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A Potato Salad with a Lemon Twist: Using a Supply-Side Shock to Study the Impact of Opportunistic Behavior on Crowdfunding Platforms[1]

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Crowdfunding platforms are peer-to-peer two-sided markets that enable amateur entrepreneurs to raise money online for their ventures. However, in allowing practically anyone to enter, such platforms enable opportunistic suppliers to flood the market with offerings, many of which are of low quality. This situation creates choice overload for potential backers and may thus influence their investment decisions. To empirically study the implications of this phenomenon for crowdfunding performance, we use a quasi-natural experiment in the form of an exogenous media shock that occurred on Kickstarter.com. The shock was followed by a sharp increase in the number of campaigns, particularly low-quality ones, offered on the supply side of the market; no such increase was observed on the demand side of the market. These unique conditions enable us to estimate how crowdfunding platforms are affected by the presence of an atypically large number of low-quality campaigns, while controlling for fluctuations in demand. We use two identification strategies, which enable us to control for changes in quality, to show that an increase in low-quality supply significantly decreases the performance of the average crowdfunding campaign, manifested in a lower likelihood of success (reaching funding goals) and less money raised per campaign. We also offer a new measure to estimate campaign quality and study the moderating role of campaign quality in the observed effects. We find that high-quality campaigns are less affected than low-quality campaigns by the influx of low-quality offerings. We discuss theoretical implications as well as managerial implications for entrepreneurs and platform designers.

Keywords: Crowdfunding, peer-to-peer platforms, peer economy, share economy, supply-side shocks, quasi-natural experiment, exogenous shock, choice overload, market of lemons

Introduction

Crowdfunding platforms enable entrepreneurs to raise money online for their products or services (Agrawal et al. 2015; Belleflamme et al. 2014). Such platforms serve as intermediaries in a two-sided market, bringing together entrepreneurs on one side (the supply side) and potential investors, called backers, on the other side (the demand side; Mollick 2014). The type of two-sided markets facilitated by crowdfunding platforms is referred to as the peer economy, or the share economy (Fournier et al. 2013; Sundararajan 2013). Such markets are characterized as having amateurs on both sides (Howe 2008) and blurred dichotomy between the parties (Zvilichovsky et al. 2013).

Crowdfunding platforms are particularly useful for novice entrepreneurs, providing off-the-shelf technology and frameworks that can streamline their first steps toward launching their ventures (Agrawal et al. 2015) and, in some cases, enable them to raise as much funding as more experienced entrepreneurs. Indeed, accessibility to novices is not incidental but rather is inherent to the ideology underlying the

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The appendices for this paper are located in the "Online Supplements" section of *MIS Quarterly*'s website (https://misq.org).

peer economy, which strives to encourage all members of the community to participate. This principle of democratization manifests in the relatively open acceptance policies adopted by numerous crowdfunding platforms, which are implemented through various platform design choices. For example, in order to launch a crowdfunding campaign on the popular platform Indiegogo.com, the entrepreneur is only required to fill out an online form; the campaign is then launched immediately without being subjected to any review process by the platform. Kickstarter.com, the Internet's largest and most popular crowdfunding platform, has been implementing a similar open access approach since June 2014, by relying on a machine-learning algorithm that automatically approves campaigns that meet its basic quality criteria. These streamlined approval processes make it straightforward to launch new campaigns, and they support entrepreneurs' agility and market responsiveness.

Although a democratic platform creates the romantic possibility that a "diamond in the rough" might emerge (Agrawal et al 2014; Gleasure and Feller 2016), accessibility may come with a cost: It effectively eliminates barriers to opportunistic behavior, wherein suppliers enter the market with the sole purpose of seizing on an opportunity to profit, with little consideration for the value that they contribute to the community. Indeed, recent findings suggest that such behavior occurs in crowdfunding environments (Hildebrand et al. 2016; Kim et al 2017). Opportunistic behavior, in turn, can expose a crowdfunding platform to the risk of being flooded with low-quality offerings.

Herein, we explore how opportunistic behavior on the supply side of a crowdfunding platform—which is indeed shown to result in a flood of low-quality campaigns—influences the performance of campaigns on the platform. We suggest that, in general, when faced with a large number of campaigns, investors may experience choice overload, in which excessive availability of options affects the decision-making process. Choice overload has been shown to influence purchase decisions and, specifically, to diminish individuals' likelihood of making any purchase at all (Schwartz 2004). Accordingly, an influx of offerings may lead to a decrease in campaign performance across the platform. This effect may be exacerbated when a large percentage of these offerings are of low quality. Indeed, Akerlof (1970) showed that when a market is inundated with low-quality offerings, or "lemons," and when buyers cannot immediately tell the difference between high-quality and low-quality offerings, sellers of high-quality products will suffer, as they are unable to sell their high-quality products at an appropriate price. However, this effect can be mitigated, and market failure averted, when sellers have some means of signaling the quality of their products, thereby reducing information asymmetry (Brealey et al. 1977; Spence 1973). In light of the fact that crowd-based platforms provide quality signaling mechanisms (for example, as studied by Fort et al. (2011) and Ipeirotis and Paritosh (2011)), we propose that the use of such mechanisms may mitigate the detrimental effects of backers' exposure to an overabundance of low-quality offerings, by enabling backers to differentiate between campaigns and to focus their attention on the smaller, more cognitively manageable subset of campaigns of higher quality.

To investigate these ideas, we use data from Kickstarter.com. Specifically, we exploit a natural experiment in which a large number of opportunistic sellers entered the market after an unusual campaign on Kickstarter—which sought to raise $10 for making a potato salad—attracted a great deal of media attention and raised more than U.S. $50,000. As we show in what follows, the new campaigns that were launched in the wake of this supply-side shock were generally of low quality (as compared with the typical campaign during the period preceding the shock).

In our investigation we combine two sources of data. The first is a comprehensive set of archival data from Kickstarter surrounding the period of the shock. The second dataset is based on a large-scale survey by which we manually evaluated numerous features of each campaign in our dataset (including prospective investors' perceptions of the entrepreneur's competence and investment of resources such as time, money, and effort). We use these features to develop new measures of quality that go beyond well-known quality signals that are embedded in the platform's structural characteristics (Burtch et al. 2013; Mollick 2014). This approach enables us to provide a more comprehensive representation of the factors that individuals actually take into account when evaluating campaigns.

We use two novel identification methods that enable us to control for quality fluctuations. The first identification method focuses on campaigns that started *before the shock* and utilizes variation in campaigns' launch dates. The second is an identification strategy based on *matching* campaigns that launched before the shock with campaigns that launched after the shock.

We find that the atypically high number of low-quality campaigns entering the market had a significant negative effect on the average likelihood of a campaign to succeed, as well as on the average amount of money pledged per campaign. Furthermore, the influx of low-quality campaigns had different effects on campaigns of different quality levels: Specifically, lower-quality campaigns were particularly susceptible to the negative effect, with respect to the two measurements of performance considered.

From a theoretical perspective, this research adds to the growing body of work on the effects of supply-side factors on various crowdfunding outcomes. As of today, relatively few works have focused on the supply side of crowdfunding platforms; several notable exceptions include the work of Burtch et al. (2018), focusing on the shift in supply between crowdfunding and the gig economy; and works focusing on biases that influence sellers' performance, such as gender bias (Marom et al. 2016) and racial bias (Rhue 2015; Younkin and Kuppuswamy 2017). In particular, although previous studies have investigated demand-side shocks in two-sided markets (Liu et al. 2015; Shankar and Bayus 2003; Zhang and Liu 2012), none, to our knowledge, has examined supply-side shocks. The dearth of research in this vein is notable in light of the unique dynamics characterizing the supply side of crowdfunding platforms: A large proportion of crowdfunding suppliers are individuals and amateur sellers, who are more likely to act impulsively and to show herding behavior as compared with suppliers in firm-based two-sided markets (see the following section for a more extensive discussion of such dynamics). As the crowdfunding industry is becoming increasingly inclusive to laypersons and to amateur suppliers, it is crucial for platform owners and market participants to better understand the supply-side phenomena that occur in these markets.

Our work further links theories of choice overload and quality signaling and provides empirical evidence of the interplay between the two constructs, with clear managerial implications. Specifically, our findings suggest that choice overload might cause campaign performance to suffer in the wake of a large influx of low-quality campaigns, and that the availability of quality signaling mechanisms can mitigate some of this damage by enabling potential investors to distinguish higher-quality campaigns from lower-quality campaigns. Still, our results suggest that, when the market is currently flooded with low-quality campaigns, the average entrepreneur who wishes to launch a crowdfunding campaign would benefit from waiting for the tide to turn.

Literature Review and Hypothesis Building

Context: How Openness Facilitates Opportunism

Before developing our hypotheses, it is important to characterize the unique environment that enables the phenomena they describe to occur: the context of an open two-sided market, which virtually anyone can enter (i.e., launch a campaign) in a quick and straightforward manner. Indeed, in recent years, it seems that the peer economy, and specifically the crowdfunding industry, is moving toward more open and democratic policies, with Indiegogo and Kickstarter's (current) acceptance policies being notable examples in the domain of crowdfunding. In effect, a platform's level of openness—that is, the extent to which the platform refrains from enforcing control and allows all prospective entrepreneurs to participate—is a design choice. It is well established that design choices affect the dynamics and performance of digital platforms (Overby et al. 2010; Tiwana et al. 2010). Crowdfunding platforms' governance decisions such as the funding models (Burtch et al. 2017) and the information disclosure policies (Burtch et al. 2015, 2016; Kim et al. 2019 influence various outcomes on these platforms, including the number of campaigns launched and the success of those campaigns.

In our context, the design feature of a platform's level of openness is inherently expected to affect the mix of offers and their performance on the platform. In particular, the presence of a relaxed acceptance policy can easily lead to the introduction of opportunistic sellers with low-quality offerings. Recent studies have provided evidence that opportunistic behavior indeed takes place on crowdfunding platforms (Burtch et al. 2018; Hildebrand et al 2016; Kim et al 2017). Hypothetically, if these platforms were to impose stricter entry barriers for suppliers, much of this behavior would be eliminated. Furthermore, we suggest that crowdfunding settings promote both the existence of low-quality offerings and rapid fluctuations in their number. These fluctuations result from the fact that many suppliers on crowdfunding platforms are individuals (rather than firms), and are therefore susceptible to herding behaviors and may react instantly to new business opportunities.

On the basis of this reasoning, we suggest that sharp increases in the supply in digital markets, and specifically sharp increases in the availability of low-quality offerings, constitute a novel phenomenon, facilitated by the particular characteristics of contemporary peer economy platforms. This work provides the first in-depth analysis of the implications of this phenomenon for the performance of the market.

Hypothesis Building

Competition and Choice Overload

Our first hypothesis aims to establish how supply-side shocks involving a large influx of low-quality offerings affect the performance of crowdfunding campaigns. In general, a large increase in the number of offerings creates a market with intense competition, which, as noted in the introduction, can prompt choice overload (also referred to in the literature as over-choice effect, the tyranny of choice, and the too-much-choice effect). Choice overload is a situation in which individuals faced with an overabundance of options to choose from experience adverse consequences (for an overview of the literature, see Scheibehenne et al. 2010). To quote Barry Schwartz's *The Paradox of Choice*: "As the number of choices grows further, the negatives escalate until we become overloaded. At this point, choice no longer liberates, but debilitates" (2004, p. 2). This effect occurs when "there is no obviously dominant option in the choice set and if the proportion of nondominated options is large" (Scheibehenne et al. 2010). This description is likely to be applicable to the market we consider, in which a large number of the offerings available are of low quality, yet still continue to compete for the attention of potential backers (Davenport and Beck 2001; Dellarocas et al. 2013).

Choice overload effects on individuals' decision-making processes have been studied extensively in the fields of marketing and psychology (e.g., Iyengar and Lepper 2000; Scheibehenne et al. 2010; Schwartz 2004). Studies in this vein have shown that choice overload may lead to confusion and anxiety (Lipowski 1970), and may decrease individuals' motivation to make any choice at all, preventing consumers from making a purchase (Iyengar et al. 2004; Iyengar and Lepper 2000). Applied to our context, these observations suggest that, when faced with an influx of low-quality campaigns, a prospective backer may experience choice overload and become less likely to invest in a given campaign that she would have invested in prior to the shock. Formally, we hypothesize:

H1: In open crowdfunding platforms, a substantial increase in the number of low-quality campaigns, will, ***on average****, reduce a given campaign's performance, as reflected in (1) the campaign's likelihood to succeed (achieve its funding goal), and (2) the amount of money pledged to the campaign*.

Quality Signaling in Crowdfunding Platforms

Our second hypothesis aims to establish how campaign quality moderates the effect of choice overload on campaign performance. To develop this hypothesis, we turn to the literature on signaling. As noted above, Akerlof (1970) used the metaphor of a market of lemons to describe how a market characterized by low-quality offerings and information asymmetry may hurt high-quality sellers, ultimately causing them to leave a marketplace. Inspired by the market of used cars, in which only sellers know the true quality of their cars, Akerlof described a scenario in which some (dishonest) sellers are tempted to sell low-quality cars (lemons) at the price of a good car (known as moral hazard and adverse selection). In such a market, sellers of high-quality products will suffer as well, as they are unable to sell their high-quality cars at an appropriate price. In order to disarm the threat of the "market of lemons," and to gain a competitive edge, high-quality agents must seek out means of signaling their quality to potential buyers (Spence 1973; for a more recent review of the literature, see Kirmani and Rao 2000). Theoretical works have argued that implementation of appropriate signaling mechanisms may reduce information asymmetry and mitigate the risks associated with a "lemonized" market (Ibrahim 2015; Tomboc 2013).

On the basis of this literature, we infer that signaling can lead to differentiation. Notably, differentiation is known to be a key element in mitigating the effect of choice overload on buyers (Scheibehenne et al. 2010). Therefore, we propose that if a platform facilitates strong quality signaling, campaigns taking advantage of these features can stand out, thereby enabling backers to reduce their choice sets and to focus their investment decisions on higher-quality campaigns. In other words, a campaign's reliance on quality signaling has the potential to alleviate the detrimental effects of choice overload on campaign performance.

Indeed, crowdfunding platforms incorporate signaling mechanisms as part of their design. Thus far, research on crowdfunding platforms has identified three main categories of signals that can express the quality of a campaign or of a campaign's owner. These quality signals have been shown to be associated with campaign performance:

(1) **Campaign-related information** (Mollick 2014): This category of signals includes features such as (a) *the inclusion of a video in the campaign page*, which serves as a proxy for the level of time, effort, and resources that the entrepreneur has invested in preparing her campaign (Mollick 2014; Zvilichovsky et al. 2013), and (b) *the number of words in the campaign description*, which is also widely used as a proxy for the entrepreneur's level of investment in a campaign and, consequently, the campaign's quality (Gafni et al. 2017; Greenberg et al. 2013). These features have been shown to predict the success of reward-based crowdfunding campaigns (see Burtch et al. 2013; Mollick 2014).

(2) **Entrepreneur-related information**: This category includes features such as (a) the number of campaigns previously backed by the entrepreneur and (b) the number of campaigns the owner created that were funded.

These characteristics have been positively linked to a campaign's likelihood to succeed (Zvilichovsky et al. 2013). The relationship between these features and campaign performance is also in line with previous literature on entrepreneurial financing, which has shown that an entrepreneur's reputation and social capital, both offline and online, serve as signals to other market participants (Krumme and Herrero 2009; Lin et al. 2013; Packalen 2007).

(3) **Campaign dynamics**: This category includes the following features:
   (a) *Fundraising progression:* Previous work in the context of microloans has shown that the progression of a campaign's funding influences subsequent backing decisions, due to herding and observational learning. Specifically, well-funded listings tend to accumulate more funding, and lenders take into consideration peer lending decisions while using observable borrower characteristics to moderate their inferences (Zhang and Liu 2012).
   (b) *Contribution frequency by others*: In the context of a public good crowdfunding marketplace, studies have shown that contributors are less likely to contribute when they feel the contribution is less important to the recipient (i.e., when the frequency of backing is high; Burtch et al. 2013).
   (c) *eWOM*: In the context of reward-based crowdfunding, it has been shown that social media buzz (in the form of posts on Twitter and Facebook) has a positive impact on subsequent campaign support. That is, prospective backers look to social media to find quality cues (Thies et al. 2014).
   (d) *Experience of previous backers*: In the context of a crowdfunding platform for mobile applications, it has been shown that early investors who have platform experience (specifically, investors with app development experience or investors with app investment experience) influence other investors in the crowd (Kim and Viswanathan 2019).

Drawing from the idea that differentiation can mitigate the detrimental effects of choice overload, coupled with the observation that backers indeed make use of quality signals, we suggest that campaigns that signal themselves as being of high quality are less likely than lower-quality campaigns to be negatively influenced (in terms of performance) by a sharp increase in the number of low-quality offerings available on the platform. Formally, we hypothesize:

H2: In open crowdfunding platforms, the effect of a substantial increase in the number of low-quality campaigns on the performance of a given campaign—as reflected in (1) likelihood to succeed (achieve the funding goal) and (2) the amount of money pledged to the campaign—is moderated by the campaign's quality, such that low-quality campaigns are affected more than high-quality campaigns.

Empirical Context

Kickstarter.com

Since Kickstarter's founding in 2009, more than 290,000 campaigns have been launched on the platform, raising pledges from over 10 million users. In 2016, a total of 57,440 Kickstarter campaigns were launched, raising approximately U.S. $650 million. Kickstarter follows the "all or nothing" funding model, in which a minimum campaign financing goal is set, and a limited time period is given for achieving the goal. The owner of the campaign receives the funds pledged to his campaign only if the campaign is "successful" (i.e., reaches or exceeds the targeted amount within the specified time period; Burch et al. 2016). Kickstarter's financial model is based on charging campaign owners a 5% fee from all funds successfully raised on the platform.[2] Kickstarter is a reward-based platform;[3] its rules specify that each campaign must create something to share with others in one of 15 categories: art, comics, crafts, dance, design, fashion, film and video, food, games, journalism, music, photography, publishing, technology, or theater.[4] Campaign success rates range from 21% for technology campaigns to 65% for dance campaigns, with an average success rate of 36% across all categories.

[2] https://www.kickstarter.com/help/fees?country=US

[3] There are several types of crowdfunding platforms: (1) reward-based crowdfunding, such as Kickstarter, where backers contribute a relatively small amount of money in exchange for a reward, (2) donation-based crowdfunding, such as GoFundMe or Crowdrise, where backers contribute small amounts of money without expecting a return beyond the gratitude of the campaign's creator, (3) equity crowdfunding, such as AngelList and Crowdfunder, where investors give rather large amounts of money in return for a small piece of equity in the company itself, and (4) debt crowdfunding, such as LendingClub, where a crowd of lenders make a loan with the expectation to make back their principal plus interest.

[4] https://www.kickstarter.com/rules

Potato Salad Shock

On July 3, 2014, Zack "Danger" Brown, a first-time entrepreneur from Columbus, Ohio, started a Kickstarter crowdfunding campaign asking for $10 for a campaign titled "Potato Salad," the stated purpose of which was: "Basically I'm just making potato salad. I haven't decided what kind yet." Surprisingly, this unusual campaign raised $55,492 from 6,911 backers, and attracted the interest of mainstream televised media outlets such as "Good Morning America" (July 8, 2014). This media attention was followed by a spike in the number of visitors to the campaign's page, and in the number of searches for the keyword "Kickstarter" on Google (see Figures 1 and 2, respectively). The media coverage also created a spike in the number of new campaigns opened for funding on Kickstarter (see Figure 3). For example, on July 2, 2014, a total of 151 new campaigns were launched on Kickstarter, whereas on July 9, a total of 927 new campaigns were initiated. As would be expected, during the weeks following the launches of these campaigns, a corresponding increase was observed in the number of live campaigns available on the platform (see Figure 4). Kickstarter confirmed in a correspondence that the sudden spike in new campaigns was attributable exclusively to the buzz created by the potato salad campaign. This interpretation indeed seems plausible, given that prospective entrepreneurs were not likely to have been aware of the spike per se, and thus to be influenced by it: at the time, Kickstarter did not publicly emphasize the massive influx in the number of campaigns, such that in order for an individual to observe this spike, he or she would have had to systematically monitor the site on a daily basis with this aspect in mind.

We consider this media-exposure-driven spike in the number of campaigns to be a supply-side shock to the Kickstarter platform. Given that the media coverage of the potato salad campaign was the source of the shock, we define the start day of the shock as July 8 (the day of the "Good Morning America" appearance) and not July 3 (the launch day of the potato salad campaign). Indeed, Figure 3 suggests that July 8 marks the beginning of the sharp increase in the number of campaigns launched on Kickstarter.

Data and Preliminary Observational Analysis

Data Collection

Archival Kickstarter Data

For this work, we needed data about campaigns launched before and after the media shock. Collecting such data is challenging because Kickstarter does not provide an API, nor does it provide access to a directory of past campaigns and users. Furthermore, its web interface does not allow for exhaustive searches. However, we have been systematically capturing and archiving Kickstarter dynamics, using a designated web crawler, which runs in parallel on multiple machines. Every 10.2 hours on average, this crawler records a snapshot comprising all the data associated with all live campaigns. The crawler was initiated on September 12, 2013, and has been running constantly since. Hence, it collected data both before and after the shock, providing us with the unique opportunity to study this media shock.

For the purpose of this study, we use data collected about campaigns that were launched between June 3, 2014 and July 14, 2014 (i.e., in proximity to the high-profile media coverage described above). This dataset contains 9,588 campaigns.[5] The following campaign attributes were collected for each campaign and were used in our analyses.

- **Campaign data:** Each campaign's description, financing goal, financing duration, use of a video (yes/no), amount of money pledged to the campaign, whether the campaign was successful, the amount collected on each day, and the category to which the campaign belongs.

- **Campaign owner's data**: Number of days from when the campaign owner joined Kickstarter until the campaign creation day; a list of campaigns the campaign's owner previously created or backed, from which we derive two variables indicating (1) the number of campaigns the campaign owner previously backed, and (1) the number of successful campaigns he or she previously owned.

Detailed descriptions and descriptive statistics for our variables are presented in Table 1.

Survey Data Using Amazon Mechanical Turk

To complement the data extracted by the crawler, and to better capture the subtle signals of quality provided in the campaign page, we developed a questionnaire regarding respondents' perceptions of campaign features that we considered to be indicative of campaign quality, and that were not covered in our Kickstarter data. (For a full description of the development of the questionnaire, see the "Quality Measures" section and Appendix A.) We then surveyed individuals

[5]We remove blockbuster projects, defined as projects that raised over U.S. $100,000 (roughly of campaigns). Campaigns included in this count are campaigns from week 5 that ended prior to the shock, campaigns from weeks 1–4, and all campaigns that launched in shock week.

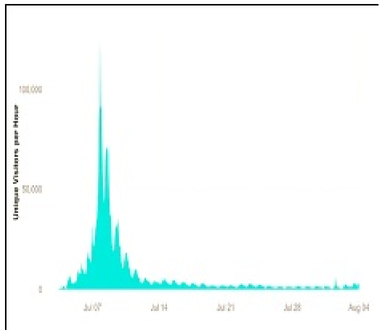


Figure 1. Unique Visitors to the Potato Salad Campaign's Page in the One-Month Period Beginning on July 4, 2014

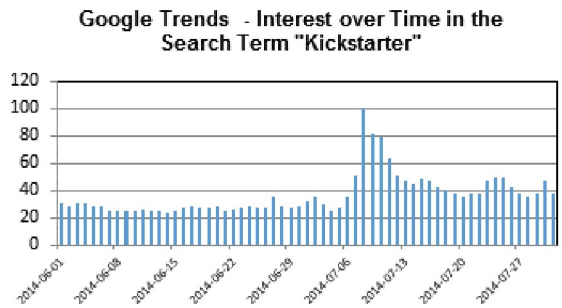


Figure 2. Search Trends (as Taken from the Google Trends Website) for the Search Term "Kickstarter" for June and July 2014

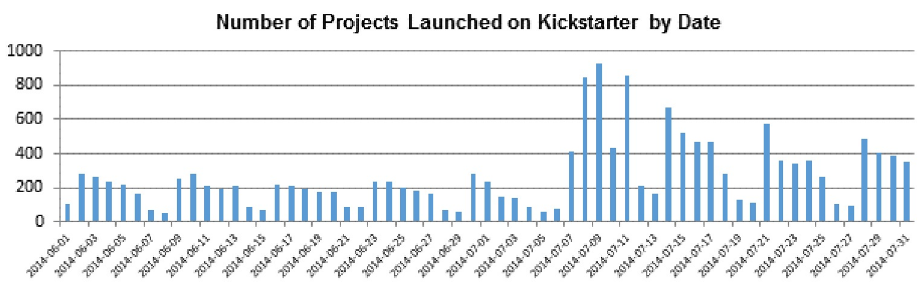
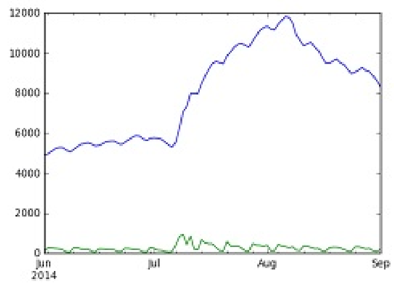
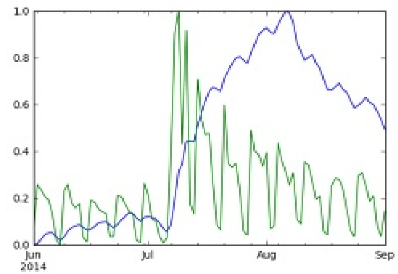


Figure 3. Number of Campaigns Launched on Kickstarter by Date



(a) Number of Live Campaigns (blue; upper line) and Number of Launched Campaigns (green; lower line) by Day



(b) Normalized Number of Live Campaigns (blue; lower line at start) and Normalized Number of Launched Campaigns (green; upper line at start) by Day

Note: We used feature scaling to normalize the data. That is, we brought all values to the range of [0, 1] using the following formula: $x' = \frac{x - x_{min}}{x_{max} - x_{min}}$. This is done separately for the two data sets, number of live campaigns, and number of launched campaigns.

Figure 4. for the Simple Model (Uncorrelated LVs)

Table 1. Descriptive Statistics for the Variables in the Kickstarter Dataset

	Description	Mean	Median	Min	Max
NumBacked	Number of campaigns previously backed by the campaign's owner	2.03	0.00	0.00	221.00
NumSucceeded	Number of successful campaigns previously created by the campaign's owner	0.11	0.00	0.00	24.00
HasVideo	Whether the campaign has a video (1 = yes, 0 = no)	0.54	1.00	0.00	1.00
NumWordsIn Description	Number of words in the campaign description	1048.23	798.0	143.0	13294.0
lnNumWords	Ln (Number of words in the campaign description)	6.72	6.68	4.96	9.50
Duration	Duration of the campaign (days)	32.27	30.00	1.00	60.00
DayJoinFromStartDate	Number of days from when the campaign owner joined Kickstarter until the campaign creation day	240.74	34.00	0.00	5305.00
OwnerTenure	Ln(dayJoinFromStartDate)	3.47	3.53	0.00	8.58
Goal	Target amount of the campaign in USD	61720.30	5000.00	1.00	168M
lnGoal	Ln(goal)	8.19	8.52	0.00	18.95
RatioGoalFirstDay	Ratio of goal attainment on the first day of the campaign. This variable serves as a proxy for campaign pre-shock momentum.	0.46	0.00	0.00	2150.36
IsSuccessful	Whether the campaign was successful	0.27	0.00	0.00	1.00
AmountPledged	Amount of money pledged to the campaign in USD	4283.70	125.00	0.00	194574.00
lnAmountPledged	Ln(AmountPledged+1)	3399.38	120.00	0.00	95031.1

Table 2. Survey Questions and Descriptive Statistics for Participants' Responses

Q#	Question	Notation	Mean	Median
Q1	How long, in your opinion, does it take to put together a campaign page like this, on a scale of 1–7 (1: small amount of time; 7: large amount of time)?	*TimeInvestment*	3.54	3.67
Q2	Would you say the page looks sloppy or professional? on a scale of 1–7 (1: sloppy; 7: professional)?	*PageQuality*	3.64	3.67
Q3	How much effort was invested in the campaign page, on a scale of 1–7? (1: No investment; 7: high investment)	*Effort*	3.47	3.33
Q4	How much money do you think the owner spent on the project before creating the campaign page, on a scale of 1–7? (1: No money; 7: large amount)	*MoneyInvestment*	2.84	2.67
Q5	Does the project have a website (besides the page on Kickstarter)? (binary)	*HasWebsite*	0.21	0.00
Q6	Does it seem like the awards were carefully planned? (binary: yes/no)	*Rewards*	0.62	0.67
Q7	Do you think the owner of the project (service) is a professional in his field? [Possible answers: The owner has no experience in this field (1) The owner is an amateur/hobbyist (2) The owner is a Professional (3)]	*Professionalism*	2.03	2.00

regarding each of the 9,588 campaigns in our dataset (of which 5,502 launched in the 5-week window before the shock, and 4,086 launched in the 1-week window after the shock). The questionnaires were administered via Amazon Mechanical Turk (MTurk). We assigned three Turkers to evaluate each campaign. The score for each question for each campaign was computed as the average response across the three evaluators. Table 2 presents the full list of questions (i.e., quality features), the response options for each question, and descriptive statistics.

Shock Statistics

To obtain a preliminary characterization of the supply-side shock created by the media coverage of the potato salad campaign, we first compared campaigns that launched in the week immediately following the shock (July 8–July 14, 2014; hereby referred to as *shock_week*) with campaigns launched during the four weeks prior to July 8. We separately examined the supply-side effects (Table 3) and the demand-side effects (Table 4).

Supply-Side Descriptive Statistics

As shown in Table 3, the number of campaigns offered on the platform during *shock_week* was 328% to 355% greater than the number of campaigns offered during each of the four weeks preceding the shock ("Count" in Table 3). As for the effect of the shock on campaign performance, we observe that the campaign success rate decreased substantially (success rates of 31% to 37% in the weeks before the shock versus 17% in the week of the shock), as did the amount of money pledged per campaign (a median of $429 to $967 in the weeks before the shock versus a median of $15 in the week of the shock).

Demand-Side Descriptive Statistics

Table 4 presents descriptive statistics regarding the changes in demand in the wake of the shock. Notably, according to our observations, the spike in supply in the wake of the shock was not accompanied by a corresponding increase in demand. For example, the total amounts pledged per week were between $6,552,491 and $10,383,634 in the weeks before the shock, as compared with $7,404,882 in the week after the shock. Most other demand-side metrics remained similarly stable during *shock_week* (see Table 4). The sharp increase in the number of campaigns coupled with the relatively stable demand provides us with an opportunity to study our hypotheses without having to account for potentially confounding demand-related effects.

We note that in order to provide further robustness to our results, we searched for additional situations on Kickstarter in which supply increased sharply with no significant effect on demand. We identified several events where there was a sharp increase in supply. However, the dates surrounding

Table 3. Supply: Descriptive Statistics by Week of Campaign Launch

	June 10– June 16, 2014 (four weeks before the shock)	June 17– June 23, 2014 (three weeks before the shock)	June 24– June 30, 2014 (two weeks before the shock)	June 31– July 7, 2014 (one week before the shock)	July 8– July 14, 2014 (*shock_week*)
Count	1233	1144	1182	1168	4086
Successful launched campaigns count	424	419	361	405	689
IsSuccessful (mean)	0.34	0.37	0.31	0.35	0.17
AmountPledged (mean)	5115.08	5540.87	4628.41	4088.82	1574.22
lnAmountPledged (mean)	5.83	6.1	5.6	5.53	3.17
AmountPledged (median)	656	943.5	449.5	423.5	15
lnAmountPledged (median)	6.49	6.85	6.11	6.05	2.71
Goal (median)	6100	6434	6053	5000	3000
lnGoal (median)	8.72	8.77	8.71	8.52	8.01

Table 4. Demand: Descriptive Statistics by Week of Campaign Launch

	June 10– June 16, 2014 (four weeks before the shock)	June 17– June 23, 2014 (three weeks before the shock)	June 24– June 30, 2014 (two weeks before the shock)	June 31– July 7, 2014 (one week before the shock)	July 8– July 14, 2014 (*shock_week*)
Money pledged (in millions of USD)	8.28	5.98	5.74	5.36	**6.16**
Number of pledges	119,978	86,182	83,683	73,478	**91,332**
Percentage of money (out of total money pledged) that was pledged to successful campaigns	76%	78%	77%	77%	**79%**
Percentage of successful pledges from total pledges	80%	82%	80%	80%	**81%**

these events overlapped substantially with one another. This overlap prevented us from ascertaining whether the demand remained stable during the events (see Appendix B for full details).

Quality Measures for Crowdfunding Campaigns

Derivation of Quality Measures

In this section, we describe in detail how we derived new measures for evaluating campaign quality. Measuring the inherent quality of a crowdfunding campaign is a challenging task. Established firm-related quality criteria from the finance literature are often inappropriate for early-stage ventures (Stuart et al. 1999). However, as discussed in the "Literature Review and Hypothesis Development" section, recent work has shown that crowdfunding platforms provide entrepreneurs with structural features that enable them to signal the quality of their ventures. These features are embedded in Kickstarter's designated campaign pages, in which entrepreneurs describe their ventures and also present their personal bios (in a designated area on the page). Indeed, measures based on these quality signaling features have been shown to predict the success of reward-based crowdfunding campaigns (see Burtch et al. 2013; Mollick 2014).

In our study, we take the following established measures into account when evaluating campaign quality: (1) *the inclusion of a video in the campaign page* (denoted *HasVideo* in our econometric models) (see Mollick 2014; Zvillichovsky et al 2013) and (2) *the number of words in the campaign description* (*NumWords*) (see Gafni et al 2017; Greenberg et al 2013). Notably, studies considering the number of words as a measure of campaign quality typically log-transform this variable to account for its variance (Burch et al 2013).

We have taken one step further to enrich our variable set to gain a more comprehensive and accurate measurement of campaign quality. As we describe below, in the spirit of prior work, we consider the extent to which the entrepreneur has invested effort and resources in the campaign, and the level of professionalism of the entrepreneur. Although Kickstarter does not provide a structured format in which to report these characteristics, we suggest that a potential backer can deduce them from the campaign page and the online biography of the entrepreneur (or the entrepreneurial team). On the basis of this rationale, we developed seven new variables that reflect entrepreneurial investment and professionalism and thus have the potential to signal a campaign's quality. We then manually evaluated all 9,652 campaigns in our dataset (using Amazon Mechanical Turk) along these variables. The use of manual (layperson-driven) evaluation enabled us to account for perceived campaign quality, in a process comparable to the evaluation made by actual site visitors during the period of the study.

Table 2 in the "Data and Preliminary Observations" section shows the exact phrasing of the seven questions used to build our quality measures. We emphasize that we focus on the quality of the *campaign* rather than on the quality of the *product or service* being funded because our dependent variables are related to the performance of the campaign (rather than the successful production of the product or service). Below we describe the derivation of the seven questions. Full details can be found in Appendix A.

Mollick (2013) has suggested that venture capitalists and crowdfunders act to rationally assess project quality, of which the entrepreneur's level of preparation is a key indicator. He hypothesizes that entrepreneurs who demonstrate more *preparedness* are more likely to be funded. We suggest that, in the domain of crowdfunding, entrepreneurial preparation is manifested in the effort and resources invested by the entrepreneur in preparation for launching a campaign. Additionally, marketing literature suggests that potential consumers take sellers' (perceived) effort and expense into account (Modig et al. 2014). In the context of crowdfunding, we can assume that consumers are sufficiently literate to deduce the levels of expense and effort invested by the seller, which they then use to infer whether the product is of better quality.

Thus, to measure potential backers' perceptions of such investment, we focused on the following campaign attributes, which a potential backer can deduce from viewing a campaign's page.

- Money spent by the entrepreneur before launching the campaign (Q4 in Table 2).
- Time and effort spent in creating the campaign page (Q1 and Q3 in Table 2, respectively).
- Careful planning of the reward structure (Q6 in Table 2).

We further draw from literature showing that potential consumers use website design as a manifestation of the seller's *ability*, and that this assessment in turn impacts their online purchase intentions (Schlosser et al 2006). Thus, we also asked about

- The level of professionalism of the design of the campaign page (Q2 in Table 2).
- The use of an additional website outside of Kickstarter domain (Q5 in Table 2).

Human capital is associated with entrepreneurial success and quality (Ahlers et al 2015; Unger et al 2011). However, the operationalization of human capital may be challenging within the context of Kickstarter, owing to the diversity of campaign categories, which range from art and food to design and technology. Hence, in building our quality measurements, we directly asked evaluators to rank the (perceived) professionalism of the entrepreneurs in the field in which they operate (Q7 in Table 2). The answers will provide insights into the degree to which the campaign page signals professionalism within the context of the specific campaign category.

Thus, our two datasets (the Kickstarter campaign data and the survey data) provided us with nine quality variables. Taken together, these variables constitute a more comprehensive quality measure than what has been previously used in the literature.

Assessment of Campaign Quality and Creation of All-Encompassing Quality Variable

In Table 5, we present a comparison of the nine quality variables corresponding to campaigns in the weeks before and after the shock. As can be seen, the shock brought with it a substantial decrease in the quality of campaigns offered. Specifically, the percentage of campaigns accompanied by a video decreased from 68%–73% to 35%, and the average number of words decreased from 1,168–1,293 to 790. Additionally, we see a post-shock decrease in the values of all our

Table 5. Mean Campaign Quality by Launch Week

	June 10-June 16, 2014 (four weeks before the shock)	June 17-June 23, 2014 (three weeks before the shock)	June 24–June 30, 2014 (two weeks before the shock)	June 31–July 7, 2014 (one week before the shock)	July 8–July 14, 2014 (*shock_week*)
HasVideo	0.7	0.71	0.68	0.63	**0.33**
NumWords	1246.21	1281.27	1248.87	1166.18	**787.24**
lnNumWords	6.93	6.97	6.93	6.86	**6.44**
TimeInvestment	3.82	4.08	3.91	3.91	**2.96**
PageQuality	3.88	4.16	4.03	3.98	**3.07**
Effort	3.71	3.95	3.84	3.79	**2.92**
MoneyInvestment	3.11	3.29	3.15	3.04	**2.37**
HasWebsite	0.26	0.27	0.25	0.25	**0.14**
Rewards	0.69	0.73	0.68	0.69	**0.5**
Professionalism	2.12	2.19	2.14	2.15	**1.85**

newly created variables. For example, when considering ratings of the perceived amount of time invested in the campaign, we see a decrease from 3.84–4.09 to 2.97.

These patterns suggest that the average quality of the campaigns launched during the week after the shock deviated from, and was lower than, the typical (pre-shock) average quality of campaigns on Kickstarter. This decrease might indicate that many of the campaigns that launched in the wake of the shock were opportunistic in nature. Accordingly, our preliminary observations that campaign performance during *shock_week* was weaker than that during the period preceding the shock are potentially attributable to one of two explanations: (1) the effect is endogenous (i.e., campaigns launched during such a period are of lower quality and hence less likely to succeed and raise money) or (2) the intense competition among low-quality offerings that emerged in the wake of the shock created choice overload and had a harmful effect on the performance of campaigns that would otherwise have been more successful. Hence, it is necessary to use an identification strategy that enables us to estimate how a given campaign of "typical" pre-shock quality would be affected by an increase in the number of low-quality campaigns on the platform *as if* all else remained equal. As elaborated in the "Methodology" section, we used two complementary identification strategies to achieve this goal.

Finally, we used principal component analysis (PCA) to reduce the dimensionality and to transform the nine variables into one all-encompassing quality variable, denoted ***QualityPca*** (the use of PCA in this manner is widely recognized in the IS literature and other social science disciplines; see, for example, Allport and Kerler 2003; Ayabakan et al. 2017; Bonaccorsi et al. 2006; Sahoo et al. 2012). In this work we define ***QualityPca*** as the first principal component of the fitted model.[6]

Methodology

Identification Strategies

Here, we present two identification strategies to address the identification challenge outlined above: namely, the need to isolate the effect of choice overload on campaigns' performance from the effect of the inherently lower quality of the campaigns themselves. Our first identification strategy focuses on pre-shock campaigns and is built on variation in the time proximity to the shock. The second strategy focuses on comparing pre-shock campaigns to post-shock campaigns using propensity score matching (PSM). Both methods are used to study both hypotheses, and rely on our newly devel-

[6]Seeing as our empirical investigation included two types of identification strategies, each using different campaigns for estimation, we fit two PCA models, once for each identification strategy. When implementing the "time proximity" identification we fit a PCA model on the nine quality features of the 4,453 campaigns used in our estimations. Seeing as PCA is sensitive to large variances in features, prior to fitting the model, we standardized the nine quality features. The first principal component captures 64% of the variation of our features. When implementing the "matching identification," we fit a PCA model on the *before*campaigns and then transformed the *after* campaigns using the fitted model. As with the time proximity method, here too we standardized the features prior to fitting the model. The first principal component captures 59% of the variation of our features. To fit the models, we used a Python implementation of PCA (see http://scikit-learn.org/stable/modules/generated/sklearn.decomposition.PCA.html).

oped quality measures. We note that the two identification strategies have slightly different advantages, and are hence complementary and provide robustness. In what follows, we discuss the two identification methods, their relative advantages, and how they are used to address each of the hypotheses.

Identification Method 1: Time Proximity to the Shock

The premise of our first identification method was to focus on campaigns whose inherent quality was not likely to have been influenced by the shock, but whose performance was likely to have been influenced by the post-shock environment. To this end, we examined campaigns that were launched briefly before the shock—such that their creation (and hence quality) was independent of the shock—yet were open for funding for some time after the shock commenced. As the average life-span of a campaign is 32 days, we focused on campaigns that started during the four weeks immediately *preceding* the shock and ended after the shock (4,453 campaigns in total).

The variation needed for identification comes from the different launch dates; we assume that campaigns launched closer to the shock are more likely to have been affected by the post-shock environment of intensified, low-quality competition, as they spent more of their "lives" in that environment. To better understand our identification strategy, consider the following illustration: Assume that campaign A was launched on July 1, 2014 (seven days before the shock), and that campaign B was launched two days later, on July 3, 2014 (five days before the shock). Given that both campaigns were launched before the shock, they are likely to be of comparable quality (or drawn from the same pre-shock quality distribution). However, campaign B may be more strongly influenced by the effect of the shock, as the shock occurred earlier in the campaign's life. Hence, any variation explained by proximity to the shock can be attributed to the effect of competing in a market of lemons. This example is illustrated in Appendix C.

An important property of this identification strategy is the fact that, by comparing among pre-shock campaigns, rather than comparing pre-shock campaigns with post-shock campaigns, we are able to control for the overall decrease in campaign quality following the shock. Further, we are able to control for any additional unobserved changes in the campaign mix that the shock might have brought. For example, some suppliers might have chosen to intensify their signaling efforts after the shock began, to better differentiate themselves from the crowd. Our identification strategy enables us to control for such unobserved changes.

We implemented this strategy to test both H1 and H2. Specifically, we created a variable that measures how many days before the shock the campaign launched, denoted as *DaysFromShockDay*. We estimated its impact on the campaign performance variables (H1) as well as the moderating effect of quality on the effect of the shock (H2), and we quantified the effect of each additional day of exposure to the post-shock conditions.

Identification Method 2: Propensity Score Matching

In our second identification method, we used PSM to match campaigns launched before the shock (before campaigns) to campaigns launched immediately after the shock (after campaigns). Briefly, we first compared the two matched groups to study the effect of the shock (i.e., the impact of being a pre-shock campaign as opposed to being a post-shock campaign) on the performance variables of interest (H1). Then, using the quality measures we developed, we conducted subsample regression analysis to test the moderating effect of quality (H2).

As mentioned, the weeks after the shock were characterized by campaigns of atypically low quality (as compared with the period before the shock). Yet, our goal is to understand the effect of the shock on campaigns of typical quality. Hence, the purpose of the matching procedure was to find two comparable groups, one that included "typical" pre-shock campaigns, and one that included campaigns that started after the shock and that are similar in their characteristics to the pre-shock campaigns. Specifically, for the before group, we used campaigns that were launched 5 or 4 weeks before the shock (between June 3 and June 16, 2014) and finished before the shock (959 campaigns); for the after group we used campaigns launched the week after the shock, between July 8 and July 14. For each before campaign we matched one after campaign using PSM.[7] Because the PSM procedure ensured that the two groups would comprise similar campaigns, performance differences between them were not susceptible to biases due to post-shock changes in the inherent characteristics of campaigns available on the platform.

The specific choice of the before period was made for a few reasons: First, clearly, we needed to choose a time period that would include a large number of campaigns that began and ended before the shock. At the same time, we sought to

[7]We conduct PSM (without replacements) to find the closest match for each project in weeks 4 and 5. For each project in weeks 4 and 5, we use 1-nearest neighbor to find the project that is nearest to it in terms of propensity score.

ensure that the launch criteria for the campaigns selected from this period would be comparable to those of the campaigns launched during the after period. On June 3, 2014, Kickstarter implemented a policy change in the platform that made it easier for campaigns to be accepted and launched.[8] This change in the platform may have affected performance measures as well as quality (Wessel et al. 2015). In order to avoid potential confounding effects resulting from the change in launch criteria, we chose campaigns that launched after the policy change went into effect, and limited our choice only to campaigns that ended prior to the shock.

We performed PSM by matching campaigns on the following three types of variables:

- General campaign characteristics, including category, duration, and goal.
- Campaign quality, including the established quality measures (video inclusion, number of words in the campaign description) as well as our seven newly developed measures (see Table 2).
- Project owner's on-platform tenure and experience. Previous works have shown that the experience that a project owner has on the platform may influence the likelihood of a project to succeed (Inbar and Barzilay 2014; Zvilichovsky et al. 2013). Entrepreneurs' tenure is often translated into social proof, which is one of the factors for entrepreneurial success (Bapna 2019; Vesterlund 2003). Hence, we include the following three measures: the number of projects the owner has previously backed, the number of successful projects that the owner has previously launched on the platform, and the tenure of the project owner on the platform at the time of creating the project (measured in days).

Estimation Equations

Outcome Variables of Interest

In this work we focus on two outcome variables that represent campaign performance. The first is whether the campaign was successful, that is, achieved its funding goal (*IsSuccessful*, a binary variable), and the second is the amount of money raised (*AmountPledged*). We used both performance variables when implementing both identification methods. *IsSuccessful* is a binary variable and *AmountPledged* is a continuous variable; thus, we analyzed the former using logistic regression,[9] and we analyzed the latter using OLS.[10] For the latter, we estimate the logarithm of the amount of money pledged rather than the absolute amount, as the large range of different types of campaigns leads to high variance in the amount of money pledged per campaign. In what follows, we present our empirical strategy and the estimation equations used to study our hypotheses. Recall that each hypothesis is tested twice, once with each of the identification methods.

Identification Method 1: Time Proximity to the Shock

Studying H1: The Average Effect of the Shock on Campaign Performance. Recall that our first identification method focuses on the effect of a campaign's time distance from the shock (*DaysFromShockDay*) on its performance. The literature indicates that backing activity is U-shaped; that is, it deteriorates toward the middle of the campaign fundraising period (Kuppuswamy and Bayus 2015). Hence, in our estimations we use the logarithm of *DaysFromShockDay*.

We first focus on the likelihood of success, using a logistic regression (with category-specific fixed effects). If the post-shock environment affects success rate, we should expect to see a higher success rate among campaigns launched earlier in the examined time period (i.e., at a greater distance from the shock). Note that we control for various factors, including the following: the funding target (goal) of the campaign, the on-platform experience and tenure of the owner, the category of the campaign, and the duration of the campaign. Another factor that may influence campaign performance is the campaign momentum achieved prior to the shock. It is reasonable to believe that a campaign that has accumulated a significant portion of its goal prior to the shock will succeed independently of the shock. Hence, as a proxy for a campaign's pre-shock momentum, we accounted for the ratio of the goal attained on the campaign's first day. Accordingly, our full regression equation is as follows:

[8]For the policy change, see https://www.kickstarter.com/blog/introducing-launch-now-and-simplified-rules-0.

[9]Note that all results presented in the paper for measuring likelihood to succeed use a logit model; however, results were consistent in direction and significance when using a probit model as well.

[10] We use OLS to estimate the effect on ln(AmountPledged). OLS is a good measurement tool for our hypothesis structure: First, we are measuring the effects on a continuous variable and as such should use an analytical tool that deals with continuous variables (such as OLS, as opposed to a regression model, which studies effects on binary or multiclass outcomes). Second, as our identification strategies (time proximity and propensity score matching), together with our control parameters, provide sufficient assurance that $E[\varepsilon|X] = 0$, it is safe to use OLS without fear of violating the exogeneity assumption.

$$IsSuccessful_1 = \alpha_0 + \alpha_1 \boldsymbol{lnDaysFromShockDay_i} + \alpha_2 \boldsymbol{Quality} + \alpha_3 numBacked_i + \alpha_4 numSucceeded + \alpha_5 Duration_i + \alpha_6 lnGoal_i + \alpha_7 RatioGoalFirstDay_i + \alpha_8 lnDayJoinFromStartDate_i + \alpha_9 CategoryFixedEffects_i + \varepsilon_i \quad (1)$$

We ran this equation with two operationalizations for the *Quality* variable. In the first we used ***QualityPca,*** the all-encompassing quality variable constructed using PCA (see the subsection on "Derivation of Quality Measures"). In the second, we used ***QualityBinary***—a binary representation of *QualityPca*, where the median of *QualityPca* serves as a threshold: observations with quality < median (*QualityPca*) are assigned the value 0 and are regarded as low-quality, whereas observations with quality > median (*QualityPca*) are assigned the value 1 and are regarded as high-quality.

Next, we estimated the impact of a campaign's distance from the shock (*DaysFromShockDay*) on the logarithm of the amount of money pledged to the campaign (*ln(AmountPledged*+1*)*), using an OLS regression (with category-specific fixed effects). If the shock environment indeed affects the amount of money pledged, we expect campaigns launched further from the shock to receive higher pledges compared with campaigns launched closer to the shock. The control variables were the same as in equation (1). As before, we ran this equation with two operationalizations for the *Quality* variable.

Studying H2: The Moderating Effect of Quality. To estimate the moderating effect of quality on each of the performance variables (likelihood to succeed and amount pledged), we estimated equation (1), specified above, by adding an interaction term between *Quality* and *lnDaysFromShockDay.* Once again, we estimated these equations twice, once using *QualityBinary* and once using *QualityPca.*

Identification Method 2: Propensity Score Matching

Studying H1: The Average Effect of the Shock on Campaign Performance. As with the first identification strategy, we used logistic regression when estimating likelihood to succeed and OLS when estimating the amount of money pledged. The variable of interest is before, which is a binary variable denoting whether the campaign started (and ended) in the pre-shock period (in which case before equals 1) or during the week immediately following the shock (in which case before equals 0). If the shock indeed had a negative effect on the average campaign performance, we expect the coefficient of before to be positive and significant. The control variables are the same as in equation (1) with the exclusion of *RatioGoalFirstDay*. This variable is no longer relevant, as in the PSM identification strategy we compare campaigns before the shock to campaigns that started during the shock, assuming that the shock has an effect on the amount pledged and specifically on the amount pledged in the first day (whereas in the first identification method, the amount pledged in the first day is not affected by the shock). As with the first identification strategy, here too we used two operationalizations of the *Quality* variable, namely, *QualityBinary* and *QualityPca.* Equation (2) is the logistic regression equation estimating the effect on likelihood to succeed; the control variables for the OLS regression estimating the effect on *AmountPledged* are the same as in equation (2).

$$IsSuccessful_1 = \alpha_0 + \alpha_1 \boldsymbol{Before} + \alpha_2 \boldsymbol{Quality} + \alpha_3 numBacked_i + \alpha_4 numSucceeded + \alpha_5 Duration_i + \alpha_6 lnGoal_i + \alpha_7 lnDayJoinFromStartDate_i + \alpha_8 CategoryFixedEffects_i + \varepsilon_i \quad (2)$$

Studying H2: The Moderating Effect of Quality. To estimate the moderating effect of quality on each of the performance variables (likelihood to succeed and amount pledged), we estimated equation (2), specified above, by adding an interaction term between *Quality* and *Before.* For each performance variable, we estimated this equation twice, once using *QualityBinary* and once using *QualityPca*. Given our hypothesis that quality moderates the effect of the shock, we expected the interaction term of *Before* and *Quality* to be negative and significant, indicating that lower-quality campaigns were influenced more by the shock.

To improve matching accuracy, our matching was not performed on the variable *QualityPca*, but rather on the individual variables attributed to quality, as well as additional campaign characteristics (as explained above in the "Identification Strategies" section). Thus we had to make sure that, for each low- and high-quality subsample (created by *QualityBinary*), *QualityPca* was balanced between the before and after groups. For the balancing test performed, see Appendix D.

Results

Identification Method 1: Time Proximity to the Shock

The results for the estimations using the first identification method are presented in Table 6. In the table, models (1) and

Table 6. Time Proximity Identification: H1 + H2 Regressions

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
lnDaysFromShockDay	0.155*** (0.046)	0.160*** (0.044)	0.305*** (0.071)	0.166*** (0.048)	0.143*** (0.039)	0.180*** (0.042)	0.265*** (0.056)	0.147*** (0.039)
QualityPca	0.629*** (0.028)			0.685*** (0.054)	0.845*** (0.017)			0.822*** (0.038)
QualityBinary		1.912*** (0.099)	2.509*** (0.246)			3.211*** (0.085)	3.671*** (0.217)	
lnDaysFromShockDay ×QualityBinary			-0.244*** (0.091)				-0.192** (0.083)	
lnDaysFromShockDay ×QualityPca				-0.024 (0.020)				0.010 (0.015)
lnGoal	-0.602*** (0.036)	-0.396*** (0.031)	-0.407*** (0.031)	-0.608*** (0.037)	-0.029 (0.023)	0.094*** (0.025)	0.089*** (0.025)	-0.026 (0.024)
lnDayJoinFromStartDate	0.054** (0.023)	0.090*** (0.022)	0.088*** (0.022)	0.054** (0.023)	0.114*** (0.019)	0.206*** (0.021)	0.204*** (0.021)	0.114*** (0.019)
NumSucceeded	0.106 (0.082)	0.108 (0.085)	0.103 (0.084)	0.105 (0.082)	0.199*** (0.054)	0.191*** (0.058)	0.190*** (0.058)	0.198*** (0.054)
NumBacked	0.024*** (0.007)	0.029*** (0.007)	0.029*** (0.007)	0.024*** (0.007)	0.023*** (0.005)	0.027*** (0.005)	0.028*** (0.005)	0.022*** (0.005)
Duration	-0.005 (0.004)	-0.007* (0.004)	-0.007* (0.004)	-0.005 (0.004)	-0.005 (0.003)	-0.009** (0.004)	-0.009** (0.004)	-0.005 (0.003)
RatioGoalFirstDay	4.246*** (0.339)	5.155*** (0.347)	5.148*** (0.346)	4.241*** (0.339)	-0.001 (0.001)	-0.000 (0.001)	-0.001 (0.001)	-0.001 (0.001)
CategoriesFixedEffects	5.607	9.051	10.524	8.638	6.289	9.9	11.245	9.281
Num. obs.	4,453	4,453	4,453	4,453	4,453	4,453	4,453	4,453
R^2					0.459	0.368	0.368	0.459
Adj. R^2					0.456	0.364	0.365	0.456
RMSE					2.383	2.575	2.574	2.383

***p <.01, **p < .05, *p < 0.1
Note: Models 1–4 correspond to logistic regressions in which the dependent variable is *IsSuccessful*. Models 5–8 correspond to OLS regressions in which the dependent variable is lnAmountPledged. For robustness, we ran models 5–8 with robust standard errors. Results were significant and in the same direction.

(2) correspond to the estimations of success likelihood. Each model uses a different operationalization of "quality," as discussed above: Model (1) uses ***QualityPca***, the continuous quality variable constructed using PCA; model (2) uses ***QualityBinary***, the binary representation of ***QualityPca***. As can be observed, in both models, the coefficient of the number of days between the launch date of a campaign and the shock is positive and significant. This means that campaigns that were open for longer periods of time in the pre-shock environment had a greater likelihood of being successful, suggesting that the shock environment led to a decrease in the likelihood of success. Specifically, the odds of being successful increase by a factor of 1.0149–1.0154 for a 10% increase in the distance from the shock (in terms of the number of days from the shock).[11] These results support H1(A).

Models (5) and (6) correspond to the estimations of amount pledged, using *QualityPca* and *QualityBinary*, respectively, to operationalize *Quality*. As shown in Table 6, the effect is significant for both models, suggesting that, after controlling for quality, the shock environment decreased the amount of money a campaign was able to raise in its lifetime. These results support H1(B). Specifically, for a 10% increase in distance from the shock, we see an increase of 1.4%–1.7% in the amount of money pledged; for a 50% increase in distance from the shock, we see an increase of 6%–7.6% in the amount pledged. For example, an average campaign that was launched on day 2 prior to the shock and raised approximately U.S. $3,000 would have raised $180 to $228 more had it started on day 3 prior to the shock, and it would have raised $780 to $1020 (26%–34%) more had it started on day 10 prior to the shock. Clearly, when considering the overall effect on all campaigns, these observations have significant implications for entrepreneurs and for the platform,

[11] For a complete calculation of the economic impacts reported in the paper, see Appendix E.

particularly in light of the large number of campaigns involved: During the week before the shock, over 1,000 new campaigns launched, and more broadly, over 4,200 campaigns launched before the shock and were open for funding during the post-shock period. All of these campaigns were potentially affected by the shock.

Models (3) and (7) correspond to the estimations that include the interaction term between *QualityBinary* and *lnDaysFromShockDay*, for likelihood to succeed and amount pledged, respectively. As can be observed, in both cases the interaction coefficients are negative, suggesting that campaign quality moderates the effect of distance from the shock on likelihood to succeed and on amount pledged. Notably, in the presence of the interaction term, the main effect (i.e., *lnDaysFromShockDay*) is still significant and positive. These results support H2(A) and H2(B). When considering likelihood to succeed, these results imply that for low-quality campaigns, the odds of being successful increase by a factor of 1.03 for a 10% increase in the distance from the shock, whereas for high-quality campaigns the odds increase by a factor of 1.006. When considering amount pledged, we find that for low-quality campaigns a 10% increase in distance from the shock is expected to yield a 2.6% increase in the amount pledged, whereas for high-quality campaigns a 10% increase in distance is expected to yield only a 0.7% increase in the amount pledged. Thus, quality moderates the effect by a factor of over 3. Models (4) and (8) correspond to the estimations that include the interaction term between *QualityPca* and *lnDaysFromShockDay*, for likelihood to succeed and amount pledged, respectively. As can be observed, while the main effects remain significant, the interaction terms are not.

Identification Method 2: Propensity Score Matching

The result of the estimations using the PSM identification method are presented in Table 7. Models (1) and (2) correspond to the estimation of success likelihood, and models (5) and (6) correspond to the estimation of the amount of money pledged. As above, each model uses a different operationalization of *Quality*: Models (1) and (5) use ***QualityPca***; models (2) and (6) use ***QualityBinary***, As can be observed, in all models the coefficient of *Before* (the variable of interest) for both performance measures is positive and significant, suggesting that the post-shock environment decreased campaigns' likelihood to succeed and the amount that they were able to raise. These results support both H1(A) and H1(B). Specifically, we observe that campaigns launched before the shock were 1.3 times more likely to succeed compared with (similar) campaigns launched after the shock (both when controlling for *QualityPca* , model (1), and when controlling for *QualityBinary*, model (2)). Similarly, campaigns launched before the shock raised 36%–43% more, on average, compared with campaigns launched after the shock.

Models (3) and (7) correspond to the estimations that include the interaction term between *QualityBinary* and *Before*, for likelihood to succeed and amount pledged, respectively. As can be observed, in both cases the interaction coefficients are negative, suggesting that campaign quality moderates the effect of being a before campaign on likelihood to succeed and on amount pledged, such that campaigns of lower quality are more negatively affected by the shock environment than campaigns of higher quality. Specifically, for low-quality campaigns, we observe that campaigns launched before the shock are 1.67 times more likely to succeed compared with campaigns launched after the shock. For high-quality campaigns, campaigns launched before the shock are only 1.11 times more likely to succeed compared with campaigns launched after the shock. Similarly, low-quality campaigns launched before the shock raised, on average, 86% more money than did low-quality campaigns launched during the week of the shock; in contrast, among high-quality campaigns, pre-shock campaigns raised only 10% more compared with post-shock campaigns. Notably, in the presence of the interaction term, the main effect (i.e., *Before)* is still significant and positive. These results support H2(A) and H2(B). Models (4) and (8) correspond to the estimations that include the interaction term between *QualityPca* and *Before*, for likelihood to succeed and amount pledged, respectively. As can be observed, as with models (3) and (7) the interaction coefficients are negative, suggesting that campaign quality moderates the effect of being before the shock on likelihood to succeed and on amount pledged. Specifically, when observing the effect on likelihood to succeed we see that a one-unit increase in *QualityPca* decreases the effect of being a before campaign by a factor of 0.887. That is, as quality increases, the effect of being launched and completed before the shock decreases. The same is observed when considering the effect on *lnAmountPledged*. Specifically, we see that a one-unit increase in quality decreases the effect of being a before campaign by a factor of 0.89.

We note that the results obtained via the PSM identification method may seem somewhat different in terms of the effect size than those obtained using the time proximity identification. This difference may be attributed to the fact that each identification method quantifies a somewhat different effect. The time proximity identification measures the strength of the effect (degree of exposure to the post-shock environment) on the campaign outcome, whereas the PSM identification measures the average effect over two groups of campaigns that ran either before or after the shock.

Table 7. Propensity Score Matching Identification: H1 + H2 Regressions

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Before	0.276** (0.120)	0.279** (0.114)	0.511*** (0.177)	0.338*** (0.124)	0.310*** (0.111)	0.360*** (0.119)	0.621*** (0.167)	0.310*** (0.111)
QualityPca	0.64*** (0.040)			0.710*** (0.052)	0.814*** (0.027)			0.872*** (0.036)
QualityBinary		1.968*** (0.139)	2.187*** (0.190)			3.037*** (0.131)	3.307*** (0.179)	
Before×QualityPca				-0.120** (0.057)				-0.116** (0.047)
Before×QualityBinary			-0.403* (0.233)				-0.528** (0.238)	
lnGoal	-0.76*** (0.052)	-0.588*** (0.046)	-0.591*** (0.046)	-0.769*** (0.053)	0.010 (0.038)	0.077* (0.040)	0.077* (0.040)	0.010 (0.037)
lnDayJoinFromStart Date	0.100*** (0.032)	0.136*** (0.030)	0.135*** (0.030)	0.099*** (0.032)	0.137*** (0.029)	0.225*** (0.030)	0.223*** (0.030)	0.134*** (0.029)
NumSucceeded	0.154* (0.086)	0.155* (0.084)	0.151* (0.083)	0.143* (0.084)	0.079 (0.055)	0.092 (0.059)	0.093 (0.059)	0.078 (0.055)
NumBacked	0.03*** (0.011)	0.037*** (0.012)	0.037*** (0.012)	0.030*** (0.011)	0.023*** (0.008)	0.025*** (0.009)	0.025*** (0.009)	0.023*** (0.008)
Duration	0.001 (0.010)	0.015* (0.009)	0.014 (0.009)	-0.000 (0.010)	0.004 (0.009)	0.026*** (0.009)	0.025*** (0.009)	0.002 (0.009)
CategoriesFixed Effects	1.441	4.002	5.041	4.431	6.377	9.842	10.843	9.313
Num. obs.	1,918	1,918	1,918	1,918	1,918	1,918	1,918	1,918
R^2					0.451	0.371	0.372	0.453
Adj. R^2					0.445	0.364	0.365	0.446
RMSE					2.417	2.588	2.585	2.414

****p* <.01, ***p* < .05, **p* < .1

Note: Models 1–4 correspond to logistic regressions in which the dependent variable is *IsSuccessful*. Models 5–8 correspond to OLS regressions in which the dependent variable is lnAmountPledged. For robustness we ran models 5–8 with robust standard errors. Results were significant and in the same direction.

Discussion

In this paper, we have studied the implications of flooding an open crowdfunding marketplace with opportunistic low-quality offerings. We developed a new approach to characterizing the quality of a campaign by factoring in the resources invested by the entrepreneur (such as time, money, and effort) and his or her perceived professionalism. Doing so, we were able to estimate how signaling differentiates between high-quality and low-quality campaigns and mitigates the effect of choice overload. Our analysis exploited a short-term period of highly visible media exposure given to Kickstarter following the launch of an unusual campaign (the "potato salad campaign"), which enabled us to avoid temporal and seasonal bias in our empirical estimates.

We suggest that a sudden influx of low-quality offerings into a marketplace represents more than just an identification opportunity. The very fact that such an event occurred highlights some of the unique characteristics that distinguish peer economy platforms from other firm-based two-sided platforms (hence, our findings may be applicable to other peer-economy platforms such as Airbnb, Uber, and Ebay). On peer-to-peer crowd-based platforms, particularly during their first years, the "crowd" occupies both sides of the marketplace. Hence, suppliers in these marketplaces may be more likely than suppliers in more traditional marketplaces to be susceptible to exogenous stimuli and to manifest herding behavior. These characteristics—coupled with an "open admissions" policy in which the platform does not strictly moderate the content that suppliers can offer—may lead to situations in which exogenous events that draw attention to a platform trigger flooding of the market with low-quality offerings. Similar supply-side shocks may not be as intense in firm-based two-sided markets, in which established companies react more slowly, and have substantial opportunity costs. Yet, we stress that our work was conducted in the context of crowdfunding, and studying similar situations in other peer-to-peer platforms constitutes an interesting avenue for future work.

Our analyses show that the sharp increase in the number of low-quality campaigns triggered by the media exposure shock had, on average, a negative effect on the performance of the campaigns launched on the platform, manifested in their success rate and the money they raised, in line with phenomena observed in research on choice overload. These effects, however, were moderated by campaign quality: Entrepreneurs who signaled higher levels of professionalism and investment of resources in developing their campaigns were less affected by the flooding than were entrepreneurs who launched lower-quality campaigns. Our estimations controlled for diverse factors that may affect campaign performance (and may be differentially affected by an influx of low-quality offerings), including the entrepreneur's tenure on the platform, experience, campaign category, and target goal. Our results were consistent across two complementary identification strategies; the first considered only campaigns starting before the influx occurred, and the other used a matching procedure to compare campaigns with similar characteristics launched before- versus after the flooding began.

Contribution and Implications

Our paper offers methodological, theoretical, and managerial contributions. From a methodological perspective, we present a novel identification method—the time proximity method—to control for quality fluctuations when studying natural experiments based on exogenous shocks. Indeed, in many cases, an exogenous shock not only changes the conditions under which observations (in our case, crowdfunding campaigns) operate but also affects the inherent characteristics (quality distribution) of the population. Our identification strategy eliminates this bias by considering only observations that were generated before the exogenous shock occurred (such that their characteristics were independent of the shock), yet whose performance was likely to have been influenced by the shock. The variation needed for identification comes from the different launch dates; in our case, we assumed that campaigns launched closer to the shock were more likely to have been affected by the post-shock environment. Second, we contribute a richer approach to measuring quality in crowdfunding platforms. We went beyond the platform's structured features (used in previous research) and, using a manual evaluation approach, sought to incorporate additional subtle quality signals that backers take into account when making investment decisions, including entrepreneurs' resource investment (time, money, effort) and (perceived) competence.

Third, our work adds to the literature on the effects of crowdfunding platform design decisions by informing the debate on open versus closed platform acceptance policies. Previous research in IS has examined this issue in several contexts. Specifically, Boudreau et al. (2010) examined the effects of different levels of platform openness in the context of computing platforms. More recently, Niculescu et al. (2018) explored the strategic decision of an incumbent platform owner to open the core technology of its platform to other competitors on the same side of the ecosystem. In the context of the peer economy, Wessel et al. (2017) have shown that market openness raises the revenues of the platform but lowers the performance of the individual seller. We add to this literature by demonstrating that platform openness can lead to the emergence of supply-side phenomena that are not possible in markets with strict barriers for entry—such as an influx in low-quality offers—and that these phenomena affect platform dynamics and performance.

From a theoretical perspective, this work is among the first to focus on supply-side shocks in share economy platforms. As elaborated above, these shocks warrant investigation in light of the particular characteristics of sellers on peer economy platforms, who are individuals (rather than firms) who watch TV and consume content online, and who act instantly to capitalize on what they consider to be business opportunities. Additionally, our work links the theory of choice overload with signaling theories, by stipulating and empirically showing that reliance on quality signaling can mitigate the detrimental effects of choice overload, by allowing for differentiation between offers in crowdfunding markets.

Finally, our paper has several important managerial implications: For entrepreneurs, we show that, on average, the performance of crowdfunding campaigns suffers when the market is flooded with low-quality campaigns. Although high-quality campaigns are somewhat less susceptible to this effect compared with lower-quality campaigns, the average entrepreneur who wishes to launch a crowdfunding campaign is advised to wait for the influx of low-quality campaigns to subside. For platform designers, we provide empirical evidence that a platform can succeed in signaling the quality of its campaigns, and thereby mitigate some of the damage caused by flooding the marketplace with low-quality offerings.

Limitations and Future Work

We acknowledge that our work has certain limitations. First, the setting of our paper and the data available to us do not enable us to empirically conclude whether the negative influence of the post-shock environment on performance was specifically due to the increase in low-quality campaigns, or whether it might have been due to the increase in the number of campaigns in general. That is, we cannot say how a steep increase in the number of high-quality campaigns would have affected the performance of campaigns on the platform. That being said, seeing as peer economy platforms keep moving toward more open and democratic policies that allow laypersons and amateurs to enter the market, it is crucial for both platform owners and participants in the market to better understand the implications of being flooded with low-quality offerings. Second, as elaborated above, a sharp increase in low-quality offerings on crowdfunding platforms is conditioned on the platform having a lenient acceptance policy that enables opportunistic entrepreneurs to enter the market. Platforms with more restrictive policies may be characterized by different dynamics that are not covered in the current investigation. Another limitation is that our empirical investigation relies on a single media shock that brought with it a sharp increase in the number of low-quality campaigns. As noted above, we did not identify any other comparable shocks on Kickstarter. Future research should seek to identify and analyze additional shocks of this nature, both on Kickstarter and on other platforms, in order to evaluate the robustness and generalizability of our conclusions. Finally, our limited observational data do not enable us to carry out an in-depth study of backers' full decision processes. Future work could delve into this further. Another interesting avenue for future research would be to model additional supply-side signaling constructs, beyond quality—such as owner signaling effort and signaling costs—and examine how they are affected by an influx of low-quality offerings.

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RESEARCH ARTICLE

A Potato Salad with a Lemon Twist: Using a Supply-Side Shock to Study the Impact of Opportunistic Behavior on Crowdfunding Platforms

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Appendix A

Deriving Quality Measures

We have made an effort and have taken one step further to enrich our variable set to gain a more comprehensive and accurate measurement of campaign quality. In the spirit of prior work, we consider the extent to which the entrepreneur has invested effort and resources in the campaign, and the level of professionalism of the entrepreneur.

Mollick (2013) has suggested that venture capitalists and crowdfunders assess entrepreneurial quality in similar ways. Specifically, both ultimately act to rationally assess project quality, of which the entrepreneur's level of preparation is a key indicator. Thus, Mollick hypothesizes that entrepreneurs who demonstrate more *preparedness* are more likely to be funded. We suggest that, in the domain of crowdfunding, entrepreneurial preparation is manifested in the effort and resources invested by the entrepreneur in preparation for launching a campaign. Additionally, marketing literature suggests that potential consumers take sellers' (perceived) effort and expense into account (Modig et al. 2014). In the context of crowdfunding, we can assume that consumers are literate enough to deduce the levels of expense and effort invested by the seller, and use them to infer whether the product is of better quality.

Thus, to measure potential backers' perceptions of such investment, we focused on the following campaign attributes, which a potential backer can deduce from viewing a campaign's page.

- Money spent by the entrepreneur before launching the campaign (Q4 in Table 2 in the paper).
- Time and effort spent in creating the campaign page (Q1 and Q3 in Table 2, respectively).
- Careful planning of the reward structure (Q6 in Table 2). This may indicate the level of detail in which the product or service was planned, and the consideration that the campaign creator has given to what is feasible to promise.

We further draw from literature showing that potential consumers use website design as a manifestation of the seller's *ability*, and that this assessment in turn impacts their online purchase intentions (Schlosser et al. 2006). Thus, in addition to Q3, which captures the effort invested by the entrepreneur in designing the campaign page, we also asked about:

- The level of professionalism of the design of the campaign page (Q2 in Table 2).
- The use of an additional website outside of Kickstarter domain (Q5 in Table 2).

Human capital is associated with entrepreneurial success and quality (Ahlers et al. 2015; Unger et al. 2011). However, the operationalization of human capital may be challenging within the context of Kickstarter, owing to the diversity of campaign categories, which range from art and food to design and technology. For example, for entrepreneurs in the technology category, an academic degree may provide a strong indication of "high" human capital (Doms et al. 2010; Levie and Gimmon 2008). However, a degree may be less useful as an indication of the quality of a dance act. Hence, in building our quality measurements, we directly asked evaluators to rank the (perceived) professionalism of the entrepreneurs in the field in which they operate (Q7 in Table 2). Again, assuming that the evaluators are not very different from the average Kickstarter backer, the answers will provide insights into the degree to which the campaign page signals professionalism within the context of the specific campaign category.

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Appendix B

Additional Supply Shocks

Our paper investigates the effects of a sharp increase in low-quality competition using one media shock that brought about a unique state on the Kickstarter platform. Specifically, following the shock, the supply on the platform (i.e., the number of campaigns offered) grew substantially, whereas the demand did not change significantly. To provide further robustness to our results, we searched for additional situations on Kickstarter in which supply increased sharply with no significant effect on demand. To this end, we identified dates in the platform's history on which spikes in supply occurred. We defined a "spike" as a day on which the number of campaigns launched was two standard deviations higher than the average number of campaigns launched in the days of the preceding two months. When searching for such dates we used data collected about all campaigns that were launched after June 3, 2014, when Kickstarter implemented a policy that lowered the entry barriers for new campaigns, and before May 2015. This dataset contained 75,872 campaigns. We identified eight events (unique days) in which there was a substantial increase in supply. These events took place on the following dates: January 20, 2015; January 21, 2015; January 26, 2015; January 27, 2015; February 2, 2015; February 9, 2015; February 17, 2015; and March 2, 2015. However, none of those events possessed the required characteristics. As can be observed, there was substantial overlap between the dates surrounding the different events. Thus, we could not correctly distinguish the demand in the weeks prior to each shock from the demand in the weeks following each shock, seeing as those weeks were influenced not only by the current shock being evaluated but most likely by other shocks as well.

Appendix C

Illustration of Time Proximity Identification Method

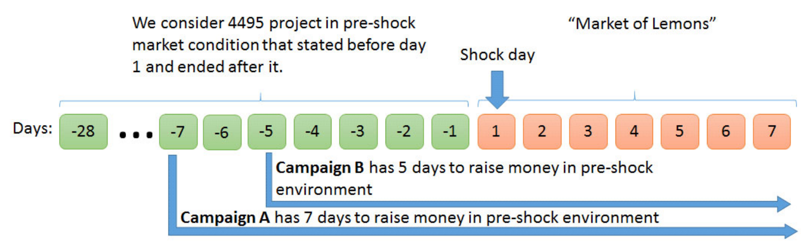

Figure C1. Illustration of Time Proximity Identification Method

Appendix D

PSM Identification: Balancing Tests for H2

Our matching was not performed on the variable *QualityPca*, but rather on the individual variables attributed to quality, as well as additional campaign characteristics. Thus we had to make sure that, for each low- and high-quality subsample (created by *QualityBinary*), *QualityPca* was balanced between the "before" and "after" groups. We tested this using both the Mann-Whitney rank test and the Wilcoxon rank-sum test. The results in Table D1 show that *QualityPca* was balanced for both the low-quality subsample and the high-quality subsample.

Table D1. Balancing Test of *QualityPca* Between "Before" and "After" Campaigns

	Mann-Whitney Rank Test	Wilcoxon Rank-Sum Test
Low quality	Statistic = 115996 ; p = 0.79	Statistic = 0.25 ; p = 0.79
High quality	Statistic = 114845 ; p = 0.99	Statistic = -0.01; p = 0.99

Appendix E

Interpretation of Coefficients and Economic Effects

In this appendix, we provide details about the calculation of the economic impacts reported in the paper. We first provide the calculations for all regression analyses in which a campaign's likelihood of success (*IsSuccessful*) was the dependent variable. Then we provide calculations for all regression analyses in which the amount pledged (*lnAmountPledged*) was the dependent variable. For each performance variable, we first present the regressions estimated using the time proximity identification, and then those estimated using the PSM identification.

For convenience of presentation, in what follows, the variable notation *DaysFromShockDay* has been shortened to *days*, *IsSuccessful* has been shortened to *success*, and *AmountPledged* has been changed to *pledged*.

Logistic Regressions Focusing on the Success Rate

Time Proximity Identification:

(a) Effect of ln(*days*) on success, no interaction term

Let **success** be the binary outcome variable indicating failure/success with 0/1, and let p be the probability of success to be 1, p = prob(success=1). Let $\ln(days)$, and $X_2 \dots X_k$ be a set of predictor variables. Then the logistic regression of success on $\ln(days)$ and $X_2 \dots X_k$ estimates parameter values for β0, β1, …, βk using the following equation.

logit(p) = log(p/(1-p))= $\beta_0 + \beta_1 * \ln(days) + \dots + \beta_k * X_k$

$$\frac{p}{1-p} = e^{\beta_0 + \beta_1 \ln(days) + \beta_{2:k}\boldsymbol{X}} = e^{\beta_0}(days)^{\beta_1} e^{\beta_{2:k}\boldsymbol{X}}$$

All else being held equal, if *days* increases by 10%, that is, by a factor of 1.1, then:

$$\frac{p}{1-p} = e^{\beta_0}(1.1days)^{\beta_1} e^{\beta_{2:k}\boldsymbol{X}} = e^{\beta_0}(days)^{\beta_1} e^{\beta_{2:k}\boldsymbol{X}} (\mathbf{1.1})^{\boldsymbol{\beta_1}}$$

That is, all else being held equal, for a 10% increase in *days* the odds of being successful change by a factor of $(\mathbf{1.1})^{\boldsymbol{\beta_1}}$
For our data this means that for a 10% increase in *days*, the odds of being successful increase by a factor of $(1.1)^{0.155}$ = **1.0149** when controlling for QualityPca and by a factor of $(1.1)^{0.16}$ = **1.0154** when controlling for QualityBinary.

(b) Effect of ln(*days*) on success, with binary interaction term

Continuing with the logic above, we examine the following equation:

logit(p) = log(p/(1-p))= $\beta_0 + \beta_1 \ln(days) + \beta_2 quality_{binary} + \beta_3 \ln(days)\, quality_{binary} + \beta_{4:k}\boldsymbol{X}$

$$\frac{p}{1-p} = e^{\beta_0 + \beta_1 \ln(days) + \beta_2 quality\_binary + \beta_3 \ln(days) quality\_binary + \beta_{4:k}\boldsymbol{X}}$$
$$= e^{\beta_0}(days)^{\beta_1} e^{\beta_2 quality\_binary} e^{\beta_3 \ln(days) quality\_binary} e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when QualityBinary = 0** then:

$$[\frac{p}{1-p} | quality\_binary = 0] = e^{\beta_0}(\boldsymbol{days})^{\boldsymbol{\beta_1}} e^{\beta_{4:k}\boldsymbol{X}}$$

That is, all else being held equal, when considering **low-quality** campaigns, a 10% increase (that is an increase by a factor of 1.1) in *days* changes the odds of being successful by a factor of $(\mathbf{1.1})^{\boldsymbol{\beta_1}}$**.**

All else being held equal, **when *QualityBinary* = 1** then:

$$[\frac{p}{1-p} | qualityBinary = 1] = e^{\beta_0}(days)^{\beta_1} e^{\beta_2} e^{\beta_3 \ln(days)} e^{\beta_{4:k}\boldsymbol{X}} = e^{\beta_0 + \beta_2}(days)^{\beta_1}(days)^{\beta_3} e^{\beta_{4:k}\boldsymbol{X}} =$$
$$e^{\beta_0 + \beta_2}(\boldsymbol{days})^{\boldsymbol{\beta_1 + \beta_3}} e^{\beta_{4:k}\boldsymbol{X}}$$

That is, all else being held equal, when considering high-quality campaigns, a 10% increase in *days* changes the odds of being successful by a factor of $(\mathbf{1.1})^{\boldsymbol{\beta_1 + \beta_3}}$

For our data this means that for low-quality campaigns, the odds of being successful increase by a factor of $(\mathbf{1.1})^{\mathbf{0.305}}$ = 1.03 for a 10% increase in the distance from the shock. In contrast, for high-quality campaigns the odds increase by a factor of $(\mathbf{1.1})^{\mathbf{0.305-0.244}}$ =1.006.

Matching:

(a) Effect of *before* on success, no interaction term

$$\text{logit(p)} = \log(\text{p}/(1-\text{p})) = \beta_0 + \beta_1 before + \beta_{2:k}\boldsymbol{X}$$

$$\frac{p}{1-p} = e^{\beta_0 + \beta_1 before + \beta_{2:k}\boldsymbol{X}}$$

$$\frac{p}{1-p} = e^{\beta_0 + \beta_1 before + \beta_{2:k}\boldsymbol{X}} = e^{\beta_0} e^{\beta_1 before} e^{\beta_{2:k}\boldsymbol{X}}$$

All else being held equal, **when QualityBinary = 0** then:

$$[\frac{p}{1-p}|Before = 0] = e^{\beta_0} e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when QualityBinary = 1** then:

$$[\frac{p}{1-p}|Before = 1] = e^{\beta_0} e^{\beta_1} e^{\beta_{4:k}\boldsymbol{X}}$$

$$\frac{\frac{p}{1-p}|Before = 1}{\frac{p}{1-p}|Before = 0} = \frac{e^{\beta_0} e^{\beta_1} e^{\beta_{4:k}\boldsymbol{X}}}{e^{\beta_0} e^{\beta_{4:k}\boldsymbol{X}}} = e^{\beta_1} \rightarrow [\frac{p}{1-p}\Big|Before = 1] = [\frac{p}{1-p}\Big| Before = 0] * \boldsymbol{e^{\beta_1}}$$

This means that, all else being held equal, launching a campaign before the shock changes the odds of being successful by a factor of $\boldsymbol{e^{\beta_1}}$.

For our data, this means, that that the odds that a campaign launched before the shock will succeed are greater by a factor of $\boldsymbol{e}^{0.276}$ =1.3 compared with the odds that a (similar) campaign launched after the shock will succeed.

(b) Effect of *before* on success, with binary interaction term

$$\text{logit(p)} = \log(\text{p}/(1-\text{p})) = \beta_0 + \beta_1 before + \beta_2 quality\_binary + \beta_3 before * quality\_binary + \beta_{2:k}\boldsymbol{X}$$

$$\frac{p}{1-p} = e^{\beta_0 + \beta_1 before + \beta_2 quality\_binary + \beta_3 before * quality\_binary + \beta_{4:k}\boldsymbol{X}}$$

$$= e^{\beta_0} e^{\beta_1 before} e^{\beta_2 qualityBinary} e^{\beta_3 before * qualityBinary} e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when before = 0 and QualityBinary = 0** then:

$$[\frac{p}{1-p}|Before = 0; qualityBinary = 0] = e^{\beta_0} e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when before = 1 and QualityBinary = 0** then:

$$[\frac{p}{1-p}|Before = 1; quality\_binary = 0] = e^{\beta_0} e^{\beta_1} e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when before = 0 and QualityBinary = 1** then:

$$[\frac{p}{1-p}|Before = 0; quality\_binary = 1] = e^{\beta_0} e^{\beta_2} e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when before = 1 and QualityBinary = 1** then:

$$[\frac{p}{1-p}|Before = 1; quality\_binary = 1] = e^{\beta_0} e^{\beta_1} e^{\beta_2} e^{\beta_3} e^{\beta_{4:k}\boldsymbol{X}}$$

When considering **low-quality** campaigns (QualityBinary = 0):

$$\frac{\frac{p}{1-p}|Before = 1; quality\_binary = 0}{\frac{p}{1-p}|Before = 0; quality\_binary = 0} = \frac{e^{\beta_0}e^{\beta_1}e^{\beta_{4:k}\boldsymbol{X}}}{e^{\beta_0}e^{\beta_{4:k}\boldsymbol{X}}} = e^{\beta_1}$$

That is, when considering low-quality campaigns, being a "before" campaign changes the odds of being successful by a factor of $\boldsymbol{e^{\beta_1}}$.

When considering high-quality campaigns (QualityBinary = 1):

$$\frac{\frac{p}{1-p}|Before = 1; quality\_binary = 1}{\frac{p}{1-p}|Before = 0; quality\_binary = 1} = \frac{e^{\beta_0}e^{\beta_1}e^{\beta_2}e^{\beta_3}e^{\beta_{4:k}\boldsymbol{X}}}{e^{\beta_0}e^{\beta_2}e^{\beta_{4:k}\boldsymbol{X}}} = e^{\beta_1}\boldsymbol{e^{\beta_3}}$$

That is, when considering high-quality campaigns, launching a campaign before the shock changes the odds of being successful by a factor of $\boldsymbol{e^{\beta_1+\beta_3}}$. Additionally, this means that compared to the change in low-quality campaigns, the effect of *before* on the odds to succeed differs by a factor of $\boldsymbol{e^{\beta_3}}$.

For our data this means that for a low-quality campaign, the odds of being successful increase by a factor of $\boldsymbol{e}^{0.511}$ = 1.67 if the campaign is launched before the shock, whereas for a high-quality campaign the odds increase only by a factor of $e^{\mathbf{0.511-0.403}}$ = 1.11.

(c) Effect of *before* on success, with continuous interaction term

$$\text{logit(p)} = \log(\text{p}/(1-\text{p})) = \beta_0 + \beta_1 before + \beta_2 quality + \beta_3 before * qualityPca + \beta_{2:k}\boldsymbol{X}$$
$$\frac{p}{1-p} = e^{\beta_0 + \beta_1 before + \beta_2 quality + \beta_3 before * qualityPca + \beta_{4:k}\boldsymbol{X}}$$
$$= e^{\beta_0}e^{\beta_1 before}e^{\beta_2 quality}e^{\beta_3 before*qualityPca}e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when before = 0** then:

$$[\frac{p}{1-p}|Before = 0] = e^{\beta_0}e^{\beta_2 qualityPca}e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when before = 1** then:

$$[\frac{p}{1-p}|Before = 1] = e^{\beta_0}e^{\beta_1}e^{\beta_2 qualityPca}e^{\beta_3 qualityPca}e^{\beta_{4:k}\boldsymbol{X}}$$

$$\frac{\frac{p}{1-p}|Before = 1}{\frac{p}{1-p}|Before = 0} = \frac{e^{\beta_0}e^{\beta_1}e^{\beta_2 qualityPca}e^{\beta_3 qualityPca}e^{\beta_{4:k}\boldsymbol{X}}}{e^{\beta_0}e^{\beta_2 qualityPca}e^{\beta_{4:k}\boldsymbol{X}}} = e^{\beta_1}e^{\beta_3 qualityPca}$$

That is, for a 1-unit increase in quality, the ratio between the odds of being successful before and after equals:

$$\frac{\frac{p}{1-p}|Before = 1}{\frac{p}{1-p}|Before = 0} = \frac{e^{\beta_0}e^{\beta_1}e^{\beta_2 qualityPca+1}e^{\beta_3 qualityPca+1}e^{\beta_{4:k}\boldsymbol{X}}}{e^{\beta_0}e^{\beta_2 quality}e^{\beta_{4:k}\boldsymbol{X}}} = e^{\beta_1}e^{\beta_3(qualityPca+1)} = e^{\beta_1}e^{\beta_3 qualityPca+\beta_3}$$
$$= e^{\beta_1}e^{\beta_3 qualityPca}\boldsymbol{e^{\beta_3}}$$

This means that for a 1-unit increase in the quality, the ratio between the odds of being successful before and after changes by a factor of $\boldsymbol{e^{\beta_3}}$.

For our data, this means that when observing the effect on the odds to succeed, a 1-unit increase in QualityPca decreases the effect of being before the shock by a factor of $\boldsymbol{e}^{-0.120} = \mathbf{0.887}$. That is, as the quality increases the effect of being before the shock decreases. That is, high quality campaigns are less affected.

OLS Regressions Focusing on the Amount of Money Pledged

Time Proximity Identification:

(a) **Effect of ln(*days*) on ln(*pledged*), no interaction term**

$$\ln(pledged) = \beta_0 + \beta_1 \ln(days) + \beta_{2:k}\boldsymbol{X}$$
$$e^{\ln(pledged)} = e^{\beta_0 + \beta_1 \ln(days) + \beta_{2:k}\boldsymbol{X}}$$
$$pledged = e^{\beta_0 + \beta_1 \ln(days) + \beta_{2:k}\boldsymbol{X}} = e^{\beta_0} e^{\beta_1 \ln(days)} e^{\beta_{2:k}\boldsymbol{X}} = e^{\beta_0} (e^{(\ln(days))})^{\beta_1} e^{\beta_{2:k}\boldsymbol{X}} = e^{\beta_0} (days)^{\beta_1} e^{\beta_{2:k}\boldsymbol{X}}$$

All else being held equal, if *days* increases by 10%, that is, by 1.1, then:

$$pledged = e^{\beta_0} (1.1days)^{\beta_1} e^{\beta_{2:k}\boldsymbol{X}} = e^{\beta_0} (\mathbf{1.1})^{\boldsymbol{\beta_1}} (days)^{\beta_1} e^{\beta_{2:k}\boldsymbol{X}}$$

That is, all else being held equal, for a 10% increase in *days*, the amount of money pledged increases by $(\mathbf{1.1})^{\boldsymbol{\beta_1}}$.

For our data this means that for a 10% increase in distance from the shock, we see an increase by a factor of $(1.1)^{0.143} =$ 1.014 when controlling for QualityPca and by a factor of $(1.1)^{0.18} = 1.017$ when controlling for QualityBinary. In other words, we see an increase of 1.4-1.7% in the average amount pledged.

If we consider a 50% increase in distance from the shock, we see an increase by a factor of $(1.5)^{0.143} = 1.06$ - $(1.5)^{0.18} =$ 1.076, that is, an increase of 6-7.6% in the average amount pledged.

(b) **Effect of ln(*days*) on ln($\boldsymbol{pledged}$) with interaction term**

$$\ln(pledged) = \beta_0 + \beta_1 \ln(days) + \beta_2 quality\_binary + \beta_3 \ln(days)\, quality\_binary + \beta_{4:k}\boldsymbol{X}$$
$$e^{\ln(pledged)} = e^{\beta_0 + \beta_1 \ln(days) + \beta_2 quality\_binary + \beta_3 \ln(days) quality\_binary + \beta_{4:k}\boldsymbol{X}}$$
$$\begin{aligned} pledged &= e^{\beta_0 + \beta_1 \ln(days) + \beta_2 quality\_binary + \beta_3 \ln(days) quality\_binary + \beta_{4:k}\boldsymbol{X}} \\ &= e^{\beta_0} e^{\beta_1 \ln(days)} e^{\beta_2 quality\_binary} e^{\beta_3 \ln(days) * quality\_binary} e^{\beta_{4:k}\boldsymbol{X}} \\ &= e^{\beta_0} (e^{(\ln(days))})^{\beta_1} e^{\beta_2 quality\_binary} e^{\beta_3 \ln(days) quality\_binary} e^{\beta_{4:k}\boldsymbol{X}} \\ &= e^{\beta_0} (days)^{\beta_1} e^{\beta_2 quality\_binary} e^{\beta_3 \ln(days) quality\_binary} e^{\beta_{4:k}\boldsymbol{X}} \end{aligned}$$

All else being held equal, **when QualityBinary = 0** then:

$$pledged | quality\_binary = 0 = e^{\beta_0} (days)^{\beta_1} e^{\beta_{4:k}\boldsymbol{X}}$$

That is, all else being held equal, for a 10% increase in *days*, the amount of money pledged to low-quality campaigns increases by a factor of $(\mathbf{1.1})^{\boldsymbol{\beta_1}}$.

All else being held equal, **when QualityBinary = 1** then:

$$pledged | quality\_binary = 1 = e^{\beta_0} (days)^{\beta_1} e^{\beta_2} e^{\beta_3 \ln(days)} e^{\beta_{4:k}\boldsymbol{X}} = e^{\beta_0 + \beta_2} (days)^{\beta_1} (days)^{\beta_3} e^{\beta_{4:k}\boldsymbol{X}} = e^{\beta_0 + \beta_2} (\boldsymbol{days})^{\boldsymbol{\beta_1 + \beta_3}} e^{\beta_{4:k}\boldsymbol{X}}$$

That is, all else being held equal, for a 10% increase in *days*, the amount of money pledged to high-quality campaigns increases by a factor of $(\mathbf{1.1})^{\boldsymbol{\beta_1 + \beta_3}}$.

For our data this means that for low-quality campaigns a 10% increase in distance from the shock is expected to yield an increase by a factor of $(1.1)^{0.265} = \mathbf{1.026}$ (2.6%), whereas for high-quality campaigns a 10% increase in distance is expected to yield only a $(1.1)^{0.265-0.192} = \mathbf{1.007}$ (0.7%) increase in the amount pledged.

Matching:

(a) **Effect of *before* on ln($\boldsymbol{pledged}$), no interaction term**

$$\ln(pledged) = \beta_0 + \beta_1 before + \beta_{2:k}\boldsymbol{X}$$
$$e^{\ln(pledged)} = e^{\beta_0 + \beta_1 before + \beta_{2:k}\boldsymbol{X}}$$
$$pledged = e^{\beta_0 + \beta_1 before + \beta_{2:k}\boldsymbol{X}} = e^{\beta_0} e^{\beta_1 before} e^{\beta_{2:k}\boldsymbol{X}}$$

All else being held equal, **when QualityBinary = 0** then:

$$pledged|Before = 0 = e^{\beta_0} e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when QualityBinary = 1 t**hen:

$$pledged|Before = 1 = e^{\beta_0} e^{\beta_1} e^{\beta_{4:k}\boldsymbol{X}}$$

$$\frac{pledged|Before = 1}{pledged|Before = 0} = \frac{e^{\beta_0} e^{\beta_1} e^{\beta_{4:k}\boldsymbol{X}}}{e^{\beta_0} e^{\beta_{4:k}\boldsymbol{X}}} = e^{\beta_1} \rightarrow [pledged|Before = 1] = [pledged|Before = 0] * e^{\beta_1}$$

These results mean that, all else being held equal, being a "before" campaign increases the amount of money pledged by a factor of $\boldsymbol{e^{\beta_1}}$.

For our data, this means that the odds of a "before" campaign succeeding are greater by a factor of $\boldsymbol{e}^{0.310}$ =1.36 (when controlling for QualityPca) compared with those of (similar) campaigns launched after the shock (when controlling for QualityBinary we see an increase by a factor of $\boldsymbol{e}^{0.360}$ =1.43).

(b) **Effect of *before* on ln($\boldsymbol{pledged}$), with binary interaction term**

$$\ln(pledged) = \beta_0 + \beta_1 before + \beta_2 quality\_binary + \beta_3 before * quality\_binary + \beta_{2:k}\boldsymbol{X}$$
$$e^{\ln(pledged)} = e^{\beta_0 + \beta_1 before + \beta_2 quality\_binary + \beta_3 before * quality\_binary + \beta_{4:k}\boldsymbol{X}}$$
$$pledged = e^{\beta_0 + \beta_1 before + \beta_2 quality\_binary + \beta_3 before * quality\_binary + \beta_{4:k}\boldsymbol{X}}$$
$$= e^{\beta_0} e^{\beta_1 before} e^{\beta_2 quality\_binary} e^{\beta_3 before * quality\_binary} e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when *before* = 0 and QualityBinary = 0** then:

$$[pledged|Before = 0; quality\_binary = 0] = e^{\beta_0} e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when *before* = 1 and QualityBinary = 0** then:

$$[pledged|Before = 1; quality\_binary = 0] = e^{\beta_0} e^{\beta_1} e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when *before* = 0 and QualityBinary = 1** then:

$$[pledged|Before = 0; qualityBinary = 1] = e^{\beta_0} e^{\beta_2} e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when *before* = 1 and QualityBinary = 1** then:

$$[pledged|Before = 1; quality\_binary = 1] = e^{\beta_0} e^{\beta_1} e^{\beta_2} e^{\beta_3} e^{\beta_{4:k}\boldsymbol{X}}$$

When considering **low-quality** campaigns (QualityBinary = 0):

$$\frac{pledged|Before = 1; qualitybinary = 0}{pledged|Before = 0; qualityBinary = 0} = \frac{e^{\beta_0} e^{\beta_1} e^{\beta_{4:k}\boldsymbol{X}}}{e^{\beta_0} e^{\beta_{4:k}\boldsymbol{X}}} = e^{\beta_1}$$

That is, for low-quality campaigns, being a "before" campaign increases the average amount pledged by a factor of $\boldsymbol{e^{\beta_1}}$.

When considering **high-quality** campaigns (QualityBinary=1):

$$\frac{pledged|Before = 1; quality\_binary = 1}{pledged|Before = 0; quality\_binary = 1} = \frac{e^{\beta_0} e^{\beta_1} e^{\beta_2} e^{\beta_3} e^{\beta_{4:k}\boldsymbol{X}}}{e^{\beta_0} e^{\beta_2} e^{\beta_{4:k}\boldsymbol{X}}} = e^{\beta_1} e^{\beta_3}$$

That is, for high-quality campaigns, being a "before" campaign increases the average amount pledged by a factor of $\boldsymbol{e^{\beta_1 + \beta_3}}$. Additionally, this means that when compared to the increase in low quality campaigns, the effect of *before* on the amount pledged to high-quality campaigns is greater by a factor of $\boldsymbol{e^{\beta_3}}$.

For our data this means that for low-quality campaigns, being a "before" campaign increases the amount of money pledged by a factor of $\boldsymbol{e}^{0.621} = 1.86$, whereas for high-quality campaigns, being a "before" campaign increases the amount of money pledged by a factor of only $e^{\mathbf{0.621-0.528}} = 1.10$.

(c) **Effect of *before* on ln($\boldsymbol{pledged}$), with a continuous interaction term**

$$\ln(pledged) = \beta_0 + \beta_1 before + \beta_2 quality + \beta_3 before * quality\_pca + \beta_{2:k}\boldsymbol{X}$$
$$e^{\ln(pledged)} = e^{\beta_0 + \beta_1 before + \beta_2 quality\_pca + \beta_3 before * quality\_pca + \beta_{4:k}\boldsymbol{X}}$$
$$pledged = e^{\beta_0 + \beta_1 before + \beta_2 quality\_pca + \beta_3 before * quality\_pca + \beta_{4:k}\boldsymbol{X}} = e^{\beta_0} e^{\beta_1 before} e^{\beta_2 quality\_pca} e^{\beta_3 before * quality\_pca} e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when *before* = 0** then:

$$[pledged|Before = 0] = e^{\beta_0} e^{\beta_2 quality\_pca} e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when *before* = 1** then:

$$[pledged|Before = 1] = e^{\beta_0} e^{\beta_1} e^{\beta_2 quality\_pca} e^{\beta_3 quality\_pca} e^{\beta_{4:k}\boldsymbol{X}}$$

$$\frac{pledged|Before = 1}{pledged|Before = 0} = \frac{e^{\beta_0} e^{\beta_1} e^{\beta_2 quality\_pca} e^{\beta_3 quality\_pca} e^{\beta_{4:k}\boldsymbol{X}}}{e^{\beta_0} e^{\beta_2 quality\_pca} e^{\beta_{4:k}\boldsymbol{X}}} = e^{\beta_1} e^{\beta_3 quality\_pca}$$

That is, for a 1-unit increase in quality, the ratio between money pledged before and money pledged after equals:

$$\frac{pledged|Before = 1}{pledged|Before = 0} = \frac{e^{\beta_0} e^{\beta_1} e^{\beta_2 quality\_pca} e^{\beta_3 quality\_pca} e^{\beta_{4:k}\boldsymbol{X}}}{e^{\beta_0} e^{\beta_2 quality\_pca} e^{\beta_{4:k}\boldsymbol{X}}} = e^{\beta_1} e^{\beta_3 (quality\_pca+1)} = e^{\beta_1} e^{\beta_3 quality\_pca + \beta_3}$$
$$= e^{\beta_1} e^{\beta_3 quality\_pca} \boldsymbol{e^{\beta_3}}$$

This means that for a 1-unit increase in quality, the ratio between the amount pledged before the shock and the amount pledged after the shock changes by a factor of $\boldsymbol{e^{\beta_3}}$.

For our data, this means that when observing the effect on the amount pledged, a 1-unit increase in *QualityPca* decreases the effect of being a "before" campaign by a factor of $\boldsymbol{e}^{-0.116} = \mathbf{0.89}$. That is, as the quality increases, the effect of being a "before" campaign decreases, such that higher-quality campaigns are less affected.