Journal of Corporate Finance 68 (2021) 101894

Contents lists available at ScienceDirect

Journal of Corporate Finance

journal homepage: www.elsevier.com/locate/jcorpfin

The round number heuristic and entrepreneur crowdfunding performance[☆]

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ARTICLE INFO

JEL classification:
D22
D81
D91
G23
G41
L26

Keywords:
Crowdfunding performance
Round number heuristic
Kickstarter
Fintech
Entrepreneur

ABSTRACT

We document a novel pattern that campaign goal amounts set by entrepreneurs on Kickstarter exhibit clear clustering at round numbers. We propose that the round number heuristic, a tendency to adopt round numbers as cognitive shortcuts when facing complicated and uncertain situations, may explain the clustering pattern and predict campaign outcomes. Based on 162,863 campaigns between 2009 and 2017, we find a negative relation between the use of round goal amounts and the likelihood of campaign success. Our findings suggest that setting a round number goal conveys useful information about entrepreneur quality that could be used by campaign backers or platforms.

1. Introduction

The human tendency to use round numbers – the round number heuristic – is pervasive.[1] It has been documented in a number of diverse contexts, ranging from retail prices to stock market trades, stock issuance, and corporate takeovers.[2] Furthermore, the disproportionate use of round numbers might imply a lack of information or cognitive limitations. D'Acunto et al. (2021) show that individuals with lower IQ are more likely to use round numbers to forecast inflation rates. Kuo et al. (2015) find that retail traders who

☆ We thank Utpal Bhattacharya, Francesco D'Acunto, Martin Holmén, Matti Keloharju, Manju Puri, and Ting Xu, as well as the seminar participants at the University of Amsterdam, Cheung Kong Graduate School of Business, Lingnan University, Central University of Finance and Economics, Xiamen University, and Shenzhen Audencia Business School, as well as the conference participants at the KWC Conference on Entrepreneurial Finance, Taiwan Finance Association Corporate Finance Seminar 2019 and Taiwan Economic Research 2019. Tse-Chun Lin gratefully acknowledges research support from the Faculty of Business and Economics at the University of Hong Kong. All errors remain the responsibility of the authors.

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[1] Throughout this paper, we use the term *round number heuristic* to denote the general tendency to adopt round numbers as cognitive shortcuts when facing complicated and uncertain situations.

[2] See Schindler and Kirby (1997) for retail prices, Harris (1991) and Bhattacharya et al. (2012) for stock market trades, Bradley, Cooney, Jr., Jordan, and Singh (2004) and Mola and Loughran (2004) for stock issuance, and Hukkanen and Keloharju (2018) for takeovers.

https://doi.org/10.1016/j.jcorpfin.2021.101894
Received 12 February 2020; Received in revised form 5 January 2021; Accepted 6 January 2021
Available online 26 January 2021
0929-1199/

rely more heavily on round numbers in their limit order submissions exhibit worse subsequent investment performance. In this paper, we study whether entrepreneurs' reliance on the round number heuristic has predictive power over their reward-based crowdfunding campaign performance.

Reward-based crowdfunding provides a way for early-stage entrepreneurs to fund creative ideas and test the demand for their products with limited financial risk. Unlike in most other sources of venture financing, the campaign backers do not receive a financial reward in reward-based crowdfunding. Instead, they pledge funds in return for a promise to receive a reward.[3] Hence, reward-based crowdfunding should be viewed as a complement rather than a substitute for more traditional forms of venture financing.[4] While most projects are small, there are plenty of cases where crowdfunding campaigns have helped entrepreneurs to launch successful businesses, often with subsequent backing by venture capitalists.[5] Mollick (2016) finds evidence of Kickstarter projects also having directly generated a significant number of jobs and patents, suggesting an increasing impact of reward-based crowdfunding on the real economy.

Prior to launching a campaign, the entrepreneur sets the campaign goal amount. If the aggregate amount pledged by backers reaches the goal amount set by the entrepreneur, the campaign is deemed successful. The entrepreneur then receives the funds and has an obligation to deliver the promised reward.[6] The goal amount should reflect the financing needs of the entrepreneur under uncertainty of product demand and investment costs. Hence, there is no rational reason why that amount should exhibit clustering at any specific number. At the same time, the prior literature discussed above would suggest that entrepreneurs' reliance on the round number heuristic might lead to goal amounts clustering at round numbers nevertheless. Furthermore, the findings of Kuo et al. (2015) and D'Acunto et al. (2021) suggest that low-quality entrepreneurs might rely on round numbers more. Accordingly, we hypothesize that i) goal amounts tend to cluster at round numbers, and ii) such use of round campaign goals is associated with either informational or cognitive limitations of the entrepreneur and is thus associated with weaker campaign performance.

In addition to revealing a lack of information or cognitive ability, there are other potential reasons why a round campaign goal number might be associated with worse campaign performance. First, a more precise goal amount may be interpreted by potential backers as a sign of entrepreneurial confidence in the project cost estimate. Uncertainty over the project cost leads to doubts about whether the backers will ultimately receive the product (e.g. Schwienbacher 2017) and hence will reduce the incentives for the crowd to back the campaign. This reasoning is in line with existing studies showing that more precise numbers reveal the communicator's confidence in their statements (e.g. Channell 1994; Yaniv and Foster 1995; Goldsmith et al. 2002; Welsh et al. 2011).

Second, imagine an entrepreneur who requires an estimated investment of $8790 to produce a widget. She may well decide to round the number up to $9000. Given the closeness of the two numbers anyway, she might even decide to set the goal at $10,000, both securing a part of the potential after-market demand early-on and reducing the risk of someone stealing the idea.[7] She is unlikely, however, to choose to round the amount down to $8000, since it would leave her with inadequate funds to produce the promised product.[8] As it is most likely that entrepreneurs round up the goal amount, campaigns with round number goals tend to overshoot what entrepreneurs can raise, compared to campaigns with more precise goal numbers. This argument is consistent with extant theoretical models of reward-based crowdfunding predicting that a higher goal combined with uncertain demand leads to a lower likelihood of campaign success (see e.g. Strausz 2017; Schwienbacher 2017; Ellman and Hurkens 2019).[9]

To test these predictions, we analyze a near-comprehensive dataset of Kickstarter campaigns.[10] We limit our sample to include only U.S. campaigns with goal amount of maximum $13,000 to avoid ambiguity in defining round number thresholds for larger-goal-amount campaigns. Imposing these filters also enables us to construct comparable control variables and have adequate frequency of campaigns with proximate goal amounts. We have a final sample of 166,819 campaigns spanning from April 2009 to August 2017.

We find that goal amounts exhibit clear clustering at round numbers. $5000 and $10,000 are the two most frequent goal amounts, representing 11.3% and 9.3% of the campaigns in our sample, respectively. Similarly, all multiples of $1000 display prominent frequency spikes, as to a slightly lesser extent do all multiples of $500. All these results provide support for our first hypothesis.

For our campaign performance analysis, we define the amounts $1000, $5000, and $10,000 as round campaign goals (*Round*), each representing the next order of magnitude for "roundness". Consistent with our second hypothesis, we find that round campaign goals are associated with significantly worse campaign performance, as measured by the likelihood of success, aggregate amount pledged, likelihood of receiving zero in pledged funds, and pledged over goal ratios. These results remain significant after controlling for

[3] This provides a valuable mechanism for entrepreneurs to learn about the potential demand for their products – see, e.g., Chemla and Tinn (2019) for a theoretical analysis. Xu (2018) provides empirical evidence of the feedback value of crowdfunding.

[4] Schwienbacher (2017) provides a theoretical framework exploring this complementarity.

[5] For examples, see: https://www.forbes.com/sites/amyfeldman/2016/04/14/ten-of-the-most-successful-companies-built-on-kickstarter/#23f8c2069e8b

[6] The mechanism described is often called "all-or-nothing" and is the way Kickstarter operates. There are other types of reward-based crowdfunding systems operated by other platforms, most importantly "keep-it-all", in which the entrepreneur receives all the pledged funds regardless of whether the campaign goal amount is reached (Cumming, Leboeuf, and Schwienbacher, 2019b).

[7] Schwienbacher (2017) shows that the risk of idea-stealing incentivizes the entrepreneur to set a higher goal amount to capture a higher share of the potential after-market before others can copy the idea.

[8] This, of course, simplistically assumes the entrepreneur has no other sources of funding. However, in many cases, it seems reasonable that the entrepreneur would attempt to cover (at least) the expected project cost from the crowdfunding proceeds.

[9] There are possible alternative arguments why round goal amounts could be positive as well. For example, round numbers could be viewed as symbolic and aspirational, and possibly easier to sell. Our results, however, are inconsistent with these arguments.

[10] Our initial web-crawled data includes roughly 87% of all Kickstarter campaigns launched until August 2017.

campaign size, campaign length, staff pick dummy, gender and race of the entrepreneur, calendar month fixed effects, sub-category-year joint fixed effects, county-year joint fixed effects, and entrepreneur campaign number fixed effects. The high-dimensional fixed effects help control for various confounding factors, including the current demand or supply of crowdfunding activities. These findings are also robust to various model specifications and various proxies of goal amount roundness. In terms of economic magnitude, the use of *Round* goals is associated with a 3.5%-point reduction in the likelihood of success, other things being equal. It is also associated with a 2.7%-point higher likelihood of receiving zero pledged funds.

We also find evidence that the use of round goal amounts provides a useful indication of entrepreneur quality. First, the use of round goal amounts in *previous* campaigns by the same entrepreneur has predictive power over the likelihood of success in the current campaign. This finding provides clear evidence that it is the entrepreneur's general reliance on the round number heuristic that predicts funding outcome. Second, we exploit a quasi-experiment provided by a Kickstarter rule change that removes mandatory campaign vetting and hence plausibly reduces the average entrepreneur quality on the platform. The rule change is associated with a significant increase in the likelihood of entrepreneurs using round goal amounts. Furthermore, the negative relationship between round campaign goals and campaign performance appears to be stronger following the rule change.

We interpret these finding as evidence of round goal amounts revealing entrepreneur quality, as it is difficult to think of other mechanisms that can plausibly explain the patterns. These results also mitigate the concern that our findings are purely driven by unobserved current campaign characteristics, such as campaign marketing quality, that cannot be perfectly measured and controlled for. Our interpretation is similar in spirit to the results of Kuo et al. (2015), who find that a higher frequency of limit orders submitted at round numbers is a proxy for lower cognitive ability of the investor and predicts lower investment performance in the subsequent year.

We also find that the likelihood of setting a round goal amount declines with entrepreneur campaign number, indicating that more experienced entrepreneurs are less likely to set round goal amounts. This result suggests a learning effect at the entrepreneur level, consistent with prior studies of entrepreneurial learning (e.g., Gompers et al. 2010; Lafontaine and Shaw 2016).

We perform a number of additional analyses to confirm the robustness of our results. First, we construct matched control samples for every round-goal-amount campaign with similar campaigns having a non-round goal amount. In the first matched control sample, we require the control campaign to be in the same sub-category, year, and county, as the round campaign. In the second matched control sample, we also require the entrepreneur gender and the campaign number to be the same. Our results remain robust to these matched control groups. We also perform a regression analysis on a subsample including campaigns with goal amounts within a narrow band from each of the three *Round* goal amounts and find that our results still hold. For a subsample of our data, we are able to construct additional control variables, e.g., the number of different pledge categories, and find qualitatively similar results.

In Internet Appendix, we also confirm that our main results hold using an extended sample of all campaigns, without imposing the upper limit of $13,000 for the campaign goal amount. Finally, the results are robust to different functional forms to control for campaign size, mitigating the potential concern of an omitted non-linear relationship between campaign performance, size, and round goal amount.

To our knowledge, this paper is the first study linking entrepreneurs' reliance on the round number heuristic and their crowdfunding performance, contributing to the existing literature in several ways. First, we add to the literature on the round number heuristic by providing new evidence in the context of entrepreneurial decision making and the funding of new ventures. Consistent with the findings of Kuo et al. (2015) and D'Acunto et al. (2021), we show that the use of round numbers conveys information about the entrepreneur quality in the reward-based crowdfunding, an increasingly important means of financing new ventures. Our paper is also related to Hervé and Schwienbacher (2018), who find that when equity crowdfunding investors face a high uncertainty, they tend to rely on round numbers in investment decisions. Our paper differs from theirs as we show that reliance on the round number heuristic is related to entrepreneur quality and thus predicts reward-based crowdfunding campaign performance.

We also contribute to the fast-growing literature on reward-based crowdfunding. Prior studies have identified several important predictors of campaign success, including social networks (Mollick 2014), moral hazard (Strausz 2017; Chemla and Tinn 2019), entrepreneur gender (Lin and Pursiainen 2018b; Gafni et al. 2021), homophily (Greenberg and Mollick 2016) and many others. Our results suggest that the precision of the chosen goal amount can be used to infer information about the entrepreneur quality. More broadly, our paper is one of the first studies of the role of behavioral biases in reward-based crowdfunding, an area that has a lot of scope for further research. Finally, our finding that entrepreneurial learning is associated with less reliance on heuristical thinking is related to a large literature on learning by doing in various contexts, including entrepreneurship (Gompers et al. 2010; Lafontaine and Shaw 2016) as well as other financial decisions like trading (Feng and Seasholes 2005; Dhar and Zhu 2006; Seru et al. 2010).

Our results on the negative relation between round number heuristic and crowdfunding performance have practical implications for both entrepreneurs and campaign backers by providing new insights on whether and how potential entrepreneurs should utilize these fundraising platforms. While our analysis cannot show that the choice of a round goal amount causally reduces the likelihood of success, we do show that entrepreneurs using round goal amounts are systematically more likely to fail. The fact that this is true even when they used round number goals only in prior campaigns suggests that the effect is not solely caused by the use of round numbers. Rather, it implies that the use of round numbers conveys information about the entrepreneur quality. This means that it could be used as an additional input by campaign backers and platforms when assessing the likelihood of the campaign to succeed.

It is also possible that entrepreneurs would be well-advised to avoid round number goal amounts. Our findings might also suggest that entrepreneurs should spend adequate time and effort to prepare and estimate project costs (as well as other campaign attributes) in order to be comfortable with a more precise estimate of project costs. This is important as entrepreneurs might waste both their human capital and funds, if they fail to raise new money for their ventures.

2. Literature review and hypothesis development

2.1. Reward-based crowdfunding and entrepreneurial finance

Crowdfunding has emerged over the last decade as a new source for venture financing. It has generated enthusiasm for its potential to democratize access to financing by removing potential barriers due to biased investment decisions.[11] At the same time, sceptics have questioned its viability and potential for exploitation.[12] A more nuanced assessment suggests that reward-based crowdfunding should be viewed as a complement rather than a substitute for more traditional forms of venture financing, like angel investing and venture capital.

Reward-based crowdfunding also provides a mechanism for entrepreneurs to learn about the market demand for their products before investing in the venture (see, e.g., Chemla and Tinn 2019; Xu 2018). It can thus be used to market-test projects and help potential entrepreneurs to launch their ventures with limited personal risk. As noted by, e.g., Schwienbacher (2017), the information on market potential that crowdfunding provides could not be obtained by a venture capitalist. In contrast, venture capitalists can provide security of follow-up funding when more money is needed. Similarly, crowdfunding cannot help entrepreneurs professionalize and scale their businesses the same way that venture capitalists do (see, e.g., Hellmann and Puri 2000, 2002).

While most reward-based crowdfunding projects are relatively small, the results of Mollick (2016) show that, in aggregate, they can generate a substantial number of jobs and patents. He estimates that from inception to May 2015, Kickstarter projects resulted in around 5135 ongoing fulltime jobs and 160,425 temporary ones, besides those of the entrepreneurs. His results also highlight the innovative nature of many crowdfunded projects, estimating that they had generated 2601 patent applications over the sample period.

2.2. Round numbers and price clustering

A substantial amount of literature suggests a general human tendency to use round numbers.[13] They are the most cognitively accessible numbers (Schindler and Kirby 1997) and act as reference points (Rosch 1975). Experiments on numerosity show that when people are asked to estimate a value, they tend to provide round numbers (Kaufman et al. 1949; Krueger 1982; Lipton and Spelke 2005). Furthermore, such a tendency to provide round numbers is more pronounced when lacking information or general knowledge (Ormerod and Ritchie 2007; Kleven and Waseem 2013; Whynes et al. 2007).

Financial decisions represent good examples of situations where assessing the exact value of the traded asset is a cognitively difficult task and hence a likely area to find evidence of the reliance on such round number heuristics. Correspondingly, the empirical literature has reported the clustering of prices at round numbers in a number of financial markets.[14] Using data from a French equity crowdfunding platform, Hervé and Schwienbacher (2018) find that investors in equity crowdfunding also exhibit a tendency to invest a round number amount, especially when facing high uncertainty.

The estimation of project costs and the corresponding choice of a crowdfunding campaign goal amount are an important and, at least in some cases, a challenging financial decision for the entrepreneur. Ultimate project costs are uncertain, as is the potential demand for the product (see, e.g., Schwienbacher 2017). Hence, given the vast amount of evidence that individuals tend to rely on the round number heuristic when facing uncertain situations, it seems intuitive that entrepreneurs' choices of goal amounts would also exhibit clustering at round numbers. We thus propose our first hypothesis:

Hypothesis 1. Goal amounts of crowdfunding campaigns cluster at round numbers.

2.3. The round number heuristic and crowdfunding

There are several reasons to expect round goal amounts to be associated with weaker crowdfunding campaign performance. First and foremost, the literature discussed above suggests that the use of round goal amounts is likely to be associated with entrepreneurs that are either less informed or cognitively more limited. The idea of cognitive limitation is supported by the results of Kuo et al. (2015) who use the limit order submission ratios at round numbers as a proxy for cognitive limitation. They show that retail investors who frequently use round numbers for limit orders are associated with worse investment performance even for those trades that are not using round order prices. D'Acunto et al. (2021) find more direct evidence that individuals with lower IQ are more likely to use round

[11] For example, current venture capital investments are highly concentrated in male-led startups. An estimated 4.9% of venture capital investments in 2016 were made in companies founded by women, and these investments accounted for only 2.2% of the dollar value of venture capital investment (PitchBook data, overview available at Fortune: http://fortune.com/2017/03/13/female-founders-venture-capital/). Furthermore, Ewens and Townsend (2020) find evidence of a gender bias in investment decisions made by male VC investors.

[12] For example, Cumming et al. (2019a) study incidents of fraud in reward-based crowdfunding, while Hildebrand et al. (2017) provide evidence of the ability of sophisticated investors to exploit others in debt crowdfunding.

[13] See, e.g., Baird et al. (1970) Dehaene and Mehler (1992) and Jansen and Pollmann (2001).

[14] Osborne (1962) is perhaps the first study documenting stock price clustering at round numbers, using closing prices from the New York Stock Exchange (NYSE). Niederhoffer (1965) shows similar clustering at limit orders. The same patterns are reported in a number of other equity markets (e.g., Harris 1991; Grossman et al. 1997; Bhattacharya et al. 2012), as well as in gold (Ball et al. 1985), FX (Grossman et al. 1997; Sopranzetti and Datar 2002), indices and index options (Donaldson and Kim 1993; ap Gwilym, Clare, and Thomas 1998), IPOs (Kandel et al. 2001), and bank deposit rates (Kahn et al. 1999).

numbers. Herrmann and Thomas (2005) show that analysts who tend to forecast earnings per share at round numbers are less informed, exert less effort, and have fewer resources.

Similarly, Garmaise (2015) shows that residential mortgage borrowers have a tendency to misreport financial assets just above round number thresholds. His results show that such misreporting is associated with significantly higher delinquency rates. The findings are most prevalent in areas with a low level of financial literacy. He proposes several potential explanations for these findings, including lack of information and optimistic, inattentive, overconfident, or deceitful borrowers.

Second, the psychology literature suggests that level of precision signals the communicator's confidence in her statements (Channell 1994; Yaniv and Foster 1995; Goldsmith et al. 2002; Welsh et al. 2011). A more precise goal amount may be interpreted by potential backers as a sign of confidence that the entrepreneur has in the project cost and product demand estimation, thus reducing the perceived uncertainty over the project. This in turn may lead to a higher likelihood of the project being finalized and the backers ultimately receiving the product.

This argument is supported by the empirical studies in various markets. For example, Hukkanen and Keloharju (2018) find that initial offer precision has a significant impact on takeover offer outcomes. While round price-per-share offers are very common, they result in adverse outcomes for the bidder, including higher purchase prices and a lower probability of completing the deal. Similar findings on the stronger anchoring effect of a more precise initial offer have been reported in the real estate market (Janiszewski and Uy 2008). Moreover, Bradley et al. (2004) find that a majority of IPOs have integer offer prices, and that the IPOs with integer offer prices exhibit significantly higher underpricing than those with fractional prices. They show that integer pricing is more common in the case of higher uncertainty. Mola and Loughran (2004) obtain similar results for seasoned equity offerings. Issues with integer offer prices are associated with larger discounts. Thomas et al. (2010) find that precise prices are judged to be smaller than round prices of similar magnitudes, and show evidence from the residential real estate market that buyers pay higher sale prices when list prices are more precise.

The last reason to expect worse campaign performance when using round goal amounts is that the entrepreneur is likely to only round the goal amount up. This is because rounding down would result in inadequate funds to complete the project, even if the campaign is successful.[15] Hence, round goal amounts could be expected to be biased upward and possibly larger than what the entrepreneurs could achieve. As shown by theoretical work on reward-based crowdfunding, a higher goal combined with uncertain demand leads to a lower likelihood of campaign success (see, e.g. Strausz 2017; Chemla and Tinn 2019; Schwienbacher 2017; Ellman and Hurkens 2019). In addition, if the potential campaign backers identify round goal amounts as probably "asking for too much", they might also be less inclined to back the campaign. In adjacent literature on negotiations, Schweinsberg, Ku, Wang, and Pillutla (2012) find experimental evidence that extreme first offers offend their recipients and cause them to walk away. This might effect might be stronger if the backers' intrinsic motivations are to some extent altruistic, as suggested by Boudreau, Jeppesen, Reichstein, and Rullani (2018).

Based on these arguments, we propose our second hypothesis:

Hypothesis 2. Round campaign goal amounts are associated with a lower likelihood of success.

3. Data and methodology

3.1. Crowdfunding data

We use a near-comprehensive, web-crawled dataset of Kickstarter campaigns initiated between April 2009 and August 2017. As summarized in Appendix B, the original raw data include the details of 315,017 campaigns in total. Compared with the Kickstarter statistics on the website,[16] which reports 364,332 projects launched to date, we 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 want to estimate gender and ethnicity of entrepreneurs based on names and control for regional characteristics on a consistent basis, we only include campaigns based in the U.S.

Our purpose is to analyze the relationship between round numbers and the outcomes of crowdfunding campaigns. We thus need a sample with adequate number of campaigns with goal amounts at these round numbers, as well as adequate number of campaigns around but near these round numbers. The distribution of campaign goals is highly skewed, with a large number of relatively small campaigns and a long tail of significantly larger campaigns with low frequencies for any given goal amount. Fig. 1 shows the cumulative distribution of campaigns by goal amount. The density of campaigns decreases substantially after the $13,000 goal amount. Hence, we use it as a cut-off value for our analysis. This last filter gives us a final sample of 166,819 campaigns.

We use the names of campaign creators to identify their gender and race or ethnicity. For estimating gender based on first names, we use the analysis by Peter Organisciak,[17] who estimates name frequencies by gender in the U.S. in 2014 according to birth name statistics and U.S. Census data on age distributions. For our analysis, we require the likelihood of assigning the correct gender to be at least 90%. This methodology gives us gender estimates for 67.4% of the sample, with the remainder classified as "No gender". This

[15] It is possible for the entrepreneur to complete the project using other sources of financing in case the crowdfunding campaign provides only a fraction of the project cost. It is, however, unlikely to be optimal for the entrepreneur.

[16] Figure as of mid-August 2017, at the time of the last campaigns in our data, available online at: https://www.kickstarter.com/help/stats

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

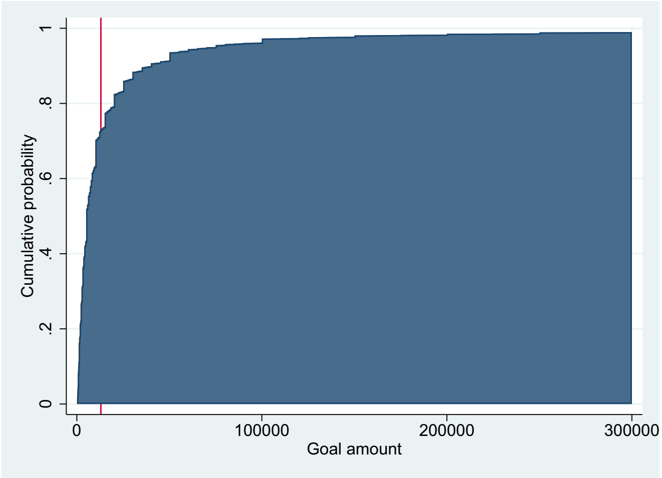

Fig. 1. Campaign goal amount - cumulative distribution. Cumulative distribution of campaign goal amounts in our initial data set. The red line indicates the goal $13,000, the cut-off value for our sample. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

third category includes individuals whose gender we cannot reliably estimate from the first name, groups of multiple individuals, or companies.

To estimate creator race or ethnicity, 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%.[18] This methodology gives us race/ethnicity estimates for 63.9% 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 also winsorize all continuous variables at the 1% and 99% levels.

3.2. Defining round numbers

For our analysis, we use a number of indicators for the precision of the goal amount. We define a dummy variable *Round*, taking the value one if a campaign goal amount is either $1000, $5000, or $10,000, each of which represents the next "order of magnitude" from the previous one. Logically, the next such number would be $50,000, equivalent to the 92nd percentile of goal amounts. But from Fig. 1, we can see that this threshold would be too high to provide a meaningful sample size at and near the number. Hence, to limit the campaign goals close enough to the *Round*, we exclude campaigns with a goal amount larger than $13,000, equivalent to approximately the 73rd percentile of all campaigns.[19] We run our analysis using the *Round* dummy, as well as including the round goal amounts as separate dummies. As alternative proxies of roundness, we use dummy variables *Divisible 1000* and *Divisible 500*, taking the value one if the goal amount is a multiple of 1000 and 500, respectively.

3.3. Descriptive statistics

Table 1 shows summary statistics for our sample. The average goal amount is slightly above $4000, and the median goal $3300. 26.7% of campaigns are classified as having a *Round* goal amount, i.e. a goal amount of either $1000, $5000, or $10,000. $5000 is the most common goal amount, with 11.3% campaigns having this number. 52.6% of campaigns have a goal amount divisible by 1000, and 75.2% divisible by 500. The average success rate is 0.461, and the average amount pledged $3204. 11.9% of campaigns end up with zero dollars pledged. The median Pledged/Goal ratio is 0.389.

Table 2 shows the number of campaigns by year in our sample, divided into those with *Round* and *Non-round* goal amounts, as well

[18] 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.

[19] We consciously set the cut-off point below $15,000, given that this number is a round number but clearly not the next order of magnitude from $10,000.

Table 1
Summary statistics.

	Mean	Std	Min	p25	p50	p75	Max
Campaign goal amounts							
Goal amount (000)	4.231	3.359	0.100	1.500	3.300	6.000	13.000
Round	0.267	0.442	0.000	0.000	0.000	1.000	1.000
Goal 1000	0.061	0.240	0.000	0.000	0.000	0.000	1.000
Goal 5000	0.113	0.317	0.000	0.000	0.000	0.000	1.000
Goal 10,000	0.093	0.290	0.000	0.000	0.000	0.000	1.000
Divisible 1000	0.526	0.499	0.000	0.000	1.000	1.000	1.000
Divisible 500	0.752	0.432	0.000	1.000	1.000	1.000	1.000
Campaign outcomes							
Successful	0.461	0.499	0.000	0.000	0.000	1.000	1.000
Failed	0.466	0.499	0.000	0.000	0.000	1.000	1.000
Canceled	0.070	0.255	0.000	0.000	0.000	0.000	1.000
Suspended	0.003	0.055	0.000	0.000	0.000	0.000	1.000
Amount pledged (000)	3.204	8.046	0.000	0.053	0.773	3.528	118.445
Zero pledged	0.119	0.324	0.000	0.000	0.000	0.000	1.000
Pledged/Goal	0.881	1.506	0.000	0.020	0.389	1.128	10.692
Campaign variables							
Camp. length (days)	33.496	12.979	9.000	30.000	30.000	35.000	85.000
Staff pick	0.061	0.239	0.000	0.000	0.000	0.000	1.000
N prior campaigns	0.356	1.053	0.000	0.000	0.000	0.000	7.000
N prior succ.	0.192	0.732	0.000	0.000	0.000	0.000	5.000
N prior failed	0.107	0.365	0.000	0.000	0.000	0.000	2.000
N prior canceled	0.036	0.187	0.000	0.000	0.000	0.000	1.000
N prior suspended	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Creator variables							
Female	0.203	0.402	0.000	0.000	0.000	0.000	1.000
Male	0.472	0.499	0.000	0.000	0.000	1.000	1.000
No gender	0.326	0.469	0.000	0.000	0.000	1.000	1.000
White	0.565	0.496	0.000	0.000	1.000	1.000	1.000
Black	0.015	0.120	0.000	0.000	0.000	0.000	1.000
Asian	0.021	0.145	0.000	0.000	0.000	0.000	1.000
Hispanic	0.038	0.191	0.000	0.000	0.000	0.000	1.000
No race	0.361	0.480	0.000	0.000	0.000	1.000	1.000
N	166,819						

Summary statistics for our full sample, including mean, standard deviation, and key percentiles. Variables are defined in Appendix A.

Table 2
Campaigns by year.

	Round				Non-round				Round - Non-round
	Successful	Unsuccessful	Total	Success rate	Successful	Unsuccessful	Total	Success rate	Δ Success rate
2009	91	110	201	0.453	284	300	584	0.486	−0.034
2010	828	1123	1951	0.424	2748	2941	5689	0.483	−0.059***
2011	2216	2929	5145	0.431	7975	7157	15,132	0.527	−0.096***
2012	3082	4178	7260	0.425	11,141	10,420	21,561	0.517	−0.092***
2013	3150	3714	6864	0.459	10,471	9227	19,698	0.532	−0.073***
2014	2859	5889	8748	0.327	10,179	13,990	24,169	0.421	−0.094***
2015	2435	4862	7297	0.334	8089	10,322	18,411	0.439	−0.106***
2016	1905	3123	5028	0.379	5723	5978	11,701	0.489	−0.110***
2017	903	1146	2049	0.441	2885	2446	5331	0.541	−0.100***
Total	17,469	27,074	44,543	0.392	59,495	62,781	122,276	0.487	−0.094***

Total number of campaigns by launch year, divided into those with *Round* and *Non-round* campaign goals. The sample period is from April 2009 to August 2017. We also include the average success rate for both groups and their difference for each year. The stars indicate significance of the difference based on a t-test.
Significance levels: * 0.1, ** 0.05, *** 0.01.

as by campaign outcome. The category *Unsuccessful* includes both campaigns that failed and campaigns that were canceled.[20] It also includes a small number of suspended campaigns. We see that the average success rate of campaigns with *Round* goal amount is lower than that of campaigns with non-round goal amount for every year in our sample.

4. Main analysis

4.1. Goal amount clustering at round numbers

Our first hypothesis predicts that goal amounts exhibit clustering at round numbers. Fig. 2 shows a clear pattern that supports the hypothesis. The highest frequencies take place at $5000 and $10,000, and there are spikes in frequency at every multiple of $1000, and slightly less pronounced ones at every multiple of $500.

Fig. 3 shows the percentage of campaigns in our sample by the roundness of the goal amount. The value zero means a goal amount including decimals. We see that the vast majority of goal amounts are set either as multiples of $100 or multiples of $1000. Campaigns with a goal of $10,000 represent 9.2% of our sample. Relatively few campaign goals are very precise, with multiples of $10 representing 7.1% and those accurate to one dollar accounting for a mere 3.9% of the sample. Only 0.1% of campaign goals include decimals.

Fig. 4 shows the digit distribution for each level of goal amount precision. From the top left chart, we see that among campaign goals that are divisible by 1000, 21.5% of them have goal amounts of $5000, and 17.5% of them have goal amounts of $10,000.[21] In the other charts, we see a clear preference for the digit five. For the goal amounts set as multiples of $100, 62.3% end with the digits 500. For the goal amounts set as multiples of $10, 78.0% end with 50. For campaign goals accurate to one dollar, 38.7% end with five. Collectively, we document a novel pattern that funding goals on Kickstarter cluster at round numbers, especially at those with a high degree of roundness.

4.2. Goal amount precision and campaign outcomes

Our second hypothesis predicts that round campaign goals are associated with a lower likelihood of success. Fig. 5 shows the average success rate of campaigns with round goal amounts, as well as those with non-round goal amounts right below or right above the round thresholds. This chart is consistent with out hypothesis, showing that campaigns with round goals have visibly lower success rates. We also test this hypothesis formally by performing regressions of the following form:

$$Successful_i = \alpha_0 + \alpha_1 \times Round_i + \alpha_2 \times ln(Goal_i) + \alpha_3 \times X_i + \epsilon_i \tag{1}$$

where $Successful_i$ is a dummy taking the value one if the campaign is successful and zero otherwise, $Round_i$ is a vector including various proxies for round number campaign goals, $Goal\ amount_i$ is the campaign goal amount set by the entrepreneur, and X_i is a vector of control variables, including dummies for entrepreneur gender and race/ethnicity, campaign length, the number of prior campaigns by outcome, month fixed effects,[22] sub-category-year joint fixed effects,[23] county-year joint fixed effects to capture any impact of local factors,[24] 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 experience. Adding such high-dimensional fixed effects mitigates the concern that confounding factors, such as changes in demand or supply of crowdfunding activities, would drive our findings.[25] We exclude suspended campaigns from these regressions (Table 3).[26]

Table 4 shows the results. The first column shows that, controlling for other factors, the use of a round goal amount is associated with 3.5%-point reduction in the likelihood of success, and the difference is statistically significant. In the second column, we include each of the round goal amounts separately and find that they are all associated with significantly lower likelihood of success. Furthermore, the reduction in success rates is similar in magnitude. Of the control variables, both ln*(Goal amount)* and *ln(Campaign length)* are significantly negatively associated with the likelihood of success, while *Staff pick* is significantly positively associated with success rates. These results are consistent with the prior literature on the determinants of campaign success (e.g., Mollick 2014; Lin and Pursiainen 2018a, 2018b).

As an alternative proxy for goal amount precision, in the third and fourth columns, we include dummy variables *Divisible 1000* and *Divisible 500*, indicating whether the goal amount is divisible by 1000 and 500, respectively. We see that a goal amount divisible by 1000 is associated with 1.5%-point reduction in the likelihood of success, while a goal amount divisible by 500 corresponds with 1.3%-

[20] A campaign creator has the option to cancel the campaign at any point in time. We therefore cannot reliably distinguish between a failed and a canceled campaign.

[21] We include 10,000 in this category, although it is included as its own precision category in Figure 3

[22] There are 101 months in our sample period.

[23] There are a total of 169 sub-categories in our data.

[24] There are 3144 counties and county-equivalents in the U.S. Our data include campaigns in 2346 different counties

[25] For example, Belleflamme et al. (2019) find that the current level of activity on a crowdfunding platform affects campaign performance.

[26] 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.

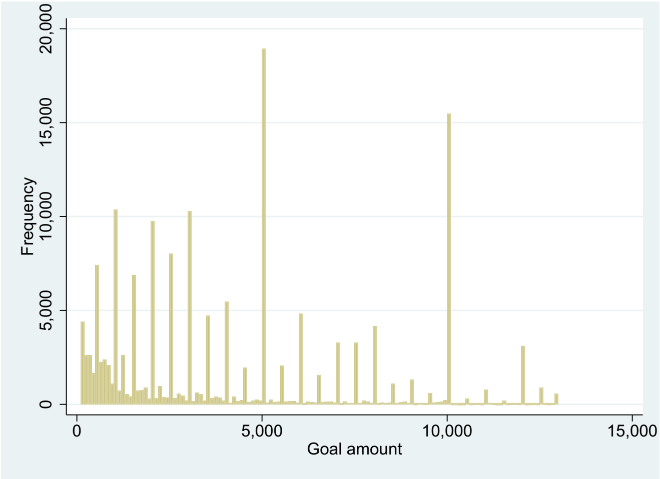

Fig. 2. Campaign goal amount histogram.
Frequency of campaign goal amounts in our sample, including all campaigns with a goal amount less than or equal to $13,000.

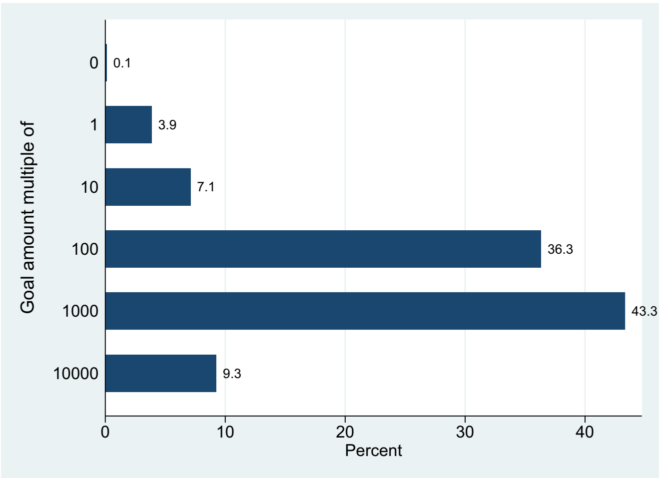

Fig. 3. Roundness of goal amount.
Percentage of campaign goals in our sample set at different levels of roundness. Multiple of 10,000 implies that the goal amount is $10,000, given the maximum campaign size in our sample is $13,000. Multiple of 0 in this chart means that the goal amount includes decimals.

points lower likelihood of success. Both of these results are also statistically significant.

In the fifth column, we include the three round goal amounts separately, as well as the indicator *Divisible 1000* and find that, once the round numbers are included, there is no remaining explanatory power for the goal amounts divisible by 1000. Similarly, in the last column we include both *Divisible 1000* and *Divisible 500* and find that *Divisible 500* becomes statistically insignificant. Collectively, these results suggest that our three round campaign goal amounts (1000, 5000, and 10,000) appear to capture most of the effect.

For a more granular analysis of different goal amounts, we perform a regression with dummies for the goal amounts $1000, $5000, and $10,000, as well as dummies for narrow intervals of other goal amounts. The results, shown in Fig. 6, are consistent with our hypothesis and suggest that *Round* amounts are indeed different from other goal amounts, with visibly lower success rates. We omit the goal amount range lower than $1000, so all coefficients are relative to this category of campaigns. We report the detailed coefficients in Internet Appendix.

Table 5 shows the results for regressions of the same form as above, but replacing the dependent variable with alternative measures for the campaign performance. In the first two columns, we see that round numbers are associated with significantly lower aggregate pledged amounts than those with more precise goal amounts. Similarly, round goal amounts are associated with significantly higher likelihood of receiving zero pledged amounts. The last two columns show that round goal amounts are also associated with lower Pledged/Goal ratios. All these results are consistent with our second hypothesis that round goal amounts are associated with adverse crowdfunding performance.

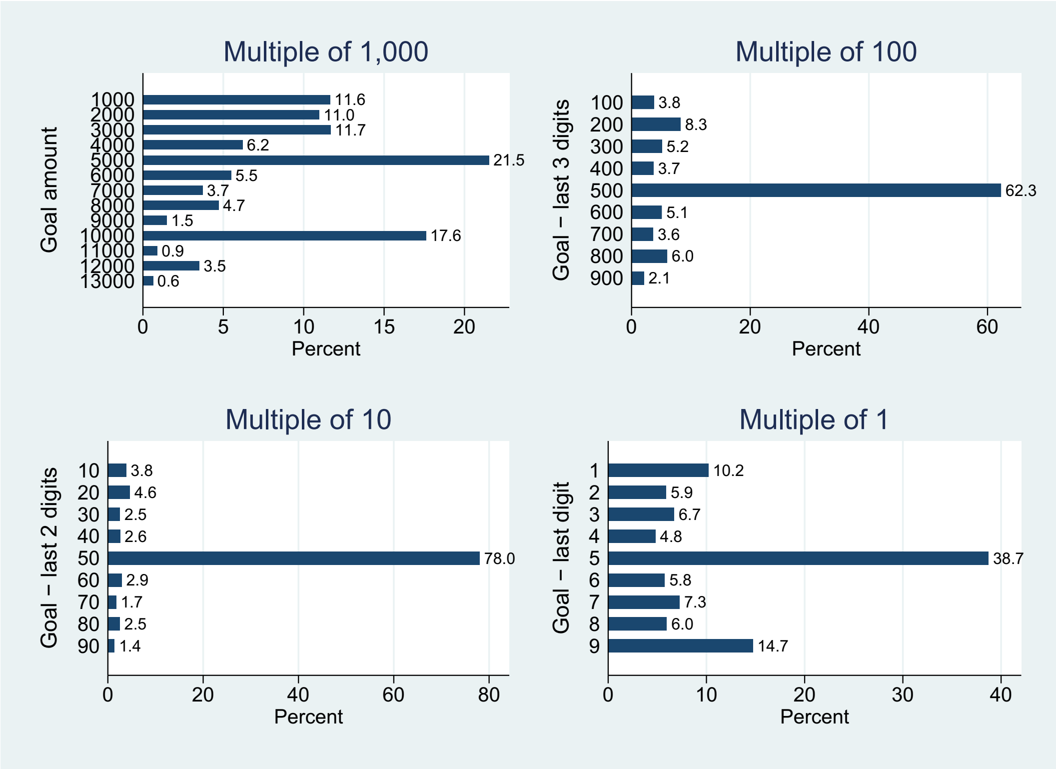

Fig. 4. Digit distribution by roundness of goal amount.
Percentage of campaign goals by digit for each level of roundness in our sample. Each chart includes only the subset of those campaigns with a goal set at the level of roundness indicated above the chart, so the percentages in each chart add up to 100.

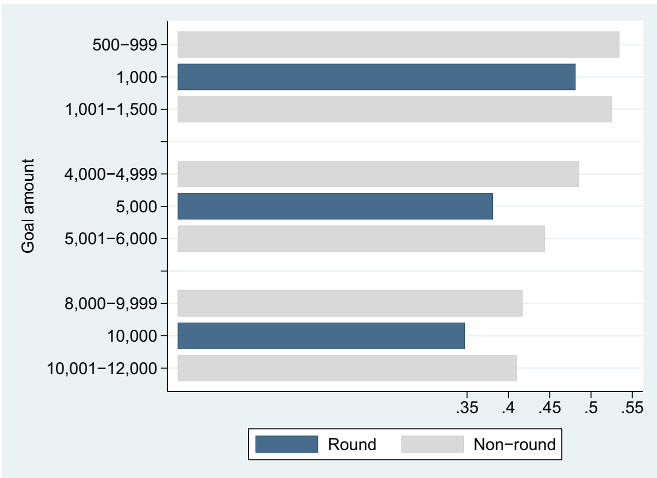

Fig. 5. Average success rate for round and non-round goal amounts.
Average success rate of campaigns by goal amount, divided into round amounts and non-round goal amounts right below and above them.

5. Additional analysis

5.1. Round numbers and entrepreneur quality

As we discuss earlier, there are multiple reasons why round campaign goals might be associated with adverse campaign performance. Our regression analyses provide strong support for the existence of this relationship. In this section, we further explore one

Table 3
Summary statistics - sample means by goal amount roundness.

	Goal amount multiple of					
	Decimal	1	10	100	1000	10,000
Campaign goal amounts						
Goal amount (000)	3.963	3.103	1.906	3.014	4.501	10.000
Round	0.000	0.000	0.000	0.000	0.403	1.000
Goal 1000	0.000	0.000	0.000	0.000	0.141	0.000
Goal 5000	0.000	0.000	0.000	0.000	0.261	0.000
Goal 10,000	0.000	0.000	0.000	0.000	0.000	1.000
Divisible 1000	0.000	0.000	0.000	0.000	1.000	1.000
Divisible 500	0.000	0.000	0.000	0.623	1.000	1.000
Campaign outcomes						
Successful	0.474	0.515	0.528	0.493	0.444	0.347
Failed	0.458	0.410	0.403	0.439	0.483	0.558
Canceled	0.068	0.070	0.063	0.065	0.071	0.092
Suspended	0.000	0.006	0.006	0.003	0.003	0.003
Amount pledged (000)	2.492	2.534	1.537	2.373	3.436	6.949
Zero pledged	0.135	0.119	0.131	0.111	0.119	0.141
Pledged/Goal	0.808	1.544	1.196	0.919	0.781	0.685
Campaign variables						
Camp. length (days)	37.979	30.609	30.194	32.584	34.500	36.059
Staff pick	0.052	0.057	0.043	0.055	0.065	0.082
N prior campaigns	0.297	0.618	0.506	0.382	0.310	0.248
N prior succ.	0.141	0.349	0.271	0.200	0.169	0.140
N prior failed	0.115	0.153	0.153	0.123	0.091	0.064
N prior canceled	0.021	0.058	0.042	0.039	0.033	0.028
N prior suspended	0.000	0.000	0.000	0.000	0.000	0.000
Creator variables						
Female	0.188	0.197	0.220	0.214	0.197	0.173
Male	0.438	0.476	0.505	0.473	0.467	0.461
No gender	0.375	0.327	0.275	0.312	0.336	0.367
White	0.578	0.541	0.587	0.576	0.561	0.532
Black	0.010	0.014	0.013	0.014	0.015	0.016
Asian	0.021	0.023	0.021	0.020	0.022	0.025
Hispanic	0.010	0.033	0.039	0.038	0.038	0.037
No race	0.380	0.389	0.339	0.352	0.363	0.390
N	192	6446	11,843	60,596	72,303	15,439

Means of variables conditional on the level of roundness the goal amount is set at. Variables are defined in Appendix A.

specific explanation, namely, round numbers as an indicator of entrepreneur quality. If reliance on round numbers indicates the quality of the entrepreneur, the use of round campaign goal numbers in the first campaign by the entrepreneur should also predict performance of the second campaign, assuming the quality of the entrepreneur does not improve enough to close the gap. Moreover, this prediction should hold even if the goal amount in the second campaign is not a round one. To test this prediction, we perform a regression analysis for the likelihood of success on a subsample including all second campaigns by entrepreneurs.

The results are shown in Table 6. In the first specification, exhibited in the first two columns, we include all second campaigns and an indicator dummy for the goal amount roundness for both current and previous campaigns. We can see that both current and previous campaign goal amount roundness have statistically significant predictive power over the outcome of the current campaign.

In columns three and four, we condition the sample on whether the current campaign goal amount is round or not and include the roundness indicator from the previous campaign as an explanatory variable. We see that the use of round goal amount in the previous campaign is associated with significantly lower likelihood of success in the current campaign, regardless of the current campaign goal roundness. The last two columns show that the same pattern holds when using *Divisible 1000* as the proxy for goal amount roundness.

These results suggest that the use of round numbers indeed acts as a proxy for entrepreneur quality, as there is no obvious reason why the roundness of the prior goal amounts would be correlated to the outcome of the current campaign performance.

5.2. Quasi-experiment: Rule change removing restrictions on campaign quality

In the previous section, we argue that the roundness of goal amount conveys information about entrepreneur quality. As the "fundamental" entrepreneur quality is not observable, the ideal experiment to test whether this is true would be an exogenous change in the quality of entrepreneurs, allowing us to measure the corresponding change in the use of round numbers. We identify an event that might capture the exogenous changes in entrepreneur quality, providing us with a natural quasi-experiment to test this. On June 3, 2014, Kickstarter changed its rules to allow entrepreneurs to launch campaigns without being subject to manual evaluation, previously mandatory for all campaigns. As discussed by, e.g., Barzilay et al. (2018), this rule change effectively allowed lower-quality campaigns to be launched on the platform. Hence, it represents a shock lowering the average entrepreneur quality on the platform and allows us to

Table 4
Likelihood of success.

	(1)	(2)	(3)	(4)	(5)	(6)
Round	−0.0348* * *					
	(0.0032)					
Goal 1000		−0.0277* * *			−0.0298* * *	
		(0.0049)			(0.0058)	
Goal 5000		−0.0424* * *			−0.0437* * *	
		(0.0044)			(0.0044)	
Goal 10,000		−0.0308* * *			−0.0318* * *	
		(0.0066)			(0.0070)	
Divisible 1000			−0.0151* * *		0.0026	−0.0130* * *
			(0.0026)		(0.0032)	(0.0030)
Divisible 500				−0.0127* * *		−0.0051
				(0.0038)		(0.0044)
ln(Goal amount)	−0.0593* * *	−0.0589* * *	−0.0599* * *	−0.0606* * *	−0.0593* * *	−0.0594* * *
	(0.0031)	(0.0032)	(0.0031)	(0.0029)	(0.0032)	(0.0029)
ln(Campaign length)	−0.0864* * *	−0.0864* * *	−0.0868* * *	−0.0869* * *	−0.0865* * *	−0.0867* * *
	(0.0066)	(0.0066)	(0.0066)	(0.0066)	(0.0066)	(0.0066)
Staff pick	0.3967* * *	0.3966* * *	0.3974* * *	0.3974* * *	0.3966* * *	0.3974* * *
	(0.0142)	(0.0142)	(0.0143)	(0.0143)	(0.0142)	(0.0143)
Gender dummies	Yes	Yes	Yes	Yes	Yes	Yes
Race dummies	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Sub-category-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Campaign N FE	Yes	Yes	Yes	Yes	Yes	Yes
N	162,863	162,863	162,863	162,863	162,863	162,863
R^2	0.273	0.273	0.272	0.272	0.273	0.272

The dependent variable, *Successful*, is a dummy taking the value 1 if the Kickstarter campaign was successful. *Round* is a dummy taking the value 1 if the campaign goal amount is either \$1000, \$5000, or \$10,000. *Goal 1000 (5000, 10,000)* is a dummy taking the value 1 if the campaign goal amount is \$1000 (\$5000, \$10,000). *Divisible 1000 (500)* is a dummy taking the value 1 if the campaign goal amount is divisible by 1000 (500). We exclude suspended campaigns. We include *Month fixed effects* based on the month the campaign was launched (101 months), *Sub-category-Year fixed effects*, based on Kickstarter category ID (169 different categories), *County-Year 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. Standard errors in parentheses.

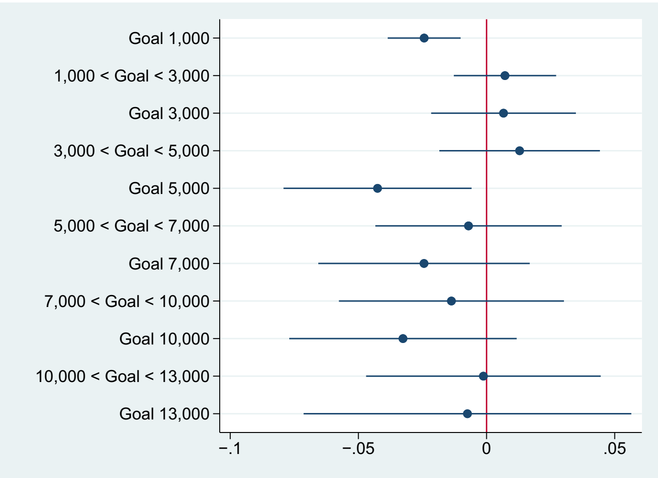

Fig. 6. Regression coefficients for likelihood of success.
Coefficient estimates for the regression analysis. The dependent variable, *Successful*, is a dummy taking the value 1 if the Kickstarter campaign was successful. The coefficient estimates are for dummies indicating a campaign goal in the range specified by the variable name. The dummy for goals smaller than \$1000 is omitted, so all coefficients are relative to this category. Suspended campaigns are excluded. The control variables include *ln (Goal amount)* as a continuous variable, *ln(Campaign length)*, *Staff pick dummy*, *Gender dummies*, *Race dummies*, *Month fixed effects* based on the month the campaign was launched, *Sub-category-Year fixed effects*, based on Kickstarter category ID (169 different categories), *County-Year fixed effects* based on the location of the campaign, and *Campaign number fixed effects*, based on the number of campaigns the same entrepreneur has launched prior to the current campaign. Confidence intervals shown based on standard errors clustered by sub-category.

Table 5
Other campaign outcome variables.

	ln(1 + Pledged)		Zero pledged		ln(1 + Pledged/Goal)	
	(1)	(2)	(3)	(4)	(5)	(6)
Round	−0.3560* * *		0.0270* * *		−0.0116**	
	(0.0259)		(0.0023)		(0.0053)	
Divisible 1000		−0.2042* * *		0.0171* * *		−0.0029
		(0.0208)		(0.0019)		(0.0041)
ln(Goal amount)	0.4857* * *	0.4894* * *	−0.0055* * *	−0.0061* * *	−0.1021* * *	−0.1027* * *
	(0.0246)	(0.0241)	(0.0018)	(0.0018)	(0.0054)	(0.0056)
ln(Campaign length)	−0.2493* * *	−0.2512* * *	0.0012	0.0012	−0.0555* * *	−0.0557* * *
	(0.0404)	(0.0405)	(0.0034)	(0.0034)	(0.0082)	(0.0082)
Staff pick	2.2280* * *	2.2346* * *	−0.0922* * *	−0.0927* * *	0.4537* * *	0.4540* * *
	(0.1036)	(0.1044)	(0.0080)	(0.0081)	(0.0210)	(0.0209)
Gender dummies	Yes	Yes	Yes	Yes	Yes	Yes
Race dummies	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Sub-category-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Campaign N FE	Yes	Yes	Yes	Yes	Yes	Yes
N	162,863	162,863	162,863	162,863	162,863	162,863
R^2	0.325	0.324	0.141	0.140	0.345	0.345

The dependent variable is shown above each model. ln*(1 + Pledged)* is the natural logarithm of one plus the amount pledged for the campaign. *Zero pledged* is a dummy taking value 1 if the Kickstarter campaign realized zero pledged funds. ln*(1 + Pledged/Goal)* is the natural logarithm of one plus the amount pledged divided by the campaign goal amount. *Round* is a dummy taking the value 1 if the campaign goal amount is either \$1000, \$5000, or \$10,000. *Goal 1000 (5000, 10,000)* is a dummy taking the value 1 if the campaign goal amount is \$1000 (\$5000, \$10,000). *Divisible 1000 (500)* is a dummy taking the value 1 if the campaign goal amount is divisible by 1000 (500). We exclude suspended campaigns. We include *Month fixed effects* based on the month the campaign was launched (101 months), *Sub-category-Year fixed effects*, based on Kickstarter category ID (169 different categories), *County-Year fixed effects* based on the location of the campaign, 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. Standard errors in parentheses.

Table 6
Likelihood of success in the second campaign.

	All campaigns		Current round		Current div. 1000	
	(1)	(2)	(3)	(4)	(5)	(6)
			Yes	No	Yes	No
Round	−0.0205**					
	(0.0084)					
Prev. Round	−0.0426* * *		−0.0423*	−0.0347**		
	(0.0111)		(0.0216)	(0.0136)		
Divisible 1000		−0.0168*				
		(0.0092)				
Prev. Divisible 1000		−0.0301* * *			−0.0482* * *	−0.0223*
		(0.0084)			(0.0139)	(0.0118)
ln(Goal amount)	−0.0488* * *	−0.0471* * *	−0.0667* * *	−0.0432* * *	−0.0523* * *	−0.0389* * *
	(0.0051)	(0.0052)	(0.0138)	(0.0050)	(0.0091)	(0.0058)
ln(Goal amount) (prev.)	−0.0081**	−0.0036	−0.0033	−0.0115* * *	0.0021	−0.0126* * *
	(0.0034)	(0.0036)	(0.0087)	(0.0039)	(0.0075)	(0.0043)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Sub-category-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	16,395	16,395	3269	12,063	7222	7931
R^2	0.331	0.330	0.481	0.345	0.394	0.367

Includes only the second campaign by each campaign creator. The dependent variable, *Successful*, is a dummy taking the value 1 if the Kickstarter campaign was successful. We exclude suspended campaigns. *Controls* include campaign controls and gender and race dummies. We include *Month fixed effects* based on the month the campaign was launched (101 months), *Sub-category-Year fixed effects*, based on Kickstarter category ID (169 different categories), *County-Year fixed effects* based on the location of the campaign, 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. Standard errors in parentheses.

study the impact of entrepreneur quality on the likelihood of using a round goal amount.

We perform a regression analysis around this rule change, including a sample period from 360 days before the change to 360 days after it. The results are shown in Table 7. Panel A shows that the likelihood of using a round goal amount increases by 2.3%-points after the rule change, and the increase is statistically significant. As a placebo check, we perform the same analysis but alter the rule change date to one year earlier (column 2) or one year later (column 3). We find no significant change in the likelihood of a round goal amount for either of the placebo tests. These results suggest that a reduction in entrepreneur quality increases the likelihood of a round goal amount, consistent with our argument that the use of round numbers conveys information about entrepreneur quality.

In Panel B, we analyze campaign performance before and after the rule change, using several measures of campaign success. For all of these campaign outcome measures, the rule change is associated with a significant decrease in campaign performance. Furthermore, the decrease in campaign performance appears somewhat stronger for the campaigns using round numbers. Taken together, these results further suggest that the use of round numbers indicates lower entrepreneur quality.

5.3. Entrepreneur experience and the use of round numbers

If goal amount roundness reflects the entrepreneur's uncertainty over potential demand or investment needs, such uncertainty might decrease in successive campaigns as the entrepreneur gains experience. In other words, we should observe that the likelihood of using a round goal amount decreases in successive campaigns by the same entrepreneur. This prediction is also consistent with the prior literature on learning by doing. To test this prediction, we perform the following regressions:

$$Round_i(Divisible_i) = \alpha_0 + \alpha_1 \times Campaign\ \ Number_i + \alpha_3 \times X_i + \epsilon_i \tag{2}$$

where $Round_i$ ($Divisible_i$) is a dummy taking the value one if the campaign goal amount is either \$1000, \$5000, or \$10,000 (divisible by

Table 7
Rule change: Removal of mandatory campaign vetting.

Panel A: Likelihood of round goal amount

	Actual	Placebo tests	
	(1)	(2)	(3)
	Jun-14	− 1 year	+ 1 year
Post change	0.0232* * *	0.0035	0.0061
	(0.0055)	(0.0040)	(0.0039)
Controls	Yes	Yes	Yes
Campaign N FE	Yes	Yes	Yes
Sub-category FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
N	59,530	51,657	54,033
R^2	0.116	0.091	0.134

Panel B: Campaign success

	Successful	ln(1 + Pledged)	Zero pledged	ln(1 + Pledged/Goal)
	(1)	(2)	(3)	(4)
Post x Round	−0.0031	−0.4172* * *	0.0315* * *	−0.0150
	(0.0089)	(0.0542)	(0.0057)	(0.0113)
Post change	−0.0650* * *	−0.7876* * *	0.0767* * *	−0.0723* * *
	(0.0134)	(0.0989)	(0.0102)	(0.0146)
Round	−0.0388* * *	−0.2045* * *	0.0172* * *	−0.0068
	(0.0078)	(0.0388)	(0.0033)	(0.0103)
Controls	Yes	Yes	Yes	Yes
Campaign N FE	Yes	Yes	Yes	Yes
Sub-category FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
N	59,530	59,530	59,530	59,530
R^2	0.242	0.329	0.120	0.296

The dependent variable in Panel A is *Round*, a dummy taking the value 1 if the campaign goal amount is either \$1000, \$5000, or \$10,000. In Panel B, the dependent variable is shown above each model. *Post change* is a dummy taking the value 1 if the campaign was launched after June 3, 2014, when Kickstarter removed the mandatory manual evaluation of campaigns and allowed entrepreneurs to launch campaigns without vetting. In Panel B, *Controls* include goal amount, gender dummies, and race and ethnicity dummies. In Panel A, they also include campaign length and staff pick dummy. We also include *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. Standard errors in parentheses.

1000 or 500) and *Campaign Number*$_i$ indicates the number of the current campaign for the given entrepreneur. X_i is a vector of control variables similar to those in Eq. (1).

The results, shown in Table 8, provide supportive evidence for our prediction. Using three different proxies for goal amount roundness, we find that the likelihood of setting a round campaign goal amount declines monotonically by campaign number. We omit the dummy for the first campaign, so the estimated coefficients are relative to the first campaigns. In columns two, four, and six, we include entrepreneur fixed effects, which reduces the sample size significantly, as only entrepreneurs with multiple campaigns can be included. Nevertheless, it also gets around a potential selection effect as in columns one, three, and five, the set of entrepreneurs is different between different campaign numbers.

6. Robustness checks

6.1. Analysis using matched control samples

In all our analyses, we control for a large number of campaign and entrepreneur characteristics, as well as an extensive set of fixed effects. However, to further confirm that our results are not driven by campaign or entrepreneur characteristics that are correlated with goal amount, we construct two matched control samples. In *Control 1* sample, we match each campaign with a round goal amount with two control campaigns, one with a goal amount above and one below the round campaign. For each, we pick a control campaign from the same sub-category, based on Kickstarter category ID (169 different categories), same year, and located in the same county. We then pick the campaign with the goal amount closest to the round campaign. In *Control 2* sample, we also require the entrepreneur gender and the campaign number to be the same. Round-number campaigns that do not have any control campaign fulfilling these criteria are excluded from the sample. The summary statistics for each of these matched control samples are shown in Panel A of Table 9.

We then perform a regression analysis of campaign outcomes using these matched control groups. The results, shown in Panels B and C of Table 9, are similar to our main results for both matched control groups and remain statistically significant for all outcomes, even though the sample size becomes substantially smaller than that of our main analysis.

6.2. Regressions on narrow bands around round goal amounts

In the previous regression analyses, we have controlled for the campaign size that alleviates any potential concern that our findings are driven by omitted campaign characteristics that are related to it. To further mitigate this issue, we perform an additional analysis for subsamples of campaigns with goal amounts within narrow bands around the *Round* number thresholds. We note that this is not the same as a regression discontinuity design, since the goal amount is perfectly controlled by the entrepreneur. Nevertheless, as long as the campaign size captures the omitted variables to a certain extent on both sides of the *Round* number thresholds, this exercise should provide a slightly cleaner identification.

Since the density of campaigns is higher at smaller goal amounts, we include narrower bands in absolute terms around the lower thresholds. The band around \$1000 ranges from \$500 to \$1500, the band around \$5000 from \$4000 to \$6000, and the band around \$10,000 from \$8000 to \$12,000. Table IA.1 in Internet Appendix shows summary statistics for these subsamples on both sides of each threshold. We see that there is a discontinuity in the success rates around each of the three *Round* thresholds; both the success

Table 8
Entrepreneur experience and the likelihood of round goal amount.

	Round		Div. 1000		Div. 500	
	(1)	(2)	(3)	(4)	(5)	(6)
2nd campaign	−0.0299* * *	−0.0504* * *	−0.0678* * *	−0.0872* * *	−0.0618* * *	−0.0763* * *
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
3rd campaign	−0.0420* * *	−0.0520* * *	−0.0931* * *	−0.1093* * *	−0.0934* * *	−0.0978* * *
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
4th campaign	−0.0661* * *	−0.0630* * *	−0.1108* * *	−0.1113* * *	−0.1157* * *	−0.1101* * *
	(0.0000)	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
5th or higher	−0.0476**	−0.0795* * *	−0.1266* * *	−0.1428* * *	−0.1628* * *	−0.1432* * *
	(0.0330)	(0.0000)	(0.0002)	(0.0000)	(0.0000)	(0.0000)
Controls	Yes	No	Yes	No	Yes	No
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Sub-category-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	No	Yes	No	Yes	No
Entrepreneur FE	No	Yes	No	Yes	No	Yes
N	162,863	42,430	162,863	42,430	162,863	42,430
R^2	0.070	0.532	0.080	0.577	0.090	0.618

The dependent variable, either *Round*, *Divisible 1000*, or *Divisible 500*, is shown above each model. We exclude suspended campaigns. *Controls* include gender dummies and race and ethnicity dummies. We include *Month fixed effects* based on the month the campaign was launched (101 months), *Sub-category-Year fixed effects*, based on Kickstarter category ID (169 different categories), *County-Year fixed effects* based on the location of the campaign, and *Entrepreneur fixed effects*. Heteroscedasticity-consistent standard errors, clustered by sub-category, are shown in parentheses.
Significance levels: * 0.1, ** 0.05, *** 0.01. Standard errors in parentheses.

Table 9
Matched control samples.

Panel A: Summary statistics

	Control 1: SC, year, county			Control 2: + gender, campaign N		
	Round	Non-round	Diff.	Round	Non-round	Diff.
Campaign outcomes						
Successful	0.436	0.492	−0.056***	0.442	0.499	−0.057***
Failed	0.483	0.437	0.046***	0.478	0.432	0.046***
Canceled	0.079	0.068	0.010***	0.077	0.066	0.011***
Suspended	0.002	0.002	0.000	0.002	0.002	−0.000
Amount pledged (000)	4.773	4.299	0.474***	4.600	3.999	0.601***
Zero pledged	0.124	0.102	0.022***	0.125	0.099	0.026***
Pledged/Goal	0.849	0.896	−0.047***	0.787	0.844	−0.056***
Campaign variables						
Goal amount (000)	5.885	5.178	0.707***	6.048	5.077	0.970***
Camp. length (days)	34.962	33.920	1.041***	35.343	34.151	1.191***
Staff pick	0.067	0.071	−0.005*	0.062	0.065	−0.003
N prior campaigns	0.342	0.334	0.009	0.148	0.126	0.022**
Creator variables						
Female	0.187	0.190	−0.003	0.168	0.166	0.001
Male	0.451	0.462	−0.011**	0.474	0.472	0.002
No gender	0.362	0.348	0.014***	0.358	0.362	−0.003
White	0.533	0.535	−0.002	0.530	0.529	0.001
Black	0.015	0.014	0.001	0.016	0.015	0.001
Asian	0.028	0.026	0.002	0.028	0.027	0.000
Hispanic	0.041	0.041	0.000	0.041	0.043	−0.002
No race	0.383	0.384	−0.001	0.386	0.386	−0.000
N	29,253	44,854	74,107	19,251	26,802	46,053

Panel B: Control group 1 (sub-category, county, year)

	Successful	ln(1 + Pledged)	Zero pledged	ln(1 + Pledged/Goal)
	(1)	(2)	(3)	(4)
Round	−0.0288* * *	−0.3000* * *	0.0197* * *	−0.0138**
	(0.0045)	(0.0386)	(0.0036)	(0.0069)
Controls	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Sub-category-Year FE	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes
Campaign N FE	Yes	Yes	Yes	Yes
N	73,928	73,928	73,928	73,928
R^2	0.273	0.326	0.146	0.361

Panel C: Control group 2 (sub-category, county, year, gender, campaign N)

	Successful	ln(1 + Pledged)	Zero pledged	ln(1 + Pledged/Goal)
	(1)	(2)	(3)	(4)
Round	−0.0273* * *	−0.3061* * *	0.0233* * *	−0.0145**
	(0.0054)	(0.0395)	(0.0035)	(0.0062)
Controls	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Sub-category-Year FE	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes
Campaign N FE	Yes	Yes	Yes	Yes
N	45,933	45,933	45,933	45,933
R^2	0.262	0.316	0.147	0.329

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)* is the natural logarithm of one plus the amount pledged for the campaign. *Zero pledged* is a dummy taking value 1 if the Kickstarter campaign realized zero pledged funds. ln*(1 + Pledged/Goal)* is the natural logarithm of one plus the amount pledged divided by the campaign goal amount. The analysis is performed for two matched control samples. In *Control 1* sample, we match each campaign with a round goal amount with two campaigns, one with goal above and one below the round campaign. For each, we pick a control campaign from the same sub-category, based on Kickstarter category ID (169 different categories), same year, and located in the same county. We then pick the campaign with the goal amount closest to the round campaign. In *Control 2* sample, we also require the entrepreneur gender and the campaign number to be the same. We exclude suspended campaigns. *Controls* include campaign controls and gender and race dummies. Heteroscedasticity-consistent standard errors, clustered by sub-category, are shown in parentheses.
Significance levels: * 0.1, ** 0.05, *** 0.01. Standard errors in parentheses.

likelihoods of campaigns right below and right above the threshold are higher than that at the threshold. We observe the same results for the likelihood of receiving zero plegded funds, which is clearly higher at the thresholds than those on either side of them.

Table 10 shows the results of regression analyses for the subsamples around each of these thresholds. The results are consistent with those in Section 4. Across all thresholds, setting a *Round* campaign goal is associated with significantly lower likelihood of success, lower amounts pledged, and higher likelihood of receiving zero pledged funds. The estimated coefficients for the Pledged/Goal ratio are also all negative, though statistically significant only for the $5000 threshold.

6.3. Additional control variables

Our sample of Kickstarter campaigns is large and comprehensive compared to earlier studies using Kickstarter data. These comprehensive data help in both making sure that our results are representative as well as in having the adequate statistical power for

Table 10
Narrow bands around round goals.

Panel A: Band around the $1000 goal amount - [500, 1500]

	Successful	ln(1 + Pledged)	Zero pledged	ln(1 + Pledged/Goal)
	(1)	(2)	(3)	(4)
Round	−0.0299* * *	−0.1536* * *	0.0132* * *	−0.0091
	(0.0057)	(0.0351)	(0.0044)	(0.0083)
Controls	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Sub-category-Year FE	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes
Campaign N FE	Yes	Yes	Yes	Yes
N	33,967	33,967	33,967	33,967
R^2	0.295	0.328	0.201	0.375

Panel B: Band around the $5000 goal amount - [4000, 6000]

	Successful	ln(1 + Pledged)	Zero pledged	ln(1 + Pledged/Goal)
	(1)	(2)	(3)	(4)
Round	−0.0477* * *	−0.4505* * *	0.0322* * *	−0.0334* * *
	(0.0059)	(0.0384)	(0.0041)	(0.0057)
Controls	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Sub-category-Year FE	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes
Campaign N FE	Yes	Yes	Yes	Yes
N	33,410	33,410	33,410	33,410
R^2	0.332	0.365	0.214	0.393

Panel C: Band around the $10,000 goal amount - [8000, 12,000]

	Successful	ln(1 + Pledged)	Zero pledged	ln(1 + Pledged/Goal)
	(1)	(2)	(3)	(4)
Round	−0.0292* * *	−0.4438* * *	0.0343* * *	−0.0111
	(0.0069)	(0.0507)	(0.0048)	(0.0085)
Controls	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Sub-category-Year FE	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes
Campaign N FE	Yes	Yes	Yes	Yes
N	26,642	26,642	26,642	26,642
R^2	0.352	0.393	0.223	0.415

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)* is the natural logarithm of one plus the amount pledged for the campaign. *Zero pledged* is a dummy taking value 1 if the Kickstarter campaign realized zero pledged funds. *ln(1 + Pledged/Goal)* is the natural logarithm of one plus the amount pledged divided by the campaign goal amount. *Round* is a dummy taking the value 1 if the campaign goal amount is either $1000, $5000, or $10,000. We exclude suspended campaigns. *Controls* include goal amount, campaign length, staff pick dummy, gender dummies, and race and ethnicity dummies. We also include *Month fixed effects* based on the month the campaign was launched (101 months), *Sub-category-Year fixed effects*, based on Kickstarter category ID (169 different categories), *County-Year 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. Standard errors in parentheses.

our various analyses. However, it imposes limits on what we can obtain in terms of additional data on campaign and entrepreneur characteristics. In this section, we perform a robustness check complementing our data with additional control variables sourced from the Kickstarter Structured Relational Database of Li (2019), maintained by Harvard Dataverse. From this database, we construct four additional control variables: *Has video*, a dummy taking the value 1 if the campaign includes a video, *Median reward price* the median price of the different reward alternatives within the campaign, *N rewards*, the number of different reward alternatives within the campaign, and ln*(1 + profile links)*, indicating the number of website and social media links included in the entrepreneur's Kickstarter profile. As these are not available for all campaigns in our data, the sample becomes smaller than our main analysis.

The results, shown in Table 11, are qualitatively similar to our main results, confirming that adding these control variables does not substantially change any conclusions made from our main analysis.

6.4. All campaigns with no upper limit in campaign goal amounts

Throughout the analysis in this paper, we exclude campaigns with goal amounts larger than $13,000. As discussed above, we do this to make sure there is an adequate number of campaigns both right below and right above the round number thresholds, so that we can more accurately exploit the discontinuities around these thresholds, as well as to avoid ambiguity in defining round number thresholds for larger amounts. To make sure this choice does not drive our results due to sample selection, we perform a regression analysis for all campaigns in our data, without any campaign size limitations. We extend the *Round* variable to indicate the goal amounts $1000, $5000, $10,000, $15,000, $20,000, 50,000, $100,000, $200,000, and $300,000.

The results are shown in Internet Appendix Table IA.4. In Panel A, we include all campaigns in the sample, similar to the analysis in Tables 4 and 5. In Panel B, we limit the sample to narrow bands around each round threshold, with a bandwidth of 20% of the round amount. This analysis is similar in principle to that in Table 10, but instead of separating each round number to different samples, we pool all campaigns into one regression analysis. We include fixed effects for each band (i.e., nearest round fixed effects).

The results in both Panels show that round goal amounts are associated with significantly worse campaign performance, consistent with our main results.

Table 11
Robustness check: additional control variables.

	Successful		ln(1 + Pledged)		Zero pledged		ln(1 + Pledged/Goal)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Round	−0.0243* * *		−0.2160* * *		0.0150* * *		−0.0090**	
	(0.0037)		(0.0215)		(0.0025)		(0.0037)	
Divisible 1000		−0.0035		−0.0827* * *		0.0073* * *		0.0022
		(0.0033)		(0.0169)		(0.0019)		(0.0031)
ln(Goal amount)	−0.1198* * *	−0.1215* * *	0.1992* * *	0.1941* * *	0.0181* * *	0.0181* * *	−0.1469* * *	−0.1483* * *
	(0.0027)	(0.0026)	(0.0269)	(0.0270)	(0.0020)	(0.0020)	(0.0050)	(0.0050)
ln(Campaign length)	−0.0961* * *	−0.0965* * *	−0.2693* * *	−0.2707* * *	−0.0015	−0.0015	−0.0634* * *	−0.0636* * *
	(0.0069)	(0.0069)	(0.0422)	(0.0426)	(0.0040)	(0.0040)	(0.0070)	(0.0071)
Staff pick	0.3417* * *	0.3421* * *	1.5776* * *	1.5815* * *	−0.0567* * *	−0.0570* * *	0.3521* * *	0.3523* * *
	(0.0242)	(0.0242)	(0.0941)	(0.0945)	(0.0066)	(0.0066)	(0.0262)	(0.0262)
Has video	0.1470* * *	0.1474* * *	1.1242* * *	1.1266* * *	−0.0988* * *	−0.0989* * *	0.1284* * *	0.1286* * *
	(0.0074)	(0.0074)	(0.0472)	(0.0473)	(0.0054)	(0.0054)	(0.0066)	(0.0066)
Median reward price	0.0004* * *	0.0004* * *	0.0011* * *	0.0011* * *	0.0001* * *	0.0001* * *	0.0004* * *	0.0004* * *
	(0.0000)	(0.0000)	(0.0003)	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
N rewards	0.0189* * *	0.0189* * *	0.1345* * *	0.1348* * *	−0.0088* * *	−0.0088* * *	0.0200* * *	0.0200* * *
	(0.0010)	(0.0010)	(0.0064)	(0.0064)	(0.0007)	(0.0007)	(0.0008)	(0.0008)
ln(1 + profile links)	0.0761* * *	0.0761* * *	0.4787* * *	0.4786* * *	−0.0327* * *	−0.0326* * *	0.0695* * *	0.0695* * *
	(0.0065)	(0.0064)	(0.0424)	(0.0423)	(0.0039)	(0.0039)	(0.0064)	(0.0064)
Gender dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sub-category-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Campaign N FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	64,992	64,992	64,992	64,992	64,992	64,992	64,992	64,992
R^2	0.271	0.271	0.316	0.315	0.155	0.155	0.321	0.321

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)* is the natural logarithm of one plus the amount pledged for the campaign. *Zero pledged* is a dummy taking value 1 if the Kickstarter campaign realized zero pledged funds. *ln(1 + Pledged/Goal)* is the natural logarithm of one plus the amount pledged divided by the campaign goal amount. *Has video* is a dummy taking the value 1 if the campaign includes a video. *Median reward price* is the median price of the different reward alternatives within the campaign. *N rewards* is the number of different reward alternatives within the campaign. *ln(1 + profile links* indicates the number of website and social media links included in the entrepreneurs Kickstarter profile. We exclude suspended campaigns. Heteroscedasticity-consistent standard errors, clustered by sub-category, are shown in parentheses.
Significance levels: * 0.1, ** 0.05, *** 0.01. Standard errors in parentheses.

6.5. Alternative specifications to control for campaign size

In our analysis of campaign performance, we control for the campaign size as measured by the natural logarithm of the goal amount. A possible concern is that our regression models misspecify the overall relationship between the campaign size and campaign outcomes. Hence, our round goal amount variable might capture non-linear dependence between campaign size and success. Although the analysis using subsamples of narrow goal bands around the *Round* number thresholds substantially mitigates this concern, to further address it, we perform the success rate regression analysis with various alternative functional forms of campaign size.

The results are shown in Internet Appendix Table IA.5. The first column shows our baseline model with ln(Goal amount) as a control variable for easier reference (Column 1 of Table 4). The second column includes a linear specification of Goal amount. In columns three to five, we incrementally add higher order polynomial terms, with column five including a fourth order polynomial form of the goal amount. In all specifications, the estimated coefficients for *Round* remain statistically significant and of similar magnitude. These results suggest that our findings are not driven by the choice of functional form in controlling the campaign size.

7. Conclusion

Our results show that entrepreneurs exhibit a strong heuristic to use round numbers as crowdfunding campaign goals. This finding is consistent with a number of studies documenting a preference for round numbers in various contexts, while we provide the first evidence that entrepreneurial financing decisions are also subject to it. Given the growing importance of crowdfunding platforms in new venture financing and creating new jobs in the knowledge-based economy, understanding the implications of heuristical thinking in this context is increasingly relevant.

Our finding that the use of round goal amounts is associated with adverse crowdfunding campaign performance of the entrepreneur is consistent with the prior literature in the context of various types of financial decision making and provides insight for both entrepreneurs wishing to crowdfund their start-ups as well as potential campaign backers assessing projects to fund. Entrepreneurs can potentially improve their chances of obtaining funding by recognizing this effect and possibly doing more work on estimating more precise funding needs and setting more precise campaign goals. This may be true of a more thorough campaign preparation generally. Campaign backers, on the other hand, may use the roundness of goal amount as an easy incremental proxy of entrepreneur quality when assessing the likelihood of the project succeeding. Our results on entrepreneurial experience reducing the reliance on the round number heuristic also provide valuable implications for entrepreneurs. Perhaps a similar learning effect can be achieved by training or better preparation, so that the likelihood of the project getting funded can be improved in the entrepreneur's first campaign.

Our study has limitations. We cannot show that the choice of a round goal amount causally reduces the likelihood of success, although we do show that entrepreneurs using round goal amounts are systematically more likely to fail. The fact that this is true even when they used round number goals only in prior campaigns suggests that the effect is not solely caused by the use of round numbers. Rather, it implies that round numbers convey information about the entrepreneur quality. This is also supported by our analysis around a rule change showing that a reduction in entrepreneur quality is associated with an increase in the use of round goal amounts. Taken together, these findings mean that goal amount precision could be used as an additional input by campaign backers when assessing the likelihood of the campaign to succeed. It is also possible that entrepreneurs would be well-advised to avoid round number goal amounts and to spend adequate effort in estimating project financing needs more precisely.

Appendix A: Definitions of variables

Variable	Definition
Goal amount	Campaign goal amount sought by the campaign creator.
Round	Dummy taking the value 1 if the campaign goal is 10,000, 5000, or 1000.
Goal 10,000	Dummy taking the value 1 if the campaign goal is 10,000.
Goal 5000	Dummy taking the value 1 if the campaign goal is 5000.
Goal 1000	Dummy taking the value 1 if the campaign goal is 1000.
Divisible 1000	Dummy taking the value 1 if the campaign goal is divisible by 1000.
Divisible 500	Dummy taking the value 1 if the campaign goal is divisible by 500.
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.
Amount pledged	Amount pledged by backers for a given campaign.
Zero pledged	Dummy taking th evalue 1 if the amount pledged is zero.
Pledged/Goal	Amount pledged divided by the goal amount.
Main category	Kickstarter main category classification. Includes 15 categories.
Sub-category	Kickstarter detailed category classification. Includes 169 categories.
Campaign length	Campaign length set by the campaign creator at the beginning of the campaign.
Staff pick	Dummy taking the value 1 if the campaign is chosen as a Staff pick.

Appendix B: Summary of the sample

This table summarizes how we filter our sample. *Kickstarter total* is the total number of campaigns reported in Kickstarter statistics online. *Our raw data - all campaigns* includes all campaigns we have globally in our data. We then exclude non-U.S.-based campaigns, on-going campaigns, and those in which the goal amount is above $13,000.

	# campaigns
Kickstarter total	364,332
Our raw data - all campaigns	315,017
Coverage	*86%*
Of which based in the US	243,887
Of which completed	233,244
Of which with a goal amount of $13,000 or below	166,819

IA.1 Internet Appendix

IA.1.1 Additional summary statistics

Table IA.1
Summary statistics - Means at and near round goal amounts

	Goal 1000			Goal 5000			Goal 10,000		
	[500,)	1000	(, 1500]	[4000,)	5000	(, 6000]	[8000,)	10,000	(,12,000]
Campaign outcomes									
Successful	0.534	0.481	0.525	0.485	0.381	0.444	0.417	0.347	0.410
Failed	0.407	0.450	0.412	0.446	0.537	0.482	0.498	0.558	0.499
Canceled	0.056	0.064	0.061	0.067	0.078	0.071	0.083	0.092	0.090
Suspended	0.004	0.004	0.002	0.002	0.003	0.003	0.002	0.003	0.002
Amount pledged (000)	0.864	1.363	1.266	3.342	3.632	4.132	5.960	6.949	7.926
Zero pledged	0.128	0.138	0.109	0.096	0.144	0.101	0.097	0.141	0.083
Pledged/Goal	1.155	1.073	0.875	0.764	0.684	0.690	0.690	0.685	0.682
Campaign variables									
Goal amount (000)	0.629	1.000	1.388	4.202	5.000	5.797	8.518	10.000	11.613
Camp. length (days)	30.541	32.584	32.123	33.967	35.279	34.573	35.001	36.059	35.203
Staff pick	0.033	0.036	0.041	0.073	0.064	0.082	0.097	0.082	0.109
N prior campaigns	0.520	0.476	0.374	0.303	0.279	0.252	0.265	0.248	0.248
N prior succ.	0.258	0.255	0.190	0.180	0.140	0.138	0.159	0.140	0.149
N prior failed	0.179	0.147	0.124	0.080	0.089	0.069	0.066	0.064	0.063
N prior canceled	0.052	0.050	0.040	0.028	0.033	0.027	0.027	0.028	0.024
N prior suspended	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Creator variables									
Female	0.219	0.195	0.206	0.203	0.197	0.215	0.203	0.173	0.176
Male	0.483	0.486	0.481	0.465	0.465	0.462	0.455	0.461	0.474
No gender	0.298	0.319	0.313	0.332	0.337	0.323	0.342	0.367	0.351
White	0.569	0.562	0.582	0.579	0.554	0.571	0.565	0.532	0.559
Black	0.013	0.014	0.012	0.014	0.016	0.016	0.016	0.016	0.012
Asian	0.023	0.022	0.018	0.019	0.024	0.021	0.021	0.025	0.023
Hispanic	0.041	0.039	0.039	0.038	0.038	0.039	0.034	0.037	0.033
No race	0.355	0.365	0.348	0.351	0.368	0.354	0.364	0.390	0.372
N	15,237	10,212	11,242	9067	18,892	8101	8668	15,439	4949

Comparison of the means of variables for campaigns with a goal amount set at $1000, $5000, or $10,000, as well as those with goal amounts below and above these values.

IA.1.2 Likelihood of success – by goal amount

Table IA.2 shows the detailed coefficients illustrated in Fig. 6.

Table IA.2
Likelihood of success – by goal amount.

	(1)	(2)	(3)	(4)
Goal 1000	−0.0689* * *	−0.0802* * *	−0.0312* * *	−0.0243* * *
1000 < Goal < 3000	−0.0462* * *	−0.0624* * *	0.0189	0.0072
Goal 3000	−0.0742* * *	−0.0912* * *	0.0139	0.0066
3000 < Goal < 5000	−0.0667* * *	−0.0841* * *	0.0338	0.0129
Goal 5000	−0.1699* * *	−0.1826* * *	−0.0512**	−0.0425**
5000 < Goal < 7000	−0.1144* * *	−0.1311* * *	0.0091	−0.0070
Goal 7000	−0.1459* * *	−0.1636* * *	−0.0151	−0.0244
7000 < Goal < 10,000	−0.1321* * *	−0.1489* * *	0.0076	−0.0137
Goal 10,000	−0.2046* * *	−0.2147* * *	−0.0477	−0.0326
10,000 < Goal < 13,000	−0.1442* * *	−0.1592* * *	0.0161	−0.0012
Goal 13,000	−0.1505* * *	−0.1663* * *	0.0141	−0.0075
ln(Goal amount)			−0.0513* * *	−0.0567* * *
Campaign controls	No	No	No	Yes
Gender dummies	No	No	No	Yes
Race dummies	No	No	No	Yes
Month FE	No	Yes	Yes	Yes
Sub-category-Year FE	No	No	No	Yes
County-Year FE	No	No	No	Yes
Campaign N FE	No	No	No	Yes
N	166,309	166,309	166,309	162,863
R^2	0.016	0.035	0.036	0.273

The dependent variable, *Successful*, is a dummy taking the value 1 if the Kickstarter campaign was successful. Suspended campaigns are excluded. We include *Month fixed effects* based on the month the campaign was launched, *Sub-category-Year fixed effects*, based on Kickstarter category ID (169 different categories), *County-Year fixed effects* based on the location of the campaign, and *Campaign number fixed effects*, based on the number of campaigns the same entrepreneur has launched prior to the current campaign. Standard errors clustered by sub-category are shown in parentheses. Significance levels: * 0.1, ** 0.05, *** 0.01.

IA.1.3 Alternative proxies for campaign goal precision

As an alternative specification, we include dummies indicating the precision level at which the goal amount is set. For example, *Precision 100* indicates that the goal amount is set as a multiple of 100. As the higherst goal amount included in our sample is $13,000, *Precision 10,000* means that the goal amount is $10,000. In the regressions, we omit the variable *Precision 1000*, so the estimated coefficients are relative to this precision level.

The results, shown in Table IA.3, provide further support for our hypothesis. If we ignore campaigns that have goal amounts including decimals, campaigns with goal amounts set as multiples of 1000 perform worse than all other precision levels except the case where the goal amount is set at $10,000. This is true across all outcome variables and model specifications apart from column two which includes separate dummies for the goal amounts $1000 and $5000 and where the difference between *Precision 1000* and *Precision 100* is not statistically significant.

Table IA.3
Goal amount precision vs. campaign outcomes.

	Successful		ln(1 + Pledged)		Zero pledged		ln(1 + Pledged/Goal)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Decimal	−0.0419	−0.0575*	−0.2333	−0.3457*	0.0245	0.0319	−0.0446*	−0.0576**
	(0.0302)	(0.0302)	(0.1811)	(0.1821)	(0.0266)	(0.0265)	(0.0246)	(0.0245)
Precision 1	0.0215* * *	0.0053	0.2061* * *	0.0978**	−0.0183* * *	−0.0113**	0.0799* * *	0.0654* * *
	(0.0068)	(0.0068)	(0.0429)	(0.0432)	(0.0053)	(0.0053)	(0.0112)	(0.0105)
Precision 10	0.0266* * *	0.0102*	0.2197* * *	0.1162* * *	−0.0120* * *	−0.0055	0.0183**	0.0027
	(0.0058)	(0.0061)	(0.0312)	(0.0302)	(0.0036)	(0.0035)	(0.0080)	(0.0070)
Precision 100	0.0113* * *	−0.0045	0.1704* * *	0.0600* * *	−0.0150* * *	−0.0078* * *	−0.0025	−0.0162* * *
	(0.0030)	(0.0034)	(0.0215)	(0.0215)	(0.0020)	(0.0023)	(0.0041)	(0.0040)
Precision 10,000	−0.0176**	−0.0326* * *	−0.2935* * *	−0.4229* * *	0.0243* * *	0.0334* * *	0.0281* * *	0.0184**
	(0.0070)	(0.0071)	(0.0487)	(0.0506)	(0.0041)	(0.0043)	(0.0071)	(0.0075)
Goal 1000		−0.0284* * *		−0.0859**		0.0026		−0.0390* * *
		(0.0058)		(0.0370)		(0.0046)		(0.0097)
Goal 5000		−0.0439* * *		−0.4019* * *		0.0288* * *		−0.0254* * *
		(0.0044)		(0.0299)		(0.0031)		(0.0042)
ln(Goal amount)	−0.0577* * *	−0.0584* * *	0.5157* * *	0.5253* * *	−0.0080* * *	−0.0090* * *	−0.1034* * *	−0.1059* * *
	(0.0031)	(0.0031)	(0.0243)	(0.0233)	(0.0018)	(0.0019)	(0.0058)	(0.0055)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(*continued on next page*)

Table IA.3 (*continued*)

	Successful		ln(1 + Pledged)		Zero pledged		ln(1 + Pledged/Goal)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sub-category-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Campaign N FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	162,863	162,863	162,863	162,863	162,863	162,863	162,863	162,863
R^2	0.273	0.273	0.325	0.326	0.141	0.142	0.346	0.347

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)* is the natural logarithm of one plus the amount pledged for the campaign. *Zero pledged* is a dummy taking value 1 if the Kickstarter campaign realized zero pledged funds. *ln(1 + Pledged/Goal)* is the natural logarithm of one plus the amount pledged divided by the campaign goal amount. We exclude suspended campaigns. *Controls* include campaign controls and gender and race dummies. We include *Month fixed effects* based on the month the campaign was launched (101 months), *Sub-category-Year fixed effects*, based on Kickstarter category ID (169 different categories), *County-Year fixed effects* based on the location of the campaign, 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.

IA.1.4 Additional robustness checks

Table IA.4
All campaigns (not limited to goal amounts of $13,000 or below).

Panel A: All campaigns

	(1)	(2)	(3)	(4)
Round (extended)	−0.0177* * *	−0.2605* * *	0.0233* * *	−0.0045
	(0.0037)	(0.0263)	(0.0021)	(0.0061)
Controls	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Sub-category-Year FE	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes
Campaign N FE	Yes	Yes	Yes	Yes
N	223,414	223,409	223,414	223,409
R^2	0.312	0.335	0.139	0.375

Panel B: 20% band around each round number

	Successful	ln(1 + Pledged)	Zero pledged	ln(1 + Pledged/Goal)
	(1)	(2)	(3)	(4)
Round (extended)	−0.0128**	−0.3858* * *	0.0333* * *	0.0029
	(0.0051)	(0.0422)	(0.0035)	(0.0087)
Controls	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Sub-category-Year FE	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes
Campaign N FE	Yes	Yes	Yes	Yes
Nearest round FE	Yes	Yes	Yes	Yes
N	96,207	96,202	96,207	96,202
R^2	0.340	0.373	0.173	0.410

The dependent variable is shown above each model. *Round (extended)* is a dummy taking the value 1 if the campaign goal amount is either $1000, $5000, $10,000, $15,000, $20,000, 50,000, $100,000, $200,000, or $300,000. We exclude suspended campaigns. *Controls* include goal amount, campaign length, staff pick dummy, gender dummies, and race and ethnicity dummies. We also include *Month fixed effects* based on the month the campaign was launched (101 months), *Sub-category-Year fixed effects*, based on Kickstarter category ID (169 different categories), *County-Year 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. In Panel B, we also include *Nearest round fixed effects*, for each round number. Heteroscedasticity-consistent standard errors, clustered by sub-category, are shown in parentheses.

Table IA.5
Alternative functional forms for campaign size.

	(1)	(2)	(3)	(4)	(5)
Round	−0.0348* * *	−0.0367* * *	−0.0326* * *	−0.0359* * *	−0.0345* * *
	(0.0032)	(0.0031)	(0.0032)	(0.0031)	(0.0032)
ln(Goal amount)	−0.0593* * *				
	(0.0031)				
Goal amount (000)		−0.0170* * *	−0.0433* * *	−0.0618* * *	−0.0835* * *
		(0.0009)	(0.0028)	(0.0057)	(0.0104)
Goal amount^2			0.0023* * *	0.0066* * *	0.0148* * *
			(0.0002)	(0.0010)	(0.0031)
Goal amount^3				−0.0002* * *	−0.0013* * *
				(0.0000)	(0.0004)
Goal amount^4					0.0000* * *
					(0.0000)
Controls	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Sub-category-Year FE	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes
Campaign N FE	Yes	Yes	Yes	Yes	Yes
N	162,863	162,863	162,863	162,863	162,863
R^2	0.273	0.270	0.273	0.273	0.273

The dependent variable, *Successful*, is a dummy taking the value 1 if the Kickstarter campaign was successful. *Round* is a dummy taking the value 1 if the campaign goal amount is either $1000, $5000, or $10,000. We exclude suspended campaigns. We include *Month fixed effects* based on the month the campaign was launched (101 months), *Sub-category-Year 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.

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