e., the self-serving bias, they will attribute their fundraising successes to internal factors but attribute their campaign failures to external factors (Campbell and Sedikides, 1999; Duval and Silvia, 2002). If this bias dominates, male managers might not reduce their goal amount in subsequent campaigns, potentially leading to no convergence of their success rate to that of female entrepreneurs. It is thus an empirical question whether the positive influence of learning-by-doing will be canceled out by that of self-serving bias.

3. Data and methodology

3.1. Crowdfunding data

We use a large, web-crawled dataset of Kickstarter campaigns conducted between April 2009 and August 2017. The original raw data include the details of 315,017 campaigns in total. Comparing this with the Kickstarter statistics on the website, which reports 364,332 projects launched to date, our data capture approximately 86% of all Kickstarter campaigns.

Our data include identifiers for each campaign and each campaign creator, names, and locations, as well as a number of other variables covering campaign characteristics. As we need to be able to estimate gender and ethnicity based on names and control for regional characteristics on a consistent basis, we only include campaigns based in the U.S. After excluding campaigns that are still active, this leaves us with 233,887 campaigns. As we need to determine whether gender differences in crowdfunding can be explained by over-optimism to test our hypothesis, we only include campaigns launched by individual entrepreneurs or teams of entrepreneurs for which we can identify the all creators' gender based on the first names.

We use the names of creators to estimate their gender and race or ethnicity. For estimating gender based on first names, we use the analysis by Peter Organisciak, who estimates name frequencies by gender in the U.S. in 2014, based on birth name statistics and U.S. Census data on age distributions.[4] For some of the analyses, we include teams of multiple individuals and classify those into female, male, or mixed teams. We exclude campaigns created by companies or entrepreneurs whose gender we cannot identify from the first name. This gives us a final dataset of 155,632 campaigns, launched by 130,588 unique entrepreneurs or teams.

To estimate creator race or ethnicity for single entrepreneur campaigns, we use the dataset compiled by Word et al. (2008), based on the U.S. Census 2000 data. They provide estimated percentages by race/ethnicity for each surname that has at least 100 occurrences in the Census data. Their classification breaks down names by race for Whites, Blacks, Asians, and Native Americans. We omit the last group from our categorization because there are very few names identified as Native American in our sample. In addition to these races, Word et al. (2008) identify names associated with Hispanic ethnicity, which we also add to our analysis. We include the estimated race/ethnicity for each surname when the likelihood of correct race/ethnicity is higher than 50%. This threshold is necessarily lower than the one that we apply for gender, as most names are present for several races or ethnicities. A 50% share for a given race is therefore relatively high, compared with the corresponding odds for other races/ethnicities having the same name. This inevitably adds some noise to the race/ethnicity estimates, but we see no reason that it should produce systematic bias in the estimation. If anything, it should only weaken the significance of our results. This methodology gives us ethnicity estimates for 78.6% of the campaigns included in our sample. The rest of the sample are classified as "No race" in our analysis. Our data include the location of each campaign, on the basis of which we add county identifiers to control for any region-specific factors. We winsorize all continuous variables at the 1% and 99% levels.

4. Results

4.1. Description of the data

Table 1 reports the number of campaigns by year in our sample. The data period is from April 2009 to August 2017. Panel A shows that campaign volumes vary by year, with 2014 having the largest number of campaigns in our sample. From Panel B, we can see that success rates also vary over time, but women's campaigns exhibit consistently higher success rates than men's for all years.

Table 2 shows the summary statistics for the full sample, including teams, as well as by campaign creator gender for individual entrepreneurs. The mean success rate in our sample is 0.380. The unsuccessful campaigns are divided into failed campaigns, accounting for 53.2% of the sample, and canceled campaigns, accounting for 8.4%. Kickstarter suspended 0.3% of the campaigns in our sample due to violations of Kickstarter's rules. The mean goal amount is $15,990, while the mean amount pledged is $4313. The mean pledged/goal ratio is 0.687.

Female entrepreneurs launched 27.4% of the campaigns in our sample, male entrepreneurs 68.1%, and the remaining 4.5% were launched by teams of multiple entrepreneurs. Whites are the largest racial group, accounting for 70.0% of the individual entrepreneurs in the sample, followed by Hispanics, Asians, and Blacks, accounting for 5.1%, 2.0%, and 1.5%, respectively. The remaining 21.4% are classified as "No race".

[4] At the time of this writing, the data are available online at: https://github.com/organisciak/names.

Table 1
Campaigns by year.

Panel A: Number of campaigns						
	Individual		Team			All
	Female	Male	Female	Male	Mixed	
2009	183	376		4	8	571
2010	1760	3991	47	58	88	5944
2011	4674	11,549	88	228	207	16,746
2012	7250	18,408	129	325	364	26,476
2013	6503	16,870	228	575	653	24,829
2014	9122	21,919	293	635	759	32,728
2015	6850	17,422	219	503	614	25,608
2016	4295	10,960	123	289	334	16,001
2017	1961	4482	45	107	134	6729
Total	42,598	105,977	1172	2724	3161	155,632

Panel B: Success rate						
	Individual		Team			All
	Female	Male	Female	Male	Mixed	
2009	0.448	0.407	.	1.000	0.750	0.429
2010	0.501	0.375	0.745	0.586	0.636	0.421
2011	0.518	0.396	0.670	0.465	0.541	0.434
2012	0.482	0.377	0.682	0.492	0.541	0.411
2013	0.495	0.400	0.618	0.466	0.547	0.432
2014	0.354	0.295	0.526	0.391	0.424	0.318
2015	0.368	0.299	0.566	0.435	0.510	0.327
2016	0.389	0.348	0.626	0.464	0.458	0.365
2017	0.472	0.410	0.600	0.514	0.425	0.431
Total	0.433	0.351	0.602	0.451	0.498	0.380

Panel A shows the total number of campaigns by launch year by creator type and by creator gender for solo-creator campaigns. Teams are divided into female, male, and mixed teams. The sample period is from April 2009 to August 2017. Panel B shows the average success rate for the corresponding category.

4.2. Campaign goals and amounts pledged

Our first hypothesis states that over-optimism should lead to men setting higher goal amounts than women. The univariate test in Table 2 is consistent with this prediction. The mean goal amount for women is \$12,286, while it is \$17,259 for men. The difference of \$4972 is economically large and statistically significant. This comparison does not account for the differences in the types of campaigns that women and men launch. To control for these differences, we test this hypothesis using multivariate OLS regressions of the following form:

$$ln(Goal)_i = \alpha_0 + \alpha_1 \times Female_i + \beta \times X_i + \epsilon_i \tag{1}$$

where $ln(Goal)_i$ is the natural logarithm of the goal amount set by the entrepreneur. $Female_i$ is a dummy taking value one if the campaign creator is female and zero if male. X_i is a vector of control variables, including dummies for creator race/ethnicity, campaign length, the number of prior campaigns by outcome, month fixed effects, subcategory fixed effects, county fixed effects to capture any impact of local factors, and campaign number fixed effects, referring to how many campaigns the same creator has created before the current campaign, which is intended to capture the effect of campaign experience. We exclude suspended campaigns from these regressions.[5]

The results, shown in the first two columns of Panel A of Table 3, support our hypothesis. Female entrepreneurs set significantly lower goal amounts than their male counterparts. To gain further insight into campaign performance, we also perform a regression analysis on the pledged amount, using regressions of the following form:

$$ln(1 + Pledged)_i = \alpha_0 + \alpha_1 \times Female_i + \beta \times X_i + \epsilon_i, \tag{2}$$

where $ln(1 + Pledged)_i$ is the natural logarithm of one plus the amount pledged by campaign backers. The vector of controls, X_i, is the same as in the previous equation, except that we add a dummy for staff pick campaigns (campaigns highlighted by the Kickstarter platform).

The results are shown in columns two and three of Panel A in Table 3. We see that independent of the campaign goal amount, women tend to receive significantly more in pledged amounts than men, indicating that women exhibit a better campaign success rate, not just because they set lower goal amounts.

Finally, we perform the same regression analysis using *ln(1+Proceeds)* as the dependent variable. Proceeds is the amount of money the entrepreneur actually receives from the campaign and equals the pledged amounts for the campaigns that are successful, while unsuccessful campaigns result in zero proceeds (the All-or-Nothing model). The results, shown in the last two columns of Panel A of Table 3, are similar to those on pledged amounts, with women achieving significantly higher proceeds.

In Panel B, we repeat the same analysis including teams of entrepreneurs. We find that teams generally set larger goal amounts than individual entrepreneurs, regardless of gender. They also achieve higher pledged amounts. Interestingly, the gender dynamics within teams look very similar to those of individual entrepreneurs. Female teams set lower goals than male teams but achieve higher pledged amounts and campaign proceeds. Mixed teams rank between female and male teams on all of these measures.

Collectively, these results provide support for our hypothesis that male underperformance is driven by over-optimism. Men set higher goal amounts but receive substantially less in pledged funds and campaign proceeds. These findings are consistent with male entrepreneurs systematically overestimating the demand for their products and therefore setting higher goal amounts and pursuing lower quality projects.

4.3. Gender differences in campaign success

Our first hypothesis also predicts that female entrepreneurs exhibit a higher likelihood of success than male entrepreneurs. The univariate tests shown in Table 2 support this prediction. The mean success rate for women is 8.7 percentage points higher than that for men, and the difference is highly statistically significant. The same conclusion can be drawn when we use the logarithm of the pledged/goal ratio as the measure of success. The difference in the means of the logarithm is significant at the 1% level.

We formally test for gender differences using OLS regressions of the following form:

$$Successful_i = \alpha_0 + \alpha_1 \times Female_i + \beta \times X_i + \epsilon_i, \tag{3}$$

where $Successful_i$ is a dummy taking value one if the campaign is successful and zero otherwise.[6] The vector of controls, X_i, is the same as above.

For the ratio of amount pledged to the goal amount, we estimate the impact of campaign attributes on this ratio using OLS regressions of the following form:

$$ln(1 + Pledged/Goal)_i = \alpha_0 + \alpha_1 \times Female_i + \beta \times X_i + \epsilon_i, \tag{4}$$

where $ln(1 + Pledged/Goal)_i$ is the natural logarithm of one plus the amount pledged divided by the goal amount for campaign i. We take logarithms due to the highly skewed distribution of the ratio and add one to be able to include campaigns with zero pledged amounts.

[5] We do not observe the specific reasons for each campaign suspension, but generally, these are campaigns found to be in violation of Kickstarter's rules. The number of suspended campaigns is very small relative to our sample size, and including them in the regressions would not result in any significant changes in the results.

[6] Failed and canceled campaigns are both classified as unsuccessful. Since the entrepreneur has the option to cancel the campaign, we cannot distinguish between a failed campaign and a campaign canceled due to weak demand. Excluding canceled campaigns and campaigns with goal amounts below \$1000 does not materially change the results.

Table 2
Summary statistics by gender.

	All		Female		Male		Female–Male
	Mean	Std	Mean	Std	Mean	Std	Δ Mean
Campaign outcomes							
Successful	0.380	0.485	0.433	0.495	0.351	0.477	0.082***
Failed	0.532	0.499	0.493	0.500	0.555	0.497	−0.061***
Canceled	0.084	0.278	0.072	0.258	0.090	0.287	−0.019***
Suspended	0.003	0.056	0.002	0.043	0.004	0.061	−0.002***
Pledged/Goal	0.687	1.179	0.683	0.982	0.677	1.247	0.006
ln(1+Pledged/Goal)	0.390	0.462	0.414	0.430	0.374	0.474	0.040***
Pledged (USD '000)	4.313	10.252	3.994	8.843	4.134	10.318	−0.140*
Proceeds (USD '000)	3.700	10.073	3.496	8.719	3.512	10.114	−0.015
Launch another	0.168	0.374	0.132	0.338	0.186	0.389	−0.055***
Campaign variables							
Goal amount ('000)	15.990	36.375	12.286	28.946	17.259	38.985	−4.972***
Camp. length (days)	34.213	12.918	33.776	12.846	34.420	13.024	−0.644***
Staff pick	0.064	0.245	0.069	0.253	0.059	0.236	0.010***
N prior campaigns	0.360	1.650	0.231	1.019	0.422	1.869	−0.191***
N prior succ.	0.193	1.110	0.133	0.867	0.221	1.209	−0.088***
N prior failed	0.125	0.819	0.072	0.340	0.151	0.964	−0.079***
N prior canceled	0.041	0.265	0.026	0.183	0.049	0.296	−0.023***
Creator variables							
Female	0.274	0.446	1.000	0.000	0.000	0.000	1.000
Male	0.681	0.466	0.000	0.000	1.000	0.000	−1.000
Female team	0.008	0.086	0.000	0.000	0.000	0.000	0.000
Male team	0.018	0.131	0.000	0.000	0.000	0.000	0.000
Mixed team	0.020	0.141	0.000	0.000	0.000	0.000	0.000
White	0.700	0.458	0.681	0.466	0.708	0.455	−0.027***
Black	0.015	0.122	0.017	0.129	0.015	0.120	0.002***
Asian	0.020	0.140	0.023	0.150	0.019	0.136	0.004***
Hispanic	0.051	0.219	0.043	0.203	0.054	0.225	−0.011***
No race	0.214	0.410	0.237	0.425	0.205	0.404	0.031***
N	155,632		42,598		105,977		148,575

This table shows the summary statistics for the full sample, including teams of entrepreneurs, and separately for individual entrepreneurs divided by gender. The variable definitions are provided in Appendix. Stars indicate the significance level of the difference in means based on a t-test. Significance levels: * 0.1, ** 0.05, *** 0.01.

Panel A of Table 4 reports the results of these regressions. The first two columns show the regression results for the success rate. Across model specifications, women are associated with a significantly higher likelihood of success than men, consistent with our hypothesis. As predicted by theoretical models (e.g., Strausz, 2017; Schwienbacher, 2018; Ellman and Hurkens, 2019), setting a higher goal amount makes campaign success less likely. Similarly, a longer campaign length makes success less likely, while being chosen as a staff pick is associated with a higher success rate. Prior campaign performance predicts current performance: the number of prior successful campaigns increases the success rate, while having prior failed or canceled campaigns does the opposite.

Columns three to four show qualitatively similar results when we use $ln(1 + Pledged/Goal)$ as the performance measure. Women also significantly outperform men based on this metric, and the coefficients of all other variables are directionally consistent with those reported in the first two columns.

In Panel B, we repeat the same analysis including teams. Male teams appear no different from individual male entrepreneurs, while female teams outperform individual females and other teams. Again, mixed teams rank between male and female teams.

4.4. Gender differences in successive campaigns

Our second hypothesis predicts that if the higher goal amounts and weaker campaign performance by male entrepreneurs are driven by over-optimism, this difference should be reduced over time in successive campaigns by the same entrepreneur, as experience mitigates the impact of over-optimism. We begin our analysis by plotting campaign outcome variables by campaign number, shown in Fig. 1. Panel A shows the mean values by campaign number. Panel B shows the residuals from a regression of each of the same variables on campaign sub-category dummies, effectively adjusting the means by the type of campaign. Campaign performance generally improves for both genders in successive campaigns. This is consistent with entrepreneurial learning from past campaign experience.

These charts exhibit patterns that are consistent with our hypothesis. With all measures of campaign success, including successful dummy, pledged/goal ratio, pledged amount, and the proceeds amount, men initially underperform women but converge toward them by campaign number. In contrast, men initially set substantially higher campaign goal amounts but then adjust them downwards more strongly than women.

The results in Table 5 show these same patterns. Panel A shows that goal amounts decrease with campaign number for both male and female entrepreneurs, but the decrease is more pronounced for men. Similarly, amounts pledged, success rates, and pledged/goal ratios increase for both genders, but more strongly for men. Panel B shows the same statistics including only the entrepreneurs that have at least three campaigns in our sample, to ensure the group of individuals in the sample is constant across campaign numbers.

Panel C shows the difference between men and women for the full sample as well as for the subsample with at least three campaigns, with t-statistics for the difference. We see that women set significantly lower goal amounts in their first campaigns, but this difference decreases substantially in the second and third campaigns. The reverse is true for success rates. Women have significantly higher average success rates in their first campaigns. However, by the third campaign, this difference decreases substantially. For the average pledged/goal ratio, women significantly outperform in the first campaign. This result reverses in the subsequent campaigns, and men actually have slightly higher average pledged/goal ratios in their third campaigns.

Reassuringly, the patterns for the subsample of entrepreneurs that have at least three campaigns are broadly the same, although there are

Table 3
Goal amount and amount pledged.

Panel A: Individual entrepreneurs

	ln(Goal)		ln(1+Pledged)		ln(1+Proceeds)	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	−0.1018***	−0.0900***	0.4248***	0.4399***	0.5837***	0.5496***
	(0.0212)	(0.0206)	(0.0384)	(0.0371)	(0.0467)	(0.0497)
ln(Goal amount)				0.1604***		−0.3617***
				(0.0239)		(0.0216)
ln(Campaign length)		0.9244***	0.0131	−0.1354***	−0.8608***	−0.5260***
		(0.0264)	(0.0406)	(0.0350)	(0.0559)	(0.0560)
Staff pick			2.8396***	2.7699***	4.0563***	4.2135***
			(0.0954)	(0.0991)	(0.1638)	(0.1635)
ln(1+prior succ.)	−0.5151***	−0.4259***	2.2800***	2.3540***	2.6069***	2.4400***
	(0.0860)	(0.0778)	(0.1262)	(0.1257)	(0.1633)	(0.1668)
ln(1+prior failed)	−0.7565***	−0.7433***	−0.4216***	−0.3066**	−0.8892***	−1.1486***
	(0.0753)	(0.0681)	(0.1183)	(0.1183)	(0.1632)	(0.1625)
ln(1+prior canceled)	−0.3849***	−0.3661***	−0.1802	−0.1261	−0.8344***	−0.9564***
	(0.0901)	(0.0818)	(0.1269)	(0.1214)	(0.1729)	(0.1873)
Race controls	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Sub-category FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Campaign N FE	Yes	Yes	Yes	Yes	Yes	Yes
N	147,635	147,635	147,635	147,634	147,635	147,634
R^2	0.197	0.243	0.287	0.291	0.258	0.272

Panel B: Including teams

	ln(Goal)		ln(1+Pledged)		ln(1+Proceeds)	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	−0.1059***	−0.0941***	0.4150***	0.4318***	0.5776***	0.5423***
	(0.0209)	(0.0204)	(0.0391)	(0.0377)	(0.0475)	(0.0504)
Female team	0.1987*	0.2182**	1.1686***	1.1379***	1.1120***	1.1764***
	(0.1147)	(0.1059)	(0.2055)	(0.2000)	(0.3440)	(0.3518)
Male team	0.4043***	0.3748***	0.7510***	0.6911***	0.1014	0.2271
	(0.0981)	(0.0913)	(0.1783)	(0.1756)	(0.2996)	(0.3013)
Mixed team	0.3558***	0.3530***	0.9672***	0.9120***	0.5239*	0.6398**
	(0.1049)	(0.0995)	(0.1821)	(0.1789)	(0.3146)	(0.3149)
ln(Team size)	−0.2239*	−0.2120*	0.5891**	0.6235**	1.0927***	1.0204**
	(0.1258)	(0.1160)	(0.2431)	(0.2398)	(0.4066)	(0.4039)
ln(Goal amount)				0.1710***		−0.3592***
				(0.0240)		(0.0216)
ln(Campaign length)		0.9259***	0.0171	−0.1416***	−0.8607***	−0.5275***
		(0.0266)	(0.0414)	(0.0359)	(0.0572)	(0.0585)
Staff pick			2.8040***	2.7303***	4.0628***	4.2177***
			(0.0909)	(0.0946)	(0.1609)	(0.1608)
ln(1+prior succ.)	−0.5076***	−0.4183***	2.2971***	2.3743***	2.6363***	2.4740***
	(0.0847)	(0.0767)	(0.1204)	(0.1197)	(0.1632)	(0.1659)
ln(1+prior failed)	−0.7555***	−0.7415***	−0.4170***	−0.2950**	−0.8598***	−1.1159***
	(0.0731)	(0.0664)	(0.1162)	(0.1159)	(0.1666)	(0.1654)
ln(1+prior canceled)	−0.3868***	−0.3649***	−0.1596	−0.1023	−0.8113***	−0.9315***
	(0.0872)	(0.0787)	(0.1223)	(0.1167)	(0.1751)	(0.1879)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Sub-category FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Campaign N FE	Yes	Yes	Yes	Yes	Yes	Yes
N	154,677	154,677	154,677	154,676	154,677	154,676
R^2	0.200	0.245	0.290	0.295	0.258	0.272

Panel A includes all campaigns by individual entrepreneurs. Panel B also includes teams of multiple individuals. The dependent variable is shown above each model. *ln(Goal)* is the natural logarithm of the campaign goal amount. *ln(1+Pledged)* is the natural logarithm of one plus the amount pledged for the campaign. *ln(1+Proceeds)* is the natural logarithm of one plus the amount of proceeds the entrepreneur received from the campaign. We exclude suspended campaigns. We include *Month fixed effects* based on the month the campaign was launched (101 months), *Sub-category fixed effects*, based on Kickstarter category ID (169 different categories), *County fixed effects* based on the location of the campaign (our data include campaigns in 2346 counties), and *Campaign number fixed effects*, based on the number of campaigns the same creator has launched prior to the current campaign. Heteroscedasticity-consistent standard errors, clustered by sub-category, are shown in parentheses. Significance levels: * 0.1, ** 0.05, *** 0.01.

differences in the values and significance levels of gender differences, which are partly driven by the smaller sample size. We see that serial campaign creators perform better in their first campaigns, as evidenced by higher success rates and pledged/goal ratios in the first campaign in Panel B vs. Panel A. Similarly, women have significantly higher average success rates in the first campaign, while the difference decreases in subsequent campaigns. For the pledged/goal ratio, the pattern is the same as in Panel A.

We also perform a multiple regression analysis on the impact of gender and campaign number on goal amount, pledged amount, proceeds amount, success rate, and pledged/goal ratio. The regression models are of the same form as shown above, with the addition of interaction

Table 4
Campaign success.

Panel A: Individual entrepreneurs

	Successful			ln(1+Pledged/Goal)		
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.0732***	0.0714***	0.0643***	0.0481***	0.0464***	0.0378***
	(0.0050)	(0.0049)	(0.0054)	(0.0050)	(0.0050)	(0.0057)
ln(Goal amount)			−0.0746***			−0.0910***
			(0.0028)			(0.0038)
ln(Campaign length)		−0.1422***	−0.0731***		−0.1303***	−0.0461***
		(0.0073)	(0.0064)		(0.0072)	(0.0069)
Staff pick	0.3956***	0.3945***	0.4269***	0.4050***	0.4040***	0.4435***
	(0.0160)	(0.0159)	(0.0155)	(0.0177)	(0.0178)	(0.0173)
ln(1+prior succ.)	0.3482***	0.3345***	0.3001***	0.3519***	0.3394***	0.2974***
	(0.0185)	(0.0187)	(0.0186)	(0.0301)	(0.0312)	(0.0295)
ln(1+prior failed)	−0.0463**	−0.0484**	−0.1019***	−0.0912***	−0.0931***	−0.1584***
	(0.0231)	(0.0233)	(0.0222)	(0.0266)	(0.0270)	(0.0262)
ln(1+prior canceled)	−0.0611***	−0.0640***	−0.0892***	−0.0981***	−0.1008***	−0.1315***
	(0.0227)	(0.0226)	(0.0247)	(0.0244)	(0.0245)	(0.0236)
Race controls	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Sub-category FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Campaign N FE	Yes	Yes	Yes	Yes	Yes	Yes
N	147,636	147,636	147,635	147,634	147,634	147,634
R^2	0.230	0.241	0.284	0.271	0.281	0.351

Panel B: Including teams

	Successful			ln(1+Pledged/Goal)		
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.0726***	0.0708***	0.0635***	0.0475***	0.0459***	0.0369***
	(0.0051)	(0.0050)	(0.0055)	(0.0051)	(0.0051)	(0.0058)
Female team	0.1167***	0.1138***	0.1272***	0.0983***	0.0957***	0.1120***
	(0.0350)	(0.0360)	(0.0373)	(0.0344)	(0.0346)	(0.0348)
Male team	−0.0131	−0.0085	0.0176	0.0204	0.0246	0.0564
	(0.0323)	(0.0324)	(0.0328)	(0.0432)	(0.0432)	(0.0420)
Mixed team	0.0395	0.0401	0.0641*	0.0452	0.0457	0.0749*
	(0.0341)	(0.0345)	(0.0346)	(0.0392)	(0.0390)	(0.0381)
ln(Team size)	0.1317***	0.1298***	0.1149***	0.0802	0.0785	0.0603
	(0.0435)	(0.0436)	(0.0430)	(0.0536)	(0.0528)	(0.0513)
ln(Goal amount)			−0.0745***			−0.0908***
			(0.0028)			(0.0039)
ln(Campaign length)		−0.1423***	−0.0732***		−0.1294***	−0.0452***
		(0.0074)	(0.0066)		(0.0074)	(0.0075)
Staff pick	0.3955***	0.3941***	0.4263***	0.4036***	0.4023***	0.4415***
	(0.0153)	(0.0152)	(0.0149)	(0.0181)	(0.0182)	(0.0178)
ln(1+prior succ.)	0.3509***	0.3373***	0.3036***	0.3536***	0.3412***	0.3002***
	(0.0182)	(0.0184)	(0.0182)	(0.0300)	(0.0310)	(0.0294)
ln(1+prior failed)	−0.0422*	−0.0445*	−0.0976***	−0.0913***	−0.0934***	−0.1581***
	(0.0233)	(0.0235)	(0.0224)	(0.0258)	(0.0260)	(0.0255)
ln(1+prior canceled)	−0.0583**	−0.0617***	−0.0867***	−0.0967***	−0.0999***	−0.1302***
	(0.0230)	(0.0229)	(0.0248)	(0.0238)	(0.0238)	(0.0230)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Sub-category FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Campaign N FE	Yes	Yes	Yes	Yes	Yes	Yes
N	154,678	154,678	154,677	154,676	154,676	154,676
R^2	0.230	0.240	0.283	0.269	0.279	0.348

Panel A includes all campaigns by individual entrepreneurs. Panel B also includes teams of multiple individuals. The dependent variable is shown above each model. *Successful* is a dummy taking value 1 if the Kickstarter crowdfunding campaign was successful. *ln(1+Pledged/Goal)* is the natural logarithm of one plus the amount pledged divided by the campaign goal amount. We exclude suspended campaigns. We include *Month fixed effects* based on the month the campaign was launched, *Sub-category fixed effects*, based on Kickstarter category ID (169 different categories), *County fixed effects* based on the location of the campaign (our data include campaigns in 2346 counties), and *Campaign number fixed effects*, based on the number of campaigns the same creator has launched prior to the current campaign. Heteroscedasticity-consistent standard errors, clustered by sub-category, are shown in parentheses. Significance levels: * 0.1, ** 0.05, *** 0.01.

terms between gender and campaign experience. Panel A of Table 6 shows the results of these regressions.

First, we see that campaign goal amounts decrease in a monotonic fashion with campaign number. In contrast, amounts pledged, success rates, and pledged/goal ratios increase with campaign number. Second, the gender differences decrease substantially in successive campaigns. Women set significantly lower goal amounts in their first campaigns, but the difference is reduced to one third in magnitude in third or higher campaigns and is no longer statistically significant. Similarly, women are significantly more likely to succeed in their first campaign than men, but this difference is smaller in magnitude in the second campaign, and even smaller and statistically insignificant in the following campaigns. Similarly, women achieve significantly higher pledged/goal ratios in the first campaign, but the difference is close to zero and statistically insignificant in the second campaign. In their third or higher campaigns men actually outperform women, and the

Panel A: Average values

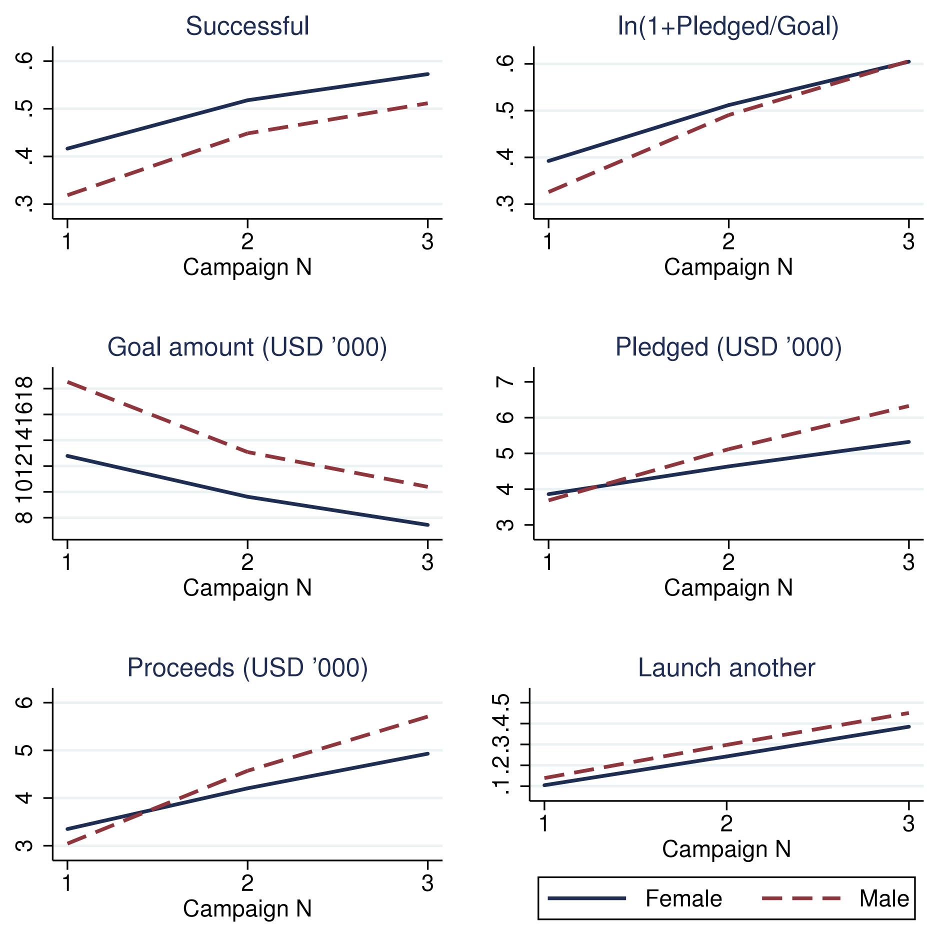

Fig. 1. Successive campaigns.
This figure illustrates the average goal amounts and outcome variables by campaign number. Panel A shows average values of the raw variables. Panel B shows residuals from a regression controlling for sub-category fixed effects. *Successful* is a dummy taking value 1 if the Kickstarter crowdfunding campaign was successful. *ln(1+Pledged/Goal)* is the natural logarithm of one plus the amount pledged divided by the campaign goal amount. *Goal amount* is the natural logarithm of the campaign goal amount. *Pledged* is the amount pledged for the campaign. *Proceeds* is the amount of proceeds the entrepreneur received from the campaign. *Launch another* is a dummy taking the value 1 if the same entrepreneur launches another campaign afterwards.

difference is statistically significant. In the Internet Appendix Section IA.3, we show that these results are robust to including entrepreneur fixed effects.

We also perform a separate regression analysis that includes interaction terms of gender and campaign experience by outcome. The results are shown in Table 7. As noted above, prior campaign performance predicts current performance measured by both success rates and pledged/goal ratios, with the number of successful prior campaigns increasing the likelihood of success, and the number of unsuccessful campaigns doing the opposite. However, this effect differs by gender. The positive relationship between prior successful campaigns and current campaign success is significantly weaker for women. However, the negative impact of prior failed campaigns is more negative for women than for men. Thus, women generally seem to benefit less from prior experience than men do. This finding parallels the results of Kuppuswamy and Mollick (2016), who find that women are less likely to attempt a second campaign when they have succeeded or failed by a large margin in their first campaign.

Column 1 of Table 7 also suggests that goal amounts generally decrease in successive campaigns for both successful and failed campaigns. There are at least two reasons why successful campaigns might also be followed by smaller campaign goal amounts. First, a successful campaign generates profits for the entrepreneur, who is thus less reliant on external financing in subsequent campaigns. As discussed by Schwienbacher (2018), the optimal goal amount may decrease with increasing access to alternative sources of financing that reduce the dependence of project completion on the success of the crowdfunding campaign. This argument suggests that a less-financially-constrained entrepreneur should set lower goal amounts. Second, there are likely to be synergies or economies of scale in producing consecutive products, thereby lowering the investment required for producing the second product. For example, the machinery and equipment purchased for the first product may be used for producing another (relatively similar) product. By definition, such investments would only take place following a successful prior campaign. Hence, this effect leads to similar predictions as the loosening of financial constraints. It seems likely that the aggregate dynamics include both of these effects.

All these results are consistent with our second hypothesis that male entrepreneurs' performance and goal amounts converge toward those of female entrepreneurs in successive campaigns as male entrepreneurs' over-optimism is mitigated by campaign experience.

Panel B: Residuals from a regression controlling for sub-category FE

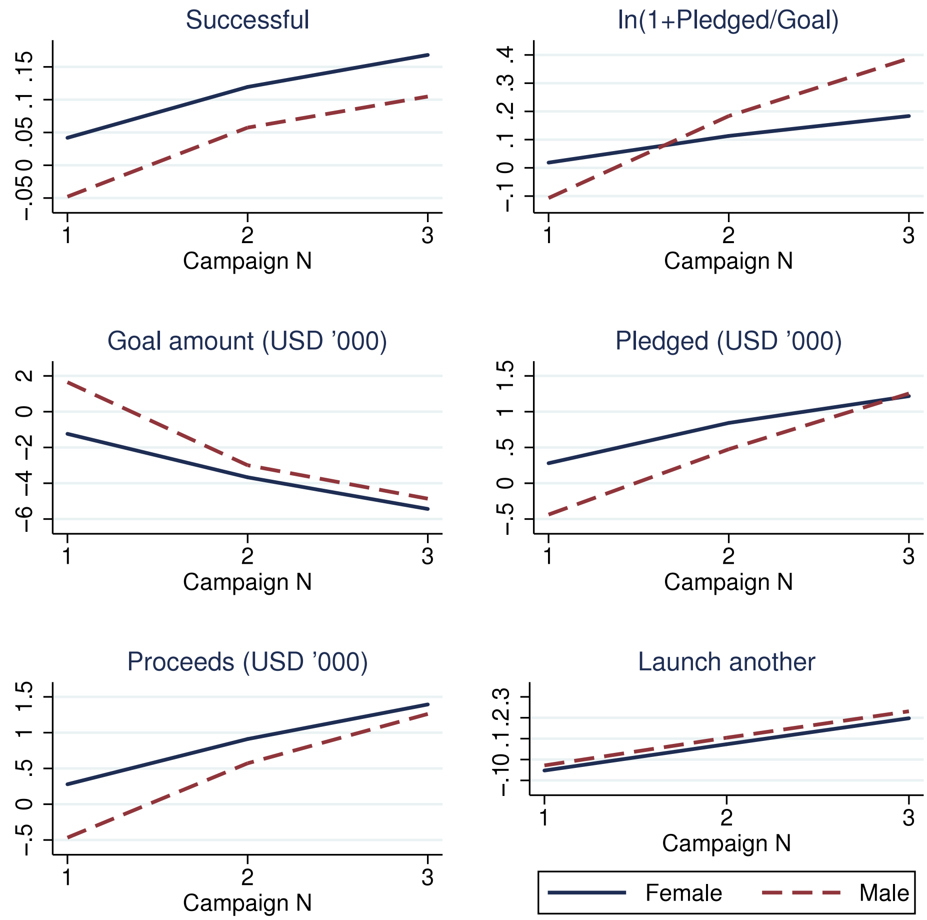

Fig. 1. (*continued*).

4.5. Additional analysis and robustness checks

In the Internet Appendix, we perform a number of additional analyses and robustness checks. These include repeating our main analysis but controlling for campaign likelihood, testing for gender differences in the sensitivity to campaign outcomes, and an analysis of second campaigns where we control for differences from the first campaign by the same entrepreneur. We also include a discussion of several alternative explanations and perform related analyses. For example, we control for cultural uncertainty aversion to confirm that our results are not driven by risk aversion. We also test for gender-based homophily (Greenberg and Mollick, 2017) but do not find evidence supporting it. We perform an analysis with matched control samples to mitigate the possible impact of unobserved project characteristics. We also perform a separate analysis using only "gender-neutral" product sub-categories. Our results are robust to each of these alternative specifications.

5. Conclusion

In this paper, we explore the role of gender in crowdfunding performance and empirically document a number of gender differences. We show that female entrepreneurs' significant outperformance in campaign success rates and pledged amounts received relative to campaign goals can be explained by the relative over-optimism of male entrepreneurs. This over-optimism manifests in male entrepreneurs overestimating the demand for their products and thus setting significantly higher campaign goal amounts than their female counterparts.

Our findings on successive campaigns by the same entrepreneurs both further support the over-optimism argument and suggest that entrepreneurial experience and learning by doing can mitigate the effects of over-optimism. Men begin with significantly higher goals and lower success rates and pledged/goal ratios in the first campaigns relative to women. However, the differences decrease in the subsequent campaigns. This finding is robust to further controlling for entrepreneur fixed effects and consistent with men exhibiting relative over-optimism in their first campaigns and then "learning away" the over-optimism through campaign experience.

The economic impact of male over-optimism appears large. During our sample period, an improvement of seven percentage points in the success rate of male entrepreneurs, equal to the gender difference that we estimate in our multivariate regressions, would have resulted in ca. 7500 more projects being successfully funded. This corresponds to a 20% increase in the number of successful male-led projects or a 14% increase in successful projects overall. In our tests of alternative explanations, we also find that female outperformance is significantly less pronounced in states with low gender equality. This finding, consistent with prior literature, suggests that a discriminatory institutional environment may curtail some of the potential of female entrepreneurs.

To the best of our knowledge, our study is the most comprehensive analysis of gender differences in crowdfunding success to date and the first to identify over-optimism as a key driver of crowdfunding performance. We also provide some of the first and most comprehensive empirical evidence that entrepreneurs can mitigate the harmful impact of over-optimism by learning through experience.

Table 5
Means by campaign number.

Panel A: Means by gender by campaign number (all)

	Female, campaign #			Male, campaign #		
	1	2	3	1	2	3
Goal amount ('000)	12.788	9.623	7.442	18.521	13.087	10.391
Pledged (USD '000)	3.862	4.637	5.322	3.686	5.120	6.328
Proceeds (USD '000)	3.350	4.205	4.930	3.044	4.572	5.709
Successful	0.416	0.518	0.573	0.319	0.448	0.512
ln(1+Pledged/Goal)	0.392	0.512	0.605	0.326	0.491	0.606
N	37,160	3817	852	87,040	11,724	3229

Panel B: Means by gender by campaign number (same individuals only)

	Female, campaign #			Male, campaign #		
	1	2	3	1	2	3
Goal amount ('000)	10.567	7.370	7.442	14.821	11.739	10.389
Pledged (USD '000)	4.425	4.888	5.322	5.802	6.077	6.331
Proceeds (USD '000)	3.913	4.486	4.930	5.231	5.559	5.712
Successful	0.527	0.552	0.573	0.424	0.499	0.512
ln(1+Pledged/Goal)	0.574	0.605	0.605	0.508	0.605	0.606
N	852	852	852	3227	3228	3227

Panel C: Female–Male difference by campaign number

	Campaign # (All)			Campaign # (Same ind.)		
	1	2	3	1	2	3
Goal amount ('000)	−5.734***	−3.464***	−2.949**	−4.254**	−4.369***	−2.947**
Pledged (USD '000)	0.175**	−0.482*	−1.006*	−1.377**	−1.188*	−1.009*
Proceeds (USD '000)	0.306***	−0.368	−0.779	−1.317**	−1.073*	−0.782
Successful	0.098***	0.070***	0.061**	0.103***	0.053**	0.061**
ln(1+Pledged/Goal)	0.066***	0.021*	−0.001	0.066**	0.000	−0.001

Panel A shows the averages of variables of interest by gender and by the number of campaigns for all Kickstarter campaigns launched by individual entrepreneurs. Panel B shows the same statistics but only includes entrepreneurs with at least three campaigns, i.e., the same set of individuals for each campaign number. Panel B shows the difference in the averages of variables between females and males in panels A and B, and stars indicate the significance of the difference based on a *t*-test. Significance levels: * 0.1, ** 0.05, *** 0.01.

Table 6
Campaign number vs. gender.

	(1) ln(Goal)	(2) ln(1+Pledged)	(3) ln(1+Proceeds)	(4) Successful	(5) ln(1+Pledged/Goal)
1st campaign x Female	−0.0914***	0.5013***	0.6273***	0.0721***	0.0481***
	(0.0221)	(0.0380)	(0.0497)	(0.0056)	(0.0053)
2nd campaign x Female	−0.0593	0.2883***	0.3413***	0.0438***	0.0148
	(0.0373)	(0.0606)	(0.0942)	(0.0100)	(0.0116)
3rd or higher x Female	−0.0586	−0.0154	0.0325	0.0200	−0.0510
	(0.0606)	(0.1173)	(0.2267)	(0.0240)	(0.0352)
2nd campaign	−0.4081***	0.2877***	0.5313***	0.0588***	0.0749***
	(0.0246)	(0.0529)	(0.0754)	(0.0083)	(0.0108)
3rd or higher	−0.6986***	0.7032***	1.0987***	0.1181***	0.2183***
	(0.0498)	(0.1167)	(0.1981)	(0.0198)	(0.0301)
Race controls	Yes	Yes	Yes	Yes	Yes
Campaign controls	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Sub-category FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
N	147,668	147,667	147,667	147,668	147,667
R^2	0.241	0.275	0.253	0.267	0.325

The dependent variable is shown below for each model. *ln(Goal)* is the natural logarithm of the campaign goal amount. *ln(1+Pledged)* is the natural logarithm of one plus the amount pledged for the campaign. *ln(1+Proceeds)* is the natural logarithm of one plus the amount of proceeds the entrepreneur received from the campaign. *Successful* is a dummy taking value 1 if the Kickstarter crowdfunding campaign was successful. *ln(1+Pledged/Goal)* is the natural logarithm of one plus the amount pledged divided by the campaign goal amount. We exclude suspended campaigns. We include *Month fixed effects* based on the month the campaign was launched (101 months), *Sub-category fixed effects*, based on Kickstarter category ID (169 different categories), *County fixed effects* based on the location of the campaign (our data include campaigns in 2346 counties), and *Campaign number fixed effects*, based on the number of campaigns the same creator has launched prior to the current campaign. Heteroscedasticity-consistent standard errors, clustered by sub-category, are shown in parentheses. Significance levels: * 0.1, ** 0.05, *** 0.01.

Our findings are relevant not only for entrepreneurs launching new projects but also for those financing new ventures. A mere 4.9% of venture capital investments in 2016 were in companies founded by women, and these investments accounted only for 2.2% of the dollar

Table 7
Prior experience vs. gender.

	(1) ln(Goal)	(2) ln(1+Pledged)	(3) ln(1+Proceeds)	(4) Successful	(5) ln(1+Pledged/Goal)
ln(1+prior succ.) x Female	0.0489	−0.5608***	−0.6622***	−0.0561***	−0.1290***
	(0.0540)	(0.0889)	(0.1032)	(0.0125)	(0.0204)
ln(1+prior fail.) x Female	−0.0585	−0.1816*	−0.2734**	−0.0407***	−0.0023
	(0.0558)	(0.0992)	(0.1159)	(0.0150)	(0.0160)
ln(1+prior canc.) x Female	−0.1471	−0.0732	−0.0349	−0.0016	0.0025
	(0.0954)	(0.1457)	(0.1761)	(0.0207)	(0.0247)
Female	−0.0923***	0.4871***	0.6050***	0.0700***	0.0458***
	(0.0220)	(0.0374)	(0.0491)	(0.0055)	(0.0053)
ln(1+prior succ.)	−0.3909***	1.7361***	2.4487***	0.2702***	0.3737***
	(0.0475)	(0.0875)	(0.0877)	(0.0110)	(0.0188)
ln(1+prior failed)	−0.6658***	−0.8337***	−1.0116***	−0.1093***	−0.1048***
	(0.0322)	(0.0715)	(0.0760)	(0.0103)	(0.0089)
ln(1+prior canceled)	−0.2583***	−0.6717***	−0.9586***	−0.1119***	−0.0880***
	(0.0711)	(0.1158)	(0.1391)	(0.0153)	(0.0155)
Race controls	Yes	Yes	Yes	Yes	Yes
Campaign controls	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Sub-category FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
N	147,668	147,667	147,667	147,668	147,667
R^2	0.247	0.291	0.271	0.283	0.350

The dependent variable is shown below for each model. *ln(Goal)* is the natural logarithm of the campaign goal amount. *ln(1+Pledged)* is the natural logarithm of one plus the amount pledged for the campaign. *ln(1+Proceeds)* is the natural logarithm of one plus the amount of proceeds the entrepreneur received from the campaign. *Successful* is a dummy taking value 1 if the Kickstarter crowdfunding campaign was successful. *ln(1+Pledged/Goal)* is the natural logarithm of one plus the amount pledged divided by the campaign goal amount. We exclude suspended campaigns. We include *Month fixed effects* based on the month the campaign was launched (101 months), *Sub-category fixed effects*, based on Kickstarter category ID (169 different categories), and *County fixed effects* based on the location of the campaign (our data include campaigns in 2346 counties). Heteroscedasticity-consistent standard errors, clustered by sub-category, are shown in parentheses. Significance levels: * 0.1, ** 0.05, *** 0.01.

Table A.1
Definitions of variables.

Variable	Definition
Successful	Dummy taking the value 1 if the campaign is successful.
Failed	Dummy taking the value 1 if the campaign fails.
Canceled	Dummy taking the value 1 if the campaign is canceled.
Suspended	Dummy taking the value 1 if the campaign is suspended.
Unsuccessful	Dummy taking the value 1 if the campaign fails or is canceled or suspended.
Pledged/Goal	Amount pledged divided by the goal amount.
Sub-category	Kickstarter detailed category classification. Includes 169 categories.
Main category	Kickstarter main category classification. Includes 15 categories.
Amount pledged	Amount pledged by backers for a given campaign.
Proceeds	The amount of proceeds the entrepreneur receives from the campaign.
Goal amount	Campaign goal amount sought by the entrepreneur.
Campaign length	Campaign length set by the entrepreneur at the beginning of the campaign.
Staff pick	Dummy taking the value 1 if the campaign is chosen as a Staff pick.
N prior campaigns	Number of campaigns launched by the same entrepreneur before current campaign.
N prior successful	Number of prior successful campaigns by the same entrepreneur.
N prior failed	Number of prior failed campaigns by the same entrepreneur.
N prior canceled	Number of prior canceled campaigns by the same entrepreneur.
N prior suspended	Number of prior suspended campaigns by the same entrepreneur.
Female	Dummy taking the value 1 if the entrepreneur is female.
Male	Dummy taking the value 1 if the entrepreneur is male.
White	Dummy taking the value 1 if the race of the entrepreneur is white.
Black	Dummy taking the value 1 if the race of the entrepreneur black.
Asian	Dummy taking the value 1 if the race of the entrepreneur Asian.
Hispanic	Dummy taking the value 1 if the ethnicity of the entrepreneur is Hispanic.
No race	Dummy taking the value 1 if no race/ethnicity could be estimated based on last name.

value of VC investments.[7] Our results may provide further support for those arguing that backing female entrepreneurs is good business, especially at an early stage when the entrepreneur's experience is limited.

Data availability

The authors do not have permission to share data.

Appendix

See Table A.1.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jfi.2022.101001.

[7] PitchBook data, overview available at Fortune: http://fortune.com/2017/03/13/female-founders-venture-capital/.

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