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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ABSTRACT

Crowdfunding platforms are peer-to-peer two-sided markets that enable amateur entrepreneurs to raise money for their ventures over the Internet. However, in allowing practically anyone to enter, such markets risk being flooded with low-quality offerings, a situation often referred to as a "market of lemons". 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 method 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 by the "market of lemons" than low-quality campaigns are. We discuss theoretical implications as well as managerial implications for entrepreneurs and platform designers.

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

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INTRODUCTION

Crowdfunding platforms enable entrepreneurs to raise money for their products or services over the Internet (Belleflamme et al. 2014; Agrawal et al. 2015). 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 market facilitated by crowdfunding platforms is referred to as the peer economy, or the share economy (Sundararajan 2013; Fournier et al. 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 them with off-the-shelf technology and frameworks that can streamline their very first steps towards launching their ventures (Agrawal et al. 2015). Indeed, this accessibility can enable unknown entrepreneurs to shine[1], a feature that is enhanced by the fact that many crowdfunding platforms have a relatively open acceptance policy. For example, in order to launch a crowdfunding campaign on the popular crowdfunding 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 implemented a similar approach in early June 2014 with a feature called "Launch Now". Nowadays, Kickstarter relies on a machine-

1 https://www.kickstarter.com/discover/most-funded (visited 18 July 2016)

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. Thus, effectively, open crowdfunding platforms democratize the process of gaining access to financial services by lowering the bar for entry (as compared, e.g., with seeking funding from venture capital investors), while creating the romantic possibility that a "diamond in the rough" might emerge (Agrawal et al 2014; Gleasure and Feller 2016).

However, this democratization may come with a cost. Low entry barriers facilitate opportunistic behavior, and indeed, recent findings suggest that such behavior emerges in crowdfunding environments (Hildebrand et al. 2016; Kim et al 2017). In addition, Burtch et al. (2017) found that gig-economy platforms, such as Uber, *"predominantly reduce lower quality entrepreneurial activity by offering viable employment for the un- and under-employed."* This observation suggests that these individuals turned to entrepreneurial activity because of their low opportunity costs (Block and Koellinger 2009) rather than a sincere desire to promote excellent ideas.

Taken together, these ideas suggest that opportunistic behavior can expose a crowdfunding platform to the risk of being flooded with low-quality offerings, a situation popularly known as a "market of lemons". Akerlof (1970) argues that when a market is flooded with lemons, and when information is asymmetric, high-quality sellers are also affected and ultimately leave the marketplace. Information asymmetry, however, can be mitigated by quality signals (Spence 1973). When perfect information on quality is unavailable or costly, on-platform quality signals can reduce information asymmetry, enabling better-quality campaigns to stand out. Thus, the ability of a platform to enable quality signaling is crucial to avoid market failure (Brealey et al 1977).

Recent studies have discussed design features of online crowd-based platforms (Ipeirotis and Paritosh 2011; Fort et al. 2011) that may serve as quality signals and help mitigate the risks of becoming a market of lemons. In general, these features involve increasing transparency and reducing information asymmetry. Hence, sellers on crowdfunding platforms may use established signaling mechanisms known from the marketing literature (Kirmani and Rao 2000) to designate high-quality offerings (Ibrahim 2015). For example, crowdfunding platforms may use reputation systems, friendship networks, and discussion boards to reduce information asymmetry (Tomboc 2013). While many crowdfunding platforms currently implement various quality-signaling features (Mollick 2014), few studies thus far have examined the effectiveness of such features in preventing potentially negative outcomes of the presence of low-quality offerings.

In this paper, we aim to close this gap using data from Kickstarter.com, the Internet's largest and most popular crowdfunding platform. Specifically, we examine the performance of crowdfunding campaigns when the market is in a state of an unusually high number of low-quality campaigns. First, we evaluate **the impact of a sharp increase in the number of low-quality campaigns on the average performance of all campaigns on the platform (H1)**. We focus on two performance metrics: success rate (the fraction of campaigns that reach their stated fundraising goals) and amount of money pledged per campaign. Crowdfunding platforms are characterized by high variation in quality. We suggest that if quality is well signaled in the platform, campaigns of different quality levels should be affected differently by a sharp increase in the number of low-quality campaigns. Thus, **we study whether the effects are less pronounced among campaigns of higher quality** (H2).

To address these questions, we utilize a quasi-natural experiment in the form of an exogenous shock, which occurred on Kickstarter.com and resulted in a short-term flooding of the market with low-quality campaigns. In the summer of 2014, Zack "Danger" Brown, from Columbus, Ohio, started a Kickstarter crowdfunding campaign asking for $10 in order to finance the making of a potato salad. This campaign ultimately raised tens of thousands of dollars from almost 7,000 backers, and attracted substantial coverage in popular media outlets. This media attention created a spike in the number of new campaigns opened for funding on Kickstarter. As we show in what follows, those new campaigns were mostly opportunistic and of low quality. These unique circumstances enable us to estimate how an atypically large influx of low-quality campaigns affects crowdfunding performance, while controlling for unobserved variables and endogeneity. Interestingly, this supply-side shock did not affect the demand side—hence, this potential source of a confounding effect is controlled for through our research conditions.

We combine two sources of data. The first is a comprehensive set of archival data from Kickstarter. We complement this Kickstarter dataset with a second dataset, based on a large-scale survey by which we manually evaluated the quality features of all campaigns in our dataset. This dataset provides additional measures and information for each campaign, which enable us to develop new quality indicators.

We use two identification methods to estimate both the effect of the number of low-quality campaigns on average campaign performance, as well as the differential effects of an influx of lemons on campaigns of different quality. 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 increase in 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.

Our paper carries methodological, empirical and managerial contributions.

First, we add to the growing body of work on crowdfunding campaigns by studying the supply-side effects of a sharp increase in the number of low-quality campaigns. We provide empirical evidence for the presence of signaling mechanisms in crowdfunding platforms and their moderating effect on campaign performance in situations in which the market is flooded with low-quality campaigns (“lemons”). Notably, this work is among the first to focus on supply-side shocks on share economy platforms. While previous studies have focused on demand-side shocks in two-sided markets (Shankar and Bayus 2003; Zhang and Liu 2012; Liu et al. 2015), little attention has been given thus far to supply-side fluctuations. We argue that such supply-side shocks are inherent to open peer economy platforms. More broadly, we consider opportunistic behavior of amateur sellers to be a key factor that distinguishes peer economy platforms from firm-based two-sided platforms.

From a methodological perspective, our work presents a novel identification method to control for quality fluctuations when studying natural experiments. Further, we enrich the study of crowdfunding platforms by providing new measures of campaign quality. Our suggested measures go beyond the platform's structural features and incorporate factors that individuals actually take into account when evaluating campaigns. These include the entrepreneurs' resource investment (time, money, effort) and (perceived) competence.

Finally, our work carries important managerial implications. For entrepreneurs, we show that, on average, the general performance of campaigns on a crowdfunding platform suffers when the market is flooded with low-quality campaigns. Although campaign quality moderates this effect, our observation implies that the average entrepreneur who wishes to launch a crowdfunding campaign would benefit from waiting for the tide to turn. More importantly, for platform designers, we provide empirical evidence that platforms can succeed in signaling campaigns' quality, and can mitigate some of the damage caused when the marketplace is inundated with low-quality offerings.

Our paper proceeds as follows. First, we present our theoretical background and develop our hypotheses. Then we describe our context, namely, the Kickstarter environment and the exogenous shock on which we base our analysis. Next, we present the data used in the study and carry out an in-depth descriptive analysis of the shock. In the subsequent section we develop our novel measures of campaign quality. We proceed by outlining our empirical methodology, which includes our two identification strategies. Following that, we present our results. We conclude with a discussion of our results.

THEORETICAL BACKGROUND AND HYPOTHESIS BUILDING

This paper examines the consequences of a brief period of high-profile media coverage of the crowdfunding platform Kickstarter, which led to a sharp increase in the platform’s offerings. Before we delve into these consequences, we first need to fully appreciate the market structure in which Kickstarter operates, and the conditions that enabled such an influx of new offerings to happen. To do so, we start by reviewing the crowdfunding literature. Then, we review literature on peer-to-peer platform structures and open acceptance policies, and their expected effects. We then develop hypotheses regarding the effect that a sharp increase in offerings is expected to have on the performance of crowdfunding campaigns, and we motivate our specific focus on a sharp increase in low quality offerings. We subsequently develop hypotheses regarding the moderating role of campaign quality in this effect.

Crowdfunding Platforms

IS scholars have been devoting increasing attention to crowdfunding phenomena. Research in this area encompasses multiple domains, including studying the motivation to participate in crowdfunding markets (Ryu and Kim 2016, Belleflamme et al. 2014; Schwienbacher and Larralde 2012; Gerber and Hui 2013); drivers of crowdfunding success (Mollick 2014, Agrawal et al. 2015, Ward and Ramachandran 2010; Inbar and Barzilay 2014, Zhang and Liu 2012); information used for decision making on crowdfunding platforms (Lin et al. 2013; Liu et al. 2015); signaling mechanisms on such platforms (Hildebrand et al. 2017, Kim and Viswanathan 2016, Lin et al.2013, Liu et al. 2015); the effects of “blockbusters” (campaigns that raise extremely large amounts of money) on platform performance (Liu et al. 2015); differences between crowdfunding and traditional fundraising (Ryu and Kim. 2017); and the effect of information disclosure on platform stability and performance (Kim et al. 2017, Burtch et al. 2016, Burtch et al. 2015). Several works have focused on the supply side of crowdfunding platforms, and in particular on sellers' bias, such as gender bias (Marom et al 2016) and racial bias (Rhue 2015; Younkin and Kuppuswamy 2016).

Open Acceptance Policies in the Peer Economy

Peer-to-peer crowdfunding platforms (which are an integral part of the peer economy) have two characteristics that are important for our context. First, these platforms encourage individual amateurs, rather than firms, to occupy the supplier side of the market. This approach is comparable to that of other peer-economy platforms such as eBay, or Airbnb (Edelman and Luca 2014).). In this sense, peer-economy platforms can be seen as a marketplace evolution of crowdsourcing platforms (Howe 2008). Hence, one might expect participants in such markets to exhibit behavior often typical to crowds, such as herding behavior in response to on-platform signals, exogenous shocks, and high profile media coverage. Indeed, such herding behavior has been observed on the *demand* side of crowdfunding platforms (Liu et al.2015; Zhang and Liu 2012). Less attention, however, has been given to examining whether these phenomena occur on the *supply* side of crowdfunding platforms. Still, given that crowds occupy both sides of the peer economy, we expect such behaviors to appear on the supply side as well.

Second, crowdfunding platforms, like other online peer-economy platforms (and digital markets in general), are influenced by different platform design decisions (Kim et al. 2017; Overby et al. 2010; Tiwana et al. 2010). One important design choice is the acceptance policy instituted by theses platforms. While the level of openness may vary across different platforms, it seems that the peer economy industry keeps moving towards more open and democratic policies, with Indiegogo and Kickstarter’s (revised) acceptance policies being notable examples in the domain of crowdfunding (Wessel et al. 2015).

Allowing Supply-Side Shocks in Peer Economy Platforms

The presence of individual amateur suppliers on crowdfunding platforms, coupled with these platforms' relaxed acceptance policies, can easily lead to the introduction of opportunistic sellers with low-quality offerings. The existence of opportunistic behavior has some support in recent findings (Hildebrand et al 2016; Kim et al 2017, Burtch et al. 2017). Hypothetically, if these platforms were to implement strict scrutiny on suppliers, only individuals who met specific criteria would make the cut, thus providing a higher barrier on the type of supplier and the quality of supply offered. Similarly, it seems likely that, if the supply side were occupied by firms rather than by individuals, opportunistic behavior would be moderated by the high opportunity costs of these firms. We further suggest that crowdfunding settings not only promote the existence of low-quality offerings but also allow fast fluctuations in their number. Given that individuals (the entrepreneurs) exhibit herding behaviors, they may react instantly to what they may consider to be a business opportunity.

On the basis of this reasoning, we conclude that sharp increases in the supply in digital markets, and in particular sharp increases in the availability of low-quality offerings, constitute a novel phenomenon, enabled by the particular characteristics of contemporary peer economy platforms. As the crowdfunding industry keeps moving towards more open and democratic policies that allow laypersons and amateurs to enter the market, it is crucial for platform owners as well as for market participants to better understand the implications of supply-side shocks of low-quality offerings. In this work we demonstrate the existence of such a shock, and provide the first in-depth analysis of its effect on the performance of the market. We do so in the context of the crowdfunding platform Kickstarter.

Our first hypothesis aims to establish the effect of such supply-side shocks on the performance of Kickstarter campaigns. Fundraising campaigns (the supply side of the market) compete with one another for backers' money (demand) (McAfee 1993); this is a case of *monopolistic competition*, i.e., a type of imperfect competition in which many producers sell products that are differentiated from one another (e.g. by quality or type) and hence are not perfect substitutes (Robinson 1933). In such settings, heightened competition intensity may cause demand to be split among the suppliers, leaving each supplier with less than she would have had under less-intense competition (Chamberlin 1933). In our context, such a tendency is still likely to be observed, despite the fact that most of the increase in supply is expected to be of lower quality compared with the average quality in the market before the shock. This is because it is not trivial to compare campaigns, such that even low-quality campaigns still compete for the attention that potential backers must invest to evaluate them (Burch et al. 2017; Dellarocas et al. 2013; Davenport and Beck 2001).

Therefore, we hypothesize:

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

Quality and Signaling in Crowdfunding Platforms

As stated above, the situation we describe in our paper—a sharp increase in the number of low-quality offerings in a market (namely, campaigns offered on Kickstarter) - popularly known as a "market of lemons". Akerlof (1970) uses the metaphor of a market of lemons to describe how information asymmetry may influence high-quality sellers to leave a marketplace. Inspired by the market of used cars, in which only sellers know the true quality of their cars, Akerlof describes 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). Over time, buyers are expected to update their estimations about the average quality of cars in the market, driving the prices down accordingly, and sellers of high-quality products will suffer as well, as they are unable to sell their high-quality cars at an appropriate price. Akerlof (1970) calls this end game the "economic cost of dishonesty".

In order to disarm the threat of dishonest sellers, and in order to gain a competitive edge, high-quality agents must seek out means of signaling their quality to potential buyers (see comprehensive literature review in 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 (Tomboc 2013; Ibrahim 2015). That is, when quality signals exist and work, they will mitigate the negative effect on better-quality sellers.

Indeed, digital marketplaces incorporate signaling mechanisms as part of their design. Previous studies have shown that online platform users (bidders, workers, backers) are inclined to search for the best deals across all available offerings of similar or substitutable products (e.g., in the case of online labor markets (Yang et al. 2009) and online auctions (Bapna et al. 2009; Zeithammer 2006)), and they react to weak signals that document the subtle actions of others (Umyarov et al. 2013). Most relevant to our research, the literature on information availability in crowdfunding platforms suggests that these platforms allow for information symmetry (in contrast to the market described by Akerlof, 1970), and that prospective backers use information signals when choosing which campaigns to contribute to. Specifically, the literature has mentioned three types of signals, all of which have been shown to be considered by platform users: (1) campaign-related information (Mollick 2014), (2) entrepreneur-related information (Zvilichovsky et al. 2013), and (3) campaign dynamics (Burtch et al. 2013; Kim and Viswanathan 2016; Zhang and Liu 2012; Thies et al. 2014)

These findings lead us to hypothesize that a campaign's quality will have a moderating effect on its performance in a market flooded with low quality offerings. Specifically, we suggest that high-quality campaigns are less likely to be influenced by an increase in low-quality offerings, as they will be able to signal their relative quality and distinguish themselves from the general competition. In contrast, low-quality campaigns are more likely to be hurt by a sharp increase in low-quality campaigns as they cannot signal a relatively higher quality. 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 (A) likelihood to succeed (achieve the funding goal) and (B) 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.

CONTEXT

Kickstarter.com

Kickstarter.com is the Internet's largest and most popular crowdfunding platform. Since its founding in 2009, more than 290,000 campaigns have been launched on this platform, raising pledges from over 10 million users. In 2016, 57,440 Kickstarter campaigns were launched, raising ~650 million USD. Kickstarter follows the "all or nothing" business 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 reaches the targeted amount within the specified time period (Burch et al. 2016). A campaign is said to be successful if it achieves its goal or exceeds it in the time frame allocated. 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 & Video, Food, Games, Journalism, Music, Photography, Publishing, Technology and 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.

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”, whose stated purpose was as follows: “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 8th, 2014). This media attention was followed by a spike in the number of visitors to the campaign’s

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[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

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 below). For example, on July 2, 2014, 151 new campaigns were launched on Kickstarter, whereas on July 9, 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.

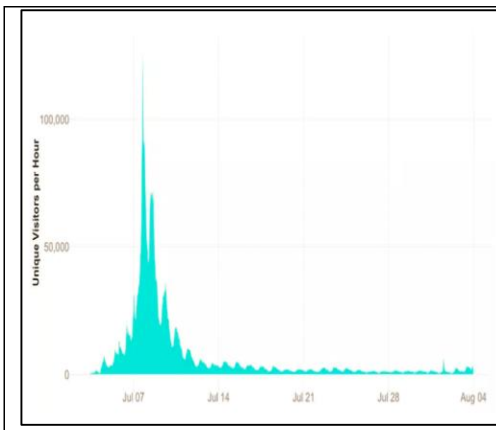


Figure 1. Unique visitors to the potato salad campaign's page in the one-month period beginning in July 4th 2014.

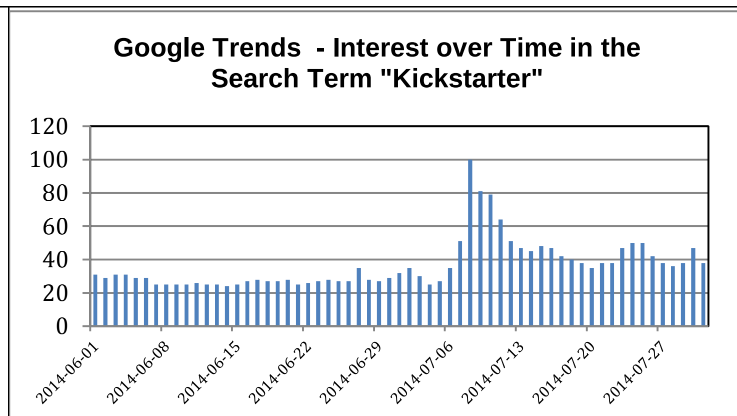


Figure 2. Search trends (as taken from the Google Trends website) for the search term "Kickstarter" for June and July 2014**.**

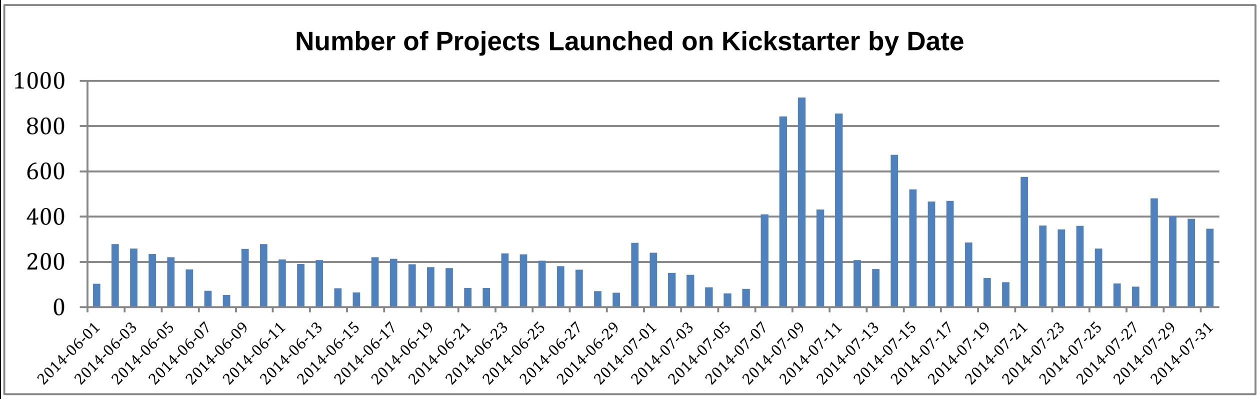
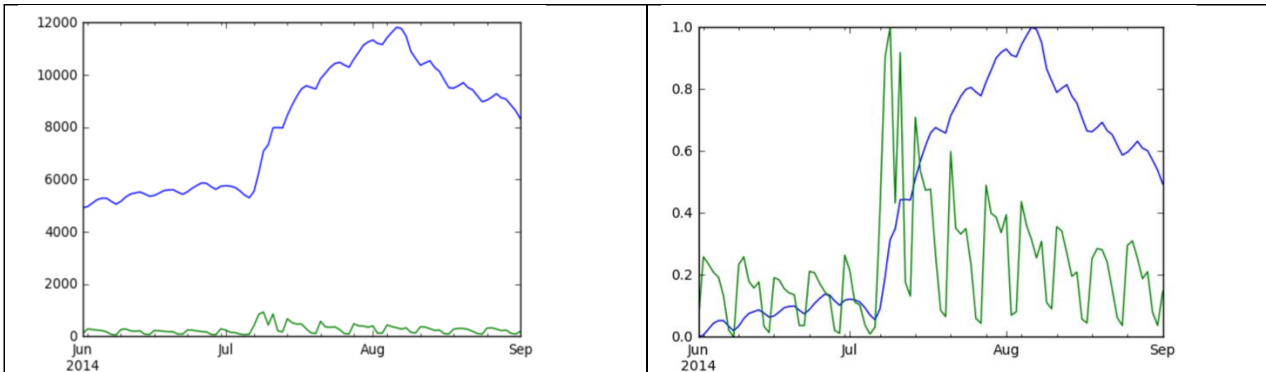


Figure 3. Number of campaigns launched on Kickstarter by date



Number of live campaigns (blue) and number of launched campaigns (green) by day	Normalized number of live campaigns (blue) and normalized number of launched campaigns (green) by day

Figure 4

This media-exposure-driven spike in the number of campaigns can be thought of as a supply-side shock to the Kickstarter platform. As elaborated in what follows, this supply-side shock is at the heart of our empirical strategy. We emphasize that, 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 8th (the day of the Good Morning America appearance) and not July 3rd (the launch day of the potato salad campaign). Indeed, Figure 3 suggest that July 8th marks the beginning of the sharp increase in the number of campaigns launched on Kickstarter.

DATA AND PRELIMINARY OBSERVATIONAL ANALYSIS

Data Collection

We combine two sources of data. The first is a comprehensive set of archival data from Kickstarter. The second is a large-scale set of survey data, in which respondents reported their impressions of each of the Kickstarter campaigns in our first dataset. The latter dataset provides additional measures and information for each campaign. As campaign quality is a key consideration in our analysis, we particularly focused on collecting data on campaign characteristics that may be indicative of quality. We discuss these characteristics in detail in the section on “Quality Measures for Crowdfunding Campaigns”.

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 9,652 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 the campaign belongs to.

- 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 (i) the number of campaigns the campaign owner previously backed, and (ii) the number of successful campaigns he or she previously owned.

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

[5] We remove blockbuster projects, defined as projects that raised over 200K USD. Campaigns included in this count are campaigns from week 5 that ended prior to the shock, campaigns from weeks 1-4, and all 4,100 campaigns that launched in shock week.

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	2.09	0.00	0.00	221.00
numSucceeded	Number of successful campaigns previously created by the campaign's owner	0.12	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	1058.42	804.00	143.00	13294
lnNumWords	Ln (Number of words in the campaign description)	6.73	6.69	4.96	9.50
duration	Duration of the campaign (days)	32.28	30.00	1.00	60.00
dayJoinFromStartDate	Number of days from when the campaign owner joined Kickstarter until the campaign creation day	242.41	34.00	0.00	1898.00
ownerTenure	Ln(dayJoinFromStartDate)	3.48	3.53	0.00	7.55
goal	Target amount of the campaign in USD	61791.2	5000.00	1.00	168M
lnGoal	Ln(goal)	8.21	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	0.28	0.00	0.00	1.00
amountPledged	Amount of money pledged to the campaign in USD	4283.70	125.00	0.00	194574
lnAmountPledged	Ln(amountPledged+1)	4.72	4.83	0.00	12.18

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 capturing 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.) We then surveyed individuals regarding each of the 9,652 campaigns in our dataset (of which 5,552 launched in the 5-week window before the shock, and 4,100 launched in the 1-week window after the shock). The questionnaires were administered via Amazon Mechanical Turk, with three Turkers assigned to evaluate each campaign. The score for each campaign was computed as the average across the three evaluators. Table 2 presents the full list of questions (i.e., quality features) and descriptive statistics.

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)?	Time investment	3.56	3.67
Q2	Would you say the page looks sloppy or professional? on a scale of 1-7 (1 - sloppy, 7 - professional)?	Page quality	3.65	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	3.48	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)	Money investment	2.85	2.67
Q5	Does the project have a website (besides the page on Kickstarter)? (binary)	Has website	0.21	0.00
Q6	Does it seem like the awards were carefully planned?	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

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 8th. 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 vs. 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 vs. a median of $15 in the week of the shock).

Table 3. Supply: Descriptive statistics by week of campaign launch[6]

	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	1247	1154	1197	1171	**4100**
Successful launched campaigns count	438	429	374	407	**703**
IsSuccessful (mean)	0.35	0.37	0.31	0.35	**0.17**
AmountPledged (mean)	6520.75	6695.73	6246.13	4494.85	**2048.28**
lnAmountPledged (mean)	5.9	6.15	5.67	5.55	**3.2**
AmountPledged (median)	684.56	967	463	429	**15**
lnAmountPledged (median)	6.53	6.87	6.14	6.06	**2.71**
Goal (median)	6500	6500	6500	5000	**3000**
lnGoal (median)	8.78	8.78	8.78	8.52	**8.01**

[6] These numbers do not include blockbuster projects, which are defined as projects that gained more than $200,000. These types of projects constitute ~0.5% of all projects in the four weeks prior to 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 $6,552,491–$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.

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)	10.38	7.63	7.49	6.55	**7.4**
Number of pledges	142,438	102,766	102,452	86,656	**106,948**
Percentage of successful money (i.e. money to campaigns that succeeded) from money pledged.	79%	80%	80%	79%	**82%**
Percentage of successful pledges from total pledges	82%	84%	83%	81%	**83%**
Percentage of repeat backers (proxy for quality of backers)	31%	31%	32%	33%	**29%**

[a] These data correspond to all projects, while the rest of the data exclude blockbusters. We did not have available to us these data without the blockbusters.

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

QUALITY MEASURES FOR CROWDFUNDING CAMPAIGNS

Derivation of Quality Measures

Campaign quality is a key consideration in our analysis. To truly understand the effect of the shock and to estimate the moderating effect of quality on campaign performance we incorporate new quality indicators from which we develop an all-encompassing quality measure, as described below.

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). To overcome this challenge, we leverage upon Kickstarter's designated campaign pages. On these pages, entrepreneurs describe their ventures and also present their personal bios (in a designated area on the page). Thus, a campaign's page provides information to potential backers about the product or service being funded, and also provides the entrepreneur with an opportunity to signal his or her competence and quality.

Recent work has used such on-platform signals to establish quality measures, and has shown that these measures predict the success of reward-based crowdfunding campaigns (see Mollick 2014; Burtch et al. 2013). These measures include: (i) *The inclusion of a video in the campaign page*: The presence of a video provides a proxy for the level of time, effort, and resources that the entrepreneur has invested in preparing her campaign (Mollick 2014; Zvillichovsky et al 2013). (ii) *The number of words in the campaign description*: The number of words 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). To account for the variance of this measure, the number of words is often log-transformed (Burch et al 2013). We incorporate these two campaign-related features (hereby denoted *HasVideo* and *NumWords*, respectively) into our econometric models.

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 in what follows, in the spirit of prior work, to estimate campaign quality we use, as proxies, 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 bio 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).

Mollick (2013) 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 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, entrepneurial preparation is manifested in the effort and resources invested by the entrepreneur in preparation for launching her campaign.

Additionally, marketing literature suggests that potential consumers take sellers' (perceived) effort and expense into account (Modig et al. 2014). Consumers are literate enough to deduce the levels of expense and effort invested by the seller, and use them to infer that 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). 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 (Unger et al 2011; Ahlers et al 2015). 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.

Thus, our two datasets (the Kickstarter campaign data and the survey data) provided us with nine quality variables: the existence of a video, the number of words in the campaign description, and the seven new variables listed in Table 2. Taken together, these variables constitute a more comprehensive quality measure than what has been previously used in the literature.

Assessment of the Quality of Pre- and Post-Shock Campaigns on the Kickstarter Platform

In Table 5 we present a comparison of the nine individual 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, effectively creating a market of lemons. Specifically, the percentage of campaigns accompanied by a video decreased from 68%-73% to 35%, and the average number of words decreased from 1168 – 1293 to 790. Additionally, we see a post-shock decrease in the values of all our newly-created variables. For example, when considering time invested in the campaign, we see a decrease from 3.84 – 4.09 to 2.97.

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	0.71	0.72	0.69	0.63	**0.33**
NumWords	1261.93	1292.63	1266.57	1168.96	**790.75**
LnNumWords	6.94	6.97	6.94	6.86	**6.45**
time_investment	3.84	4.09	3.93	3.92	**2.97**
page_quality	3.9	4.17	4.05	3.99	**3.08**
Effort	3.73	3.96	3.87	3.8	**2.93**
money_investment	3.12	3.3	3.18	3.05	**2.38**
has_website	0.26	0.27	0.25	0.25	**0.14**
Rewards	0.69	0.73	0.68	0.69	**0.5**
Professionalism	2.13	2.19	2.15	2.15	**1.85**

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; (2) the market of lemons that emerged in the wake of the shock had a harmful effect on 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 detailed below, we use two complementary identification strategies to achieve this goal.

All-Encompassing Quality Variable

We used principal component analysis (PCA) to reduce the dimensionality and to transform the nine variables into one all-encompassing quality variable, denoted ***quality_pca***. PCA is a dimension reduction procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. This transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible). PCA methodology has been used in the IS literature and other social science disciplines to perform this type of dimension reduction (for example: Ayabakan et al. 2017, Sahoo et al. 2012, Bonaccorsi et al. 2006, Allport et al. 2003). In this work we use the method by defining ***quality_pca*** as the first principal component of the fitted model.[7]

[7] 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 4495 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

METHODOLOGY

Identification Strategies

Here, we present two identification strategies to address the identification challenge outlined above: namely, the need to isolate the effect of the "market-of-lemons" environment 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-developed 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 is 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 examine 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 lifespan of a campaign is 32 days, we focus on campaigns that started during the four weeks immediately *preceding* the shock and ended after the shock (4495 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 lower-quality environment, 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 1st, 2014 (7 days before the shock), and that campaign B was launched two days later, on July 3rd, 2014 (5 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 Figure 5.

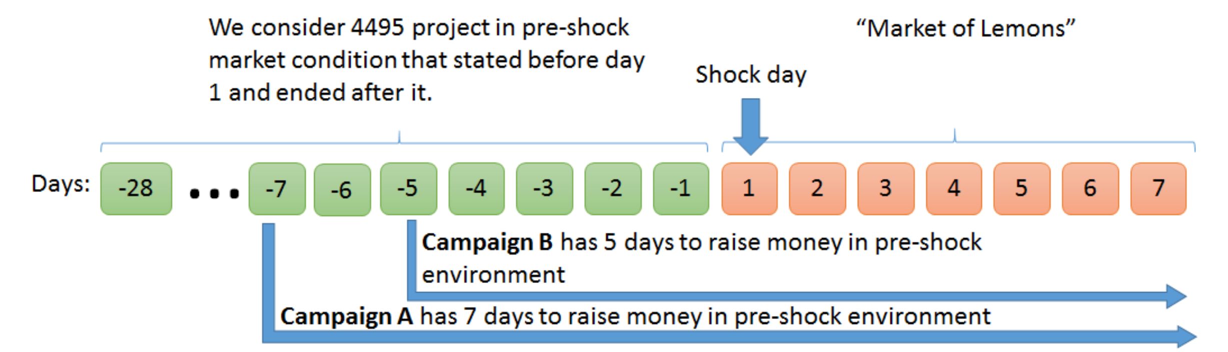


Figure 5. Illustration of time proximity identification method

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, as well as for additional unobserved changes in the campaign mix that the shock might have brought.

We implement this strategy to test both H1 and H2. Specifically, we create a variable that measures how many days before the shock the campaign launched, denoted as *DaysFromShockDay*. We estimate 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 quantify 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 use PSM to match campaigns launched before the shock ("before" campaigns) to campaigns launched immediately after the shock ("after" campaigns). Briefly, we first compare 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 conduct subsample regression analysis to test the moderating effect of quality (H2).

As mentioned, the weeks after the shock are 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 is to find two comparable groups, one that includes "typical" pre-shock campaigns, and one that includes campaigns that started after the shock and that are similar in their characteristics to the pre-shock campaigns. Specifically, for the "before" group, we use campaigns that were launched 5 weeks before the shock (between June 3^{rd} and June 9^{th} 2014) and finished before the shock (783 campaigns); for the "after" group we use campaigns launched the week after the shock, between July 8^{th} and July 14^{th}. For each "before" campaign we match one "after" campaign using PSM[8]. Because the PSM procedure ensures that the two groups comprise similar campaigns, performance differences between them are 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 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 3rd, 2014, Kickstarter implemented a policy change in the platform that made it easier for campaigns to be accepted and launched[9]. Clearly, 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 perform 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).

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[8] We conduct PSM (with replacements), to find the closest match for each project in week_5. For each project in week_5, we use 1-nearest neighbor to find the project that is nearest to it in terms of propensity score. For the 783 campaigns in week_5 we match 552 unique campaigns in shock_week (that is, our “after” sample consists of 783 campaigns, some of which are duplicates).

[9] See https://www.kickstarter.com/blog/introducing-launch-now-and-simplified-rules-0 for the policy change.

- 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 (Zvilichovsky et al. 2013; Inbar and Barzilay 2014). Entrepreneurs' tenure is often translated into social proof, which is one of the factors for entrepreneurial success (Vesterlund 2003; Bapna 2017). Hence, we include the following 3 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, i.e., achieved its funding goal (*IsSuccessful* – a binary variable), and the second is the amount of money raised (*AmountPledged*). We suggest that these are the two key performance variables for both the entrepreneur and the platform owner: As Kickstarter uses the "all or nothing" model, no money is transferred (and no commission is paid) unless the campaign "succeeds" (that is, reaches its funding goal). And given that the campaign may exceed its goal, the entrepreneur and platform owner are also interested in the actual amount pledged, given that this amount determines how much they will actually receive.

In what follows, we use both performance variables when implementing both identification methods. *IsSuccessful* is a binary variable and *AmountPledged* is a continuous variable; thus, we analyze the former using logistic regression[10], and we analyze the latter using OLS. 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 towards 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. Specifically, we control for the 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 campaign, which accumulated a significant portion of its goal prior to the shock,

[10] 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.

would succeed independently of the shock. Hence, as a proxy for campaign's pre-shock momentum, we account also for the ratio of the goal attained on the campaign's first day.

Accordingly, our full regression equation is as follows:

$$\begin{aligned} &IsSuccessful_i \\ &\quad = \alpha_0 + \alpha_1 \boldsymbol{ln}(\boldsymbol{DaysFromShockDay_i}) + \alpha_2 \boldsymbol{Quality} \\ &\quad + \alpha_3 numBacked_i + \alpha_4 numSucceded + \alpha_5 Duration_i \\ &\quad + \alpha_6 ln(Goal)_i + \alpha_7 RatioGoalFirstDay_i \\ &\quad + \alpha_8 lnDayJoinFromStartDate_i \\ &\quad + \alpha_9 CategoryFixedEffects_i + \varepsilon_i \end{aligned} \tag{1}$$

Note that we run this equation with two operationalizations for "Quality". In the first we use ***quality_pca,*** the quality variable constructed using PCA (as mentioned above, PCA was performed on the 9 quality variables discussed in the "Quality Measures" section). In the second, we use ***quality_binary*** – a binary representation of *quality_pca*, where we use the median of *quality_pca* as a threshold (i.e., observations with quality < median (*quality_pca*) are assigned the value 0 and are regarded as low-quality, whereas observations with quality > median (*quality_pca*) are assigned the value 1 and are regarded as high-quality).

Next, we estimate 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 are the same as in equation (1). As before, we run this equation with two operationalizations for "Quality".

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 estimate equations (1) and (2), specified above, using the *quality_binary* variable and adding an interaction term between *ln(daysFromShock)* and *quality_binary*. Note that the binary operationalization is chosen to enable a simple way to interpret the interaction term.

Identification Method #2: Propensity Score Matching

Studying H1: The Average Effect of the Shock on Campaign Performance: As with the first identification strategy, we use 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 that the coefficient of "before" should 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). Here, we present 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).

$$isSuccessfull_i = \alpha_0 + \alpha_1 \boldsymbol{before} + \alpha_2 \boldsymbol{qualilty\_pca}_i + \alpha_3 numBacked_i + \alpha_4 numSucceeded + \alpha_5 Duration_i + \alpha_6 lnGoal_i + \alpha_7 CategoryFixedEffects_i + \alpha_8 lnDayJoinFromStartDate_i + \varepsilon_i \quad (2)$$

Studying H2: The Moderating Effect of Quality: To empirically study H2, using the matching identification, we run subsample regressions, dividing the data into two equal-sized groups based on campaign quality (using the median of *quality_pca*). For each group (low quality/high quality), we estimate the same regression equation (2) as before, excluding *quality_pca* (obviously there is no need to control for quality, as it is the variable used to create the two subsamples). Given that we hypothesize that quality moderates the effect of the shock, we expect the “before” coefficient to be higher for low-quality campaigns, indicating that lower-quality campaigns were influenced more by the shock. Formally, we estimate the following equations:

$$IsSuccessfull_i = \alpha_0 + \alpha_1 before + \alpha_2 numBacked_i + \alpha_3 numSucceeded + \alpha_4 Duration_i + \alpha_5 lnGoal_i + \alpha_6 CategoryFixedEffects_i + \alpha_7 lnDayJoinFromStartDate_i + \varepsilon_i \quad (3)$$

$$lnAmountPledged_i = \alpha_0 + \alpha_1 before + \alpha_2 NumBacked_i + \alpha_3 numSucceeded + \alpha_4 Duration_i + \alpha_5 lnGoal_i + \alpha_6 CategoryFixedEffects_i + \alpha_7 lnDayJoinFromStartDate_i + \varepsilon_i \quad (4)$$

To improve matching accuracy, our matching was not performed on the variable *quality_pca*, 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 must make sure that, for each subsample, *quality_pca* is balanced between the before and after groups. We test this using both the Mann-Whitney rank test and the Wilcoxon rank-sum test. The results, shown in Table 6, show that *quality_pca* is balanced for both the low-quality subsample and the high-quality subsample.

Table 6. Balancing test of quality_pca between before and after campaigns.		
	Mann-Whitney rank test	**Wilcoxon rank-sum test**
Low quality	Statistic =82094 ; p=0.31	Statistic=1.02 ; p=0.31
High quality	Statistic =76793 ; p=0.46	Statistic = 0.74; p=0.46

RESULTS

Identification Method #1: Time Proximity to the Shock

The results for the estimations using the first identification method are presented in Table 7. In the table, models (1) and (2) correspond to the estimations of success likelihood. Each model uses a different operationalization of "quality", as discussed above: Model (1) uses ***quality_pca***, the continuous quality variable constructed using PCA; model (2) uses ***quality_binary*** - the binary representation of ***quality_pca***. 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 1.015-1.016 for a 10% increase in the distance from the shock (in term of number of days from shock). These results support H1(A).

Models (4) and (5) correspond to the estimations of amount pledged, using *quality_pca* and *quality_binary*, respectively, to operationalize "quality". As shown in Table 7, 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%–1.8% in the amount of money pledged; for a 50% increase in distance from the shock, we see an increase of 6.2%–8% in the amount pledged. For example, an average campaign that was launched on day 2 prior to the shock and raised ~3000 USD would have raised 186-240 USD more had it started on day 3 prior to the shock, and it would have raised 810-1050 USD (27%-35%) 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. Specifically, during the week before the shock, over 1000 new campaigns launched, and more broadly, over 4200 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 (6) correspond to the estimations that include the interaction term between *quality_binary* and *ln(DaysFromShockDay*), 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., *ln(DaysFromShockDay)*) 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 1.007. 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 0.9% increase in the amount pledged. Thus, quality moderates the effect by a factor of ~3.

Table 7. Time proximity identification: H1 + H2 regressions

	Logistic (DV - Is Successful)			OLS (DV - ln(AmountPledged+1)[11]		
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
lnDaysFromShockDay	0.16*** (0.05)	0.17*** (0.04)	0.30*** (0.07)	0.15*** (0.04)	0.19*** (0.04)	0.27*** (0.06)
quality_pca	0.63*** (0.03)			0.85*** (0.02)		
quality_binary		1.91*** (0.10)	2.47*** (0.25)		3.23*** (0.09)	3.65*** (0.22)
lnDaysFromShockDay * quality_binary			-0.23** (0.09)			-0.18** (0.08)
ownerTenure	0.05** (0.02)	0.09*** (0.02)	0.09*** (0.02)	0.11*** (0.02)	0.20*** (0.02)	0.20*** (0.02)
numBacked	0.03*** (0.01)	0.03*** (0.01)	0.03*** (0.01)	0.02*** (0.00)	0.03*** (0.00)	0.03*** (0.00)
numSucceeded	0.09 (0.08)	0.09 (0.08)	0.09 (0.08)	0.20*** (0.05)	0.20*** (0.06)	0.20*** (0.06)
duration	-0.01 (0.00)	-0.01* (0.00)	-0.01* (0.00)	-0.00 (0.00)	-0.01*** (0.00)	-0.01*** (0.00)
lnGoal	-0.58*** (0.04)	-0.38*** (0.03)	-0.39*** (0.03)	-0.01 (0.02)	0.11*** (0.02)	0.11*** (0.03)
ratioGoalFirstDay	4.52*** (0.33)	5.34*** (0.34)	5.34*** (0.34)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
category	Yes	Yes	Yes	Yes	Yes	Yes
R^2				0.47	0.37	0.37
Pseudo R^2	0.37	0.32	0.32			
N	4495	4495	4495	4495	4495	4495

Identification Method #2: Propensity Score Matching

The result of the estimations using the PSM identification method are presented in Tables 8 and 9. In Table 8, model (1) corresponds to the estimation of success likelihood, and model (2) corresponds to the estimation of the amount of money pledged. As can be observed, in both models the coefficient of *Before* (the variable of interest) for both performance measures is

[11] For robustness we ran models 4-6 with robust standard errors. Results are significant and in the same direction.

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. Similarly, campaigns launched before the shock raised 44% more, on average, compared with campaigns launched after the shock.

Table 8. PSM identification: H1 regressions

	Logistic (DV - IsSuccessful)	**OLS (DV - ln(AmountPledged+1))[12]**
	Model (1)	Model (2)
Before	0.28** (0.14)	0.37*** (0.12)
quality_pca	0.69*** (0.05)	0.86*** (0.03)
ownerTenure	0.08** (0.04)	0.13*** (0.03)
numBacked	0.05*** (0.01)	0.04*** (0.01)
numSucceeded	0.23** (0.11)	0.09 (0.06)
duration	-0.01 (0.01)	-0.01 (0.01)
lnGoal	-0.73*** (0.06)	0.02 (0.04)
category	Yes	Yes
R^2		0.49
Pseudo R^2	0.34	
N	1566	1566
Standard errors in parentheses.		
*p < .1, **p < .05, ***p < .01		

[12] For robustness we ran this analysis with robust standard errors. Results were significant and in the same direction.

Table 9 presents the results of the subsample regression analysis. In the table, models (1) and (2) correspond to the effect of the shock on the likelihood to succeed for the low-quality and high-quality subsamples, respectively. Models (3) and (4) correspond to the effect of the shock on the amount pledged for the low-quality and high-quality subsamples, respectively. We find that, for each performance metric, the coefficient of *Before* is larger in magnitude for the low-quality subsample (models (1) and (3)) than for the high-quality subsample (models (2) and (4)). Additionally, in models (1) and (2), which measure the effect of the shock on likelihood to succeed, we see that the coefficient of *Before* is significant only for the low-quality sample (model 1). Taken together, these results suggest that campaigns of lower quality are more negatively affected by the shock environment than campaigns of higher quality are. These results support H2(A) and H2(B).

Specifically, for low-quality campaigns, we observe that campaigns launched before the shock are 1.64 times more likely to succeed compared with campaigns launched after the shock. For high-quality campaigns, campaigns launched before the shock are only 1.36 times more likely to succeed compared with campaigns launched after the shock. Similarly, among low-quality campaigns, campaigns launched before the shock raised, on average, 87% more money than post-shock campaigns did; in contrast, among high-quality campaigns, pre-shock campaigns raised only 40% more compared with post-shock campaigns.

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 “market of lemons”) 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 9. PSM identification: H2 regressions				
	DV = IsSuccessful		DV = ln(AmountPledged+1) [13]	
	Model (1) low quality	**Model (2) high quality**	**Model (3) low quality**	**Model (4) high quality**
Before	**0.50**** (0.21)	**0.31*** (0.18)	**0.63***** (0.20)	**0.35**** (0.17)
ownerTenure	0.05 (0.05)	0.15*** (0.05)	0.20*** (0.05)	0.21*** (0.05)
numBacked	0.20*** (0.04)	0.05*** (0.02)	0.08*** (0.02)	0.05*** (0.01)
numSucceeded	-0.17 (0.25)	0.39*** (0.15)	0.22 (0.27)	0.11* (0.06)
duration	-0.01 (0.01)	0.00 (0.02)	-0.00 (0.01)	0.03 (0.02)
lnGoal	-0.43*** (0.07)	-0.63*** (0.08)	0.04 (0.06)	0.30*** (0.07)
Category	Yes	Yes	Yes	Yes
R^2			0.16	0.14
Pseudo R^2	0.24	0.23		
N	794	772	794	772
Standard errors in parentheses. *p < .1, **p < .05, ***p < .01				

DISCUSSION

Open crowdfunding platforms make it easy for entrepreneurs to raise money for their ventures over the Internet, bypassing institutional gatekeepers such as banks or venture capital funds. In particular, many platforms allow any campaign that meets their guidelines to start raising money, without going through a manual review process. However, these open policies create a low barrier to entry and expose the platform to a risk of being flooded with opportunistic low-quality campaigns. This situation, popularly known as a “market of lemons”, may harm the genuine entrepreneurs who invest substantial effort and resources into launching high-quality campaigns.

[13] We ran models (2) and (4) with robust standard errors. Results are significant and in the same direction.

In this paper, we have studied the implications of flooding an open marketplace with opportunistic low-quality offerings. We characterized the quality of a campaign by factoring in the resources invested by the entrepreneur (such as time, money, and effort) and the perceived professionalism of the entrepreneur. Doing so, we were able to estimate how a “market-of-lemons” environment differentially affects the performance of high-quality campaigns and of low-quality campaigns. Our analysis exploited a short-term period of highly-visible media exposure given to Kickstarter, following the launch of the “potato salad campaign”, which enabled us to factor out temporal and seasonal bias of 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.

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. These effects, however, were moderated by campaign quality: Entrepreneurs who invested resources in developing their campaigns were less affected by the flooding than were low-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.

Our paper carries methodological, theoretical and managerial contributions. First, 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 (in our case, campaigns) that were generated before the exogenous shock occurred (such that their characteristics are 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 generation (launch) dates; in our case, campaigns launched closer to the shock were more likely to have been affected by the post-shock environment, as they spent more of their "lives" in that environment.

Second, we contribute a comprehensive approach to measuring quality of crowdfunding platforms. We went beyond the platform's structured features (used in previous research) and incorporated (manual) campaign evaluation, considering entrepreneurs' resource investment (time, money, effort) and (perceived) competence.

Third, we add to the crowdfunding literature by providing empirical evidence for the presence of signaling mechanisms in crowdfunding platforms and their moderating effect on campaign performance in situations in which the market is flooded with low-quality campaigns ('market of lemons').

Fourth, from a theoretical perspective, this work is among the first to focus on supply-side shocks in share economy platforms. As mentioned above, the sellers on peer economy platforms are individuals (rather than firms); they watch TV and consume content online, and they act instantly to capitalize on what they consider to be business opportunities.

Finally, our paper carries the following 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.

We acknowledge that our work carries 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 “market-of-lemons” environment on performance was specifically due to the increase in low-quality competition, or whether it might have been due to the increase in competition in general.

That is, we cannot say how a steep increase in high-quality campaigns would affect the platform. That being said, seeing as the peer economy industry keeps moving towards 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, 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. Accordingly, the implications of our work are influenced by platforms' acceptance polices.

Our work offers some avenues for future work. First, the shock we focus on is a unique incident during which a very large increase in supply was observed and was not accompanied by a significant increase in demand. This is probably a result of the "silly" nature of the campaign that caused the shock (making a potato salad). It is possible that the astonishing success of a campaign of this nature did not attract funders, but did encourage suppliers to offer their own campaigns. Future work can look at other types of shocks and consider a more elaborate model that accounts for changes both in supply and in demand. Second, our work focuses on the crowdfunding context; future work can study similar media shocks in other peer-to-peer platforms. Finally, the long-term effects of a market-of-lemons environment should be studied.

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APPENDIX

Appendix A: Additional Supply Shocks

Our paper investigates the effects of competition in a market-of-lemons environment 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 8 events (unique days) in which there was a substantial increase in supply. Those were 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 is a high overlap between the dates that surround the different events. Thus, we cannot correctly distinguish the demand in the weeks prior to each shock from the demand in the weeks following each shock, seeing as those weeks are influenced not only by the current shock being evaluated but most likely by other shocks as well.