Open to Everyone? The Long Tail of the Peer Economy: Evidence from Kickstarter

Completed Research Paper

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Abstract

Peer-to-peer platforms remove entrance barriers characterizing traditional markets, thereby creating markets that are more democratized. Our work draws from the rich literature on the "long tail" to investigate how democratization of peer-to-peer markets affects distribution of demand. We utilize a natural experiment in the form of a policy change that occurred on Kickstarter.com and resulted in opening the market to more players, effectively raising the level of democratization. We examine how platform-openness affected the distribution of funds and backers across campaigns. Specifically, we ask whether removal of entrance barriers—which increased the quantity and variety of offers—shifted the demand from popular to niche offers (a long-tail effect). Our findings indicate that opening the platform shifted the demand towards the head: more funds and backers became concentrated in a smaller number of head-offers. We conclude that a more democratized peer-economy results in a less-even distribution of funds (a superstar effect).

Keywords: Peer-economy, Share-economy, Long tail, Superstar effect, Crowdfunding, Demand distribution, Kickstarter

Introduction

The peer-to-peer (P2P) economy (also referred to as the share economy) is a decentralized model in which individuals buy and sell goods or services directly from and to one another (Fournier et al. 2013; Sundararajan 2013). Such transactions typically take place through designated online platforms. Examples of P2P platforms include eBay, Uber, and Airbnb, as well as crowdfunding platforms such as Kickstarter and Indiegogo.

P2P platforms remove many of the entrance barriers characterizing traditional markets, in that they provide an easy way for sellers to list their offerings and to gain access to mass demand. As a result, these platforms create markets that are more democratized than traditional markets and can potentially accommodate more diverse offerings, as well as less experienced sellers. For example, an individual apartment owner can easily offer their apartment on Airbnb without the need to purchase and manage an expensive hotel. Similarly, Uber drivers get access to millions of potential riders without having to undergo the costly process of obtaining a cab license, and Kickstarter enables entrepreneurs to pitch to a crowd of users with multibillion-dollar investment potential at the click of a button. Novice sellers indeed take advantage of these opportunities, such that P2P platforms are typically populated with amateurs on both the supply side and the demand side of the marketplace, with blurred dichotomy between the parties (Zvilichovsky et al. 2013).

Still, not all P2P platforms are equally welcoming to inexperienced sellers. In particular, the extent to which a platform's entry barriers to amateurs are low depends on the extent to which the platform is "open", that is, allows all users to participate, and refrains from enforcing control (Wessel et al. 2017). In the spirit of democratization, many platform owners are choosing to adopt more open acceptance policies. The level of openness is a design decision of the platform owner, which is likely to carry economically important consequences that warrant IS research attention.

Recently, it has been shown that open acceptance policies encourage individuals with low opportunity costs to enter the marketplace and try their luck (Burtch et al. 2016; Geva and Oestreicher-Singer 2016). Accordingly, we would expect open marketplaces to contain larger quantities of offers compared with less-open marketplaces selling comparable products. Yet, an important question arises: In creating equal opportunities for entry, does democratization in the form of open acceptance policy also provide sellers with more equitable access to the demand side of the market? In other words, is the distribution of demand across offerings expected to be more equitable in a platform with an open acceptance policy, as compared with a less-open platform? Wessel et al. (2017) provide first evidence in this regard, showing that adoption of a more open policy leads total revenues of the platform to increase, yet, at the same time, leads to a decrease in the revenue per offer and in individual offers' likelihood of success.

In this paper we delve further into this issue and **study the effect of a peer-economy platform's level of democratization—as reflected in the platform's design—on the distribution of funds across participants in the platform.**

To this end, we draw from the rich literature on the "long tail". The long tail phenomenon was popularized by Anderson (2006) to describe the shift of demand from popular products ("bestsellers", or the "head") towards niche offerings (the "tail") as a result of the emergence of digital markets and digital goods (Brynjolfsson et al. 2011). While this phenomenon has been widely studied by IS researchers in a variety of contexts—mainly music, movies, and books—there are conflicting results as to the effect of an increase in the number of offerings on the distribution of demand. On the one hand, more than a few studies have pointed to a shift in consumption from bestsellers to the tail, showing that bestsellers hold a smaller market share online than they do offline (e.g., Anderson 2006; Brynjolfsson et al. 2011; Peltier and Moreau 2011). On the other hand, other studies have shown that the well-known "superstar" effect is still in play, leading the consumption-share of bestselling products to grow over time or remain unchanged (e.g., Elberse 2008; Elberse and Oberholzer-Gee 2007; Goel et al. 2010; Smyrnaios et al. 2010). This tension in the findings may be attributed to the particular contexts of the different studies, as well as to the effects of recommendation tools, which may help consumers discover new products on the one hand, yet, on the other hand, might make already-popular products even more popular (Fleder and Hosanagar 2009; Yin et al. 2012). Further, some of the contradicting findings in the literature can be attributed to different approaches to measuring consumption distribution.

Whereas the long tail literature has focused primarily on the distribution of sales in traditional online retail (online stores), our study is the first to focus on the context of the peer economy. An important distinction between the two contexts is that, whereas the long tail of ecommerce is the result of an increase in the number of products offered by one seller (e.g. Netflix and Rhapsody), the long tail in P2P platforms is driven by an increase in the number of sellers. This difference implies that P2P platforms are likely to exhibit on-platform dynamics that are not encountered in traditional ecommerce platforms. For example, Wessel et al. (2017) have shown a crowdfunding platform's adoption of an open acceptance policy led sellers to rely more extensively on tools that enabled them to signal their quality. Herein, our objective is to study the effect of P2P platform openness on the distribution of funds across offerings, to determine whether this distribution adheres to the long tail phenomenon or to the superstar phenomenon.

For this purpose, we use data from Kickstarter.com, the Internet's largest and most popular crowdfunding platform. Specifically, we utilize a natural experiment in the form of a policy change that Kickstarter initiated and that resulted in opening the market to more players, effectively raising the level of democratization on the supply side of the platform. We examine the **effect of platform openness on the distribution of funds by** studying the distribution of money and backers across campaigns that were available for funding on the platform. We ask whether removing entrance barriers, and thereby increasing the quantity and variety of offers, shifts the demand from popular offers to niche ones. In particular, we investigate whether the tail becomes longer and *fatter* (in line with the long tail phenomenon) (Anderson 2006; Brynjolfsson et al. 2011; Peltier and Moreau 2011) or longer and *flatter* (in line with the superstar phenomenon) (Elberse 2008).

Our results suggest that while an open acceptance policy can increase demand on a P2P platform (in terms of the amount of money raised by campaigns and the number of backers supporting campaigns), such a policy redistributes the demand and shifts it towards the head. That is, it creates a longer and flatter tail (in line with the observations of Elberse 2008; Goel et al. 2010) rather than a longer and fatter tail. We find that the same share of money pledged (and the same share of the total number of pledges) is achieved by a smaller number of top-campaigns (which also account for a smaller share of the campaigns). Our findings suggest that a more democratized peer-economy results (counterintuitively) in a less even distribution of funds.

Our work carries theoretical and managerial contributions. We contribute to the IS literature on the long tail by considering the long tail as a property of the peer-based marketplace, in which peers (rather than companies) offer other peers their (not-necessarily digital) products and services. Further, our findings about long tail markets in P2P platforms could be translated and applied to managerial decisions regarding the governance of online marketplaces. Specifically, we find indications that open acceptance policies increase demand in peer-based markets. However, counterintuitively, this increase is not a result of the increase in the number of campaigns that entered the market after the bar was lowered; rather, it is attributable to the top-performing campaigns.

This paper proceeds as follows. In the next section we present the context of our research – Kickstarter.com. We subsequently develop our hypotheses, discuss our data and provide relevant descriptive statistics. Next, the empirical methodology for investigating our hypotheses is presented, followed by the results of our investigation. In the last section we summarize our findings and provide conclusions.

Context

Kickstarter.com

The context of this research is the crowdfunding peer economy platform Kickstarter. 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 is "successful", i.e., reaches 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 (Kickstarter 2018a).

Kickstarter is a reward-based platform[1]; 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 (Kickstarter 2018b). Campaign success rates range from 21% for technology campaigns to 65% for dance campaigns, with an average success rate of 36% across all categories.

[1] 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.

Policy change – "Launch Now"

We utilize a natural experiment in the form of a change to Kickstarter's screening policy that resulted in opening the platform to more players. On June 3, 2014, Kickstarter removed the manual evaluation that was mandatory for each campaign and introduced a feature called "Launch Now". This feature allowed entrepreneurs to launch their campaigns directly after a simple automatic screening procedure, which only ensured that all required details (e.g., description, goal and rewards) were provided. This change enhanced the platform's democratization of supply, allowing virtually any individual to upload an offering.

Hypothesis Building

As mentioned above, our research objective is to study the distribution of demand in a democratized peer-economy. In particular, we study how democratizing the market (by removing entrance barriers) affects the distributions of funds and of backers across campaigns. Our analysis is rooted in the long tail theory (Anderson 2006), which originally referred to the effect of market democratization resulting from the emergence of digital markets.

The literature is divided with regard to the effect that opening digital markets may have on the distribution of demand across products. On the one hand, several studies have provided evidence of the existence of the long tail phenomenon, in which, as a result of the emergence of online markets, sales have shifted from the head to the tail of the distribution, leading to a less concentrated market (Anderson 2006; Brynjolfsson et al. 2011; Peltier and Moreau 2011). Anderson (2006) claims that the long tail phenomenon is driven by three forces, all of which he relates to the market's transition to digital goods and to the democratization of production: (1) *easier production*: the 'tools of production' are widely available (for example, digital technology has made it much easier to produce and reproduce music albums and movies), (2) *easier distribution*: the costs of distribution and consumption are cut, and (3) *easier matching*: digital platforms match supply and demand, for example by offering search and recommendation tools.

Interestingly, in the context of the open peer economy, in which the products or services are not necessarily digital in nature (e.g., taxi ride, hotel room, and entrepreneurial activity) and where virtually any individual can be a supplier, the above mentioned forces are still present and perhaps even stronger: (1) *easier production*: sellers in the peer economy may exploit their already existing assets and resources, such as their car, house or expertise, making "tools of production" readily available; (2) *easier distribution*: peer economy platforms provide sellers with off-the-shelf technology to facilitate transactions with their consumers, thereby cutting the costs of distribution; and (3) *easier matching*: peer economy platforms implement tools allowing potential consumers to browse, filter and discover relevant offers. In our context the transition to an ***open*** peer economy platform from a more controlled format intensifies these three forces and thus may result in long-tail behavior as well.

On the other hand, other studies have shown that while the emergence of online market places has created a longer tail in terms of number of offers, sales have not shifted to the tail. On the contrary, studies have shown that sales of bestsellers have become even stronger. For example, Elberse (2008), who discussed sales of music and DVDs, suggested that the tail represents a rapidly increasing number of titles that sell very rarely (or never), and that instead of bulking up, the tail is becoming much longer and flatter. Elberse and Oberholzer-Gee (2007), who focused on DVD movies, also showed that success is concentrated in an ever-shrinking set of bestselling titles and that the number of titles at the top 10% of weekly sales dropped significantly between the years 2000 and 2005, demonstrating a 'superstar' effect (Rosen 1981). As an explanation of such a phenomenon, Goel et al. (2010) suggested that adding infinite inventory may boost head sales by offering consumers a "one-stop-shop" for both bestsellers and niche products. Fleder (2009) argued that such a situation of 'rich-get-richer' may be a result of using popular collaborative filtering recommendation tools, which often decrease the diversity of shoppers' choices. Focusing on such a recommendation tool, Oestreicher-Singer et al. (2013) showed that the flow of attention from niche products towards the head is larger than that in the opposite direction, such that low-selling products create value not only through the demand that they generate but also by enhancing demand for more popular products—a role that may be underestimated in traditional assessments of value.

A few studies have begun to explore how the level of an openness of a peer economy platform might influence sellers' behavior and consequent demand, though they have not explicitly examined demand distributions. Wessel et al. (2017) have shown that when the Kickstarter platform adopted a more open acceptance policy, enabling more campaigns to enter the platform, platform signaling (e.g. social media shares) became more important. An explanation for this observation could be that a campaign now needs to stand out among a much larger group of campaigns. Indeed, the entrance of many new campaigns to a platform may create choice overload for potential backers, confuse them, and lead them to focus on well-known or highly popular offers. Such a choice-overload effect, sometimes referred as the *paradox of choice*, has been studied extensively in the marketing and psychology literature (Iyengar and Lepper 2000; Scheibehenne et al. 2010; Schwartz 2014). Studies in this vein have found that choice overload may lead consumers to be dissatisfied and prevent them from making a purchase (Iyengar and Lepper 2000) or it may create a status quo bias, that is, lead consumers to stick with their previously selected option (Ren 2014). In our context, an overload of campaign choices may lead backers to stick with popular campaigns and thus lead to a more concentrated market.

Taken together, the studies discussed above point to multiple competing possibilities regarding the effect of the openness of a P2P platform (in our case, Kickstarter) on the distribution of demand across platform offerings. Thus, the question we address is empirical, and we approach it using a competing-hypothesis design.

First, we hypothesize as to the effect of market openness on the concentration of the distribution of demand, as reflected by (i) the amount of money pledged to campaigns and (ii) the number of backers supporting those campaigns. Formally, we pose the following competing hypotheses:

- **H1.a**: Platform openness leads to a more concentrated distribution of (i) funds and of (ii) backers across campaigns.
  H1.b: Platform openness leads to a more equal distribution of (i) funds and of (ii) backers across campaigns.

Examining the concentration of the distribution of demand provides us with a first indication as to the overall direction and extent of the effect of platform openness on demand distribution and whether an open platform adheres to the long tail premise. However, concentration level does not inform us about the particular way in which the distribution of demand changes after a P2P platform adopts a more open acceptance policy. Specifically, even if H1.a holds, it does not necessarily point to the presence of a superstar phenomenon. For example, it could be the case that the distribution becomes more concentrated as a result of the open policy introducing a very high number of low-quality campaigns that raise extremely low funds, without changing the amount of money raised by the top-campaigns. Therefore, in order to study the existence of a superstar effect, we must examine the number of campaigns responsible for different shares of the demand. If, after adopting a more open acceptance policy, the peer-economy platform exhibits a superstar effect, we should be able to attribute a given share of the demand not only to a smaller *share* of the campaigns but also to a smaller *number* of campaigns, as compared with the situation prior to the opening of the platform.

Formally, we put forward the following competing hypotheses:

- **H2.a**: Considering campaigns near the head of the distribution: Opening the platform leads to a reduction both in the percent of campaigns and in the number of campaigns responsible for a given share of the demand (in terms of money invested and the number of backers).
  H2.b: Considering campaigns near the head of the distribution: Opening the platform leads either to an increase or to no change in the percent of campaigns responsible for a given share of the demand, and it leads to an increase in the number of campaigns responsible for that share of demand.

We further investigate **the heterogeneity of the effect of platform openness on the performance of head and tail campaigns.**

Wessel et al. (2017) showed that after Kickstarter adopted an open acceptance policy, the number of campaigns increased much more than the total amount of money raised, indicating a negative effect of platform openness on campaign performance. Herein we seek to shed more light on the nature of this effect and to determine whether it is heterogeneous along the demand distribution. Specifically, does opening the platform have different effects on head-campaigns as opposed to tail-campaigns in terms of their likelihood to succeed? Following the reasoning above, we add one more set of competing hypotheses:

- **H3.a**: Opening the platform has a negative effect on the average campaign's likelihood to succeed; however, head campaigns are **less negatively** affected than tail campaigns.
- **H3.b**: Opening the platform has a negative effect on the average campaign's likelihood to succeed; however, head campaigns are **more negatively** affected than tail campaigns.

Data and Descriptive Statistics

For the purpose of this study, we use data collected about campaigns on Kickstarter,com that were launched between June 3, 2013 and June 3, 2015, i.e., during the year before and the year after the "Launch Now" policy change. This dataset contains a total of 131,575 campaigns. For each campaign, we collected the following data: description, financing goal, financing duration, use of a video (yes/no), amount of money pledged to the campaign, whether the campaign was successful (i.e., reached its financing goal), and the category the campaign belongs to. Additionally, we collected a list of campaigns that the campaign's owner had previously created, from which we derived a variable indicating the number of campaigns he or she had previously owned.

Table 1 provides detailed descriptions and descriptive statistics for our variables. Table 2 presents descriptive statistics with regard to the demand and the supply side, from the periods before and after the policy change. As could be expected, the number of campaigns available for funding on the platform increased dramatically after the change (by 72 percent). At the same time, the number of backers and the total sum of pledges increased only moderately (by 10 percent and 18 percent, respectively). These observations indicate that the increase of offerings on the supply side was much stronger than the corresponding increase in demand, suggesting that the demand distribution across products is likely to have changed.

Table 1. Descriptive statistics

Variable	Description	Mean	Median	Min	Max
numWordsInDescription	Number of words in the campaign description	1,125	917	13	47,346
FinancingGoal	Target amount of the campaign in USD	50,600	5980	1	169,000,000
Duration	Duration of the campaign (days)	30	32.87	1	60.04
hasVideo	Whether the campaign has a video (1 = yes, 0 = no)	0.67	1	0	1
AmountPledged	Amount of money pledged to the campaign in USD	8,224	501	0	20,338,986
isSuccessful	Whether the campaign reached its financing goal	0.32	0	0	1
numCreated	Number of campaigns previously created by the campaign's owner	1.27	1	0	111
numOfBackers	Number of backers funding the campaign	99.32	10	0	219,382

Table 2. Total sum of pledges and number of backers of the campaigns one year before and after removing the entrance barriers			
	One year before the change	One year after the change	% change
# campaigns	48,312	83,263	72%
Sum of pledges (in millions of dollars)	496.12 (US$)	585.42 (US$)	18%
# backers	6,217,311	6,849,803	10%

Table 3 presents descriptive statistics at the campaign level with regard to our outcome variables of interest: the total sum of pledges and the number of backers per campaign. As can be seen, while the total demand increased (as seen in Table 2), the mean and median values (in terms of sum of pledges and the number of backers) decreased as a result of the policy change. Additionally, we see that the post-change distribution of demand is more skewed (indicating a less symmetric distribution) compared with the pre-change distribution and has higher kurtosis (indicating a more heavy-tailed distribution).

Table 3. Descriptive statistics of the dependent variables, one year before and after removing the entrance barriers and in total						
	Sum of pledges per campaign		# backers per campaign		Campaign's likelihood to succeed	
	Before	After	Before	After	Before	After
Mean	10,269	7,035	128.7	82.24	0.41	0.26
Median	1,395	201	24	5	0	0
SD	69,433.07	102,015.9	827.8	1013.44	0.49	0.43
Min	0	0	0	0	0	0
Max	6,225,355	20,338,986	105,857	219,382	1	1
Skewness	42.45	134.15	62.60	140.74		
Kurtosis	2773.45	23,260.22	6614.63	27575.7		

Empirical Methodology

H1: Platform openness and the concentration of demand distribution

To address H1 we focus on Lorenz curves and Gini coefficients – two standard measures in the long tail literature. Specifically, for each variable of interest (the sum of pledges and the number of backers), we compare the Lorenz curve and the Gini coefficient in the year before opening the market versus those in the year after. To determine whether any differences observed between the distributions are significant, we also fit the campaign-data to a Pareto curve and investigate how the relationship between the rank of a project and the pledges it raised changed after Kickstarter's adoption of the open acceptance policy.

H2: Platform openness and the superstar effect

To address H2, we first derive descriptive statistics on the number of campaigns that raised different shares of the sum of pledges (10%, 20%, 30%, …), and the amount of money raised by the top 10, 50, 100, 500, 1000, and 100,000 campaigns before versus after the opening of the platform.

We then further analyze the relationship between different shares of the money invested and the number of campaigns that raised these shares before and after the opening of the platform. To do so, we group the campaigns according to whether they were launched before or after the policy change, and we order each group of campaigns from top to bottom according to the total amount pledged. Then, for each set of ordered campaigns (before and after), beginning with the top campaign and moving down the list, we calculate the cumulative sum of pledges up to each campaign and the respective share of the total sum of pledges. We then use a linear regression to estimate the relationship between the number of campaigns and the share of money invested in them, while controlling for whether the campaign was initiated before or after the policy change.

We repeat this entire procedure to analyze the relationship between the number/share of campaigns and the share of backers that support them. We also use the Kolmogorov-Smirnov test to show that the distributions of shares of funds before versus after opening the platform are significantly different.

H3: Heterogeneity analysis

To address H3, we use a logistic regression, which estimates a campaign's likelihood to succeed while taking into account (i) whether the campaign launched before or after the opening of the platform, and (ii) the distribution quantile (in terms of the sum of pledges) to which the campaign belongs. The regression also accounts for additional campaign-related variables that characterize the campaign's quality (e.g., whether it includes a video, the number of words in its description, and the number of previous campaigns by its owners) as well as its category (e.g. video, craft, or music).

Table 4 summarizes the different variables and measurement methods used in this study.

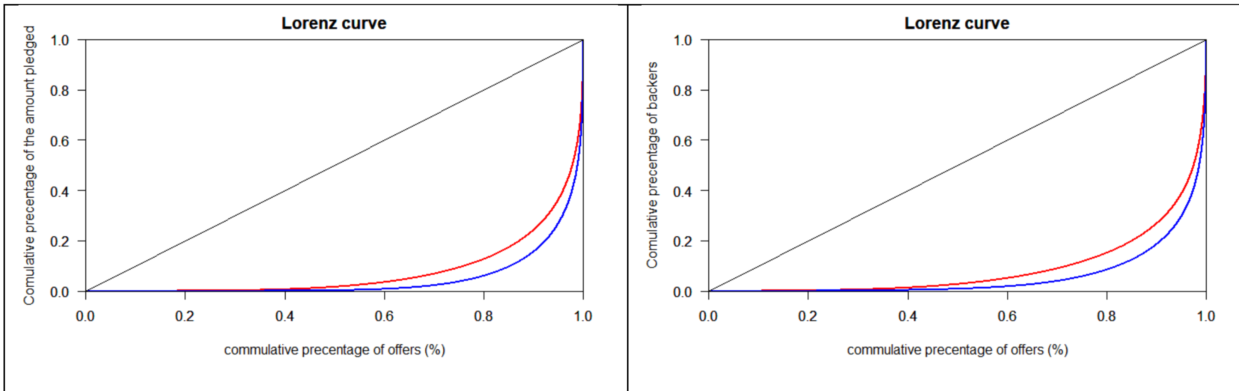
Table 4. Summary of methods and variables

	Dependent variable	method	Dependent variables
Concentration of the demand (H1)	• Number of backers per campaign • Amount of pledges per campaign	• Gini coefficient • Lorenz curve • Pareto curve	• Campaign rank • Share of total sum of pledges
Superstar effect (H2)	• Number of backers per campaign • Amount of pledges per campaign	• Descriptive statistics • Kolmogorov-Smirnov • Linear regression	• Share of the sum of pledges • Sum of pledges • Number of campaigns
Heterogeneity analysis (H3)	• Campaign's likelihood to succeed	• Logistic regression	After opening, distribution segment, hasVideo, duration, words_in_decription, num_created, category

Results

H1: Platform openness and the concentration of demand distribution

As mentioned above, we used Lorenz curves and Gini coefficients to estimate the difference between the concentration of demand before versus after the opening of the platform. Figure 1 presents two sets of Lorenz curves, one for each variable of interest: the sum of pledges (Figure 1.A) and the number of backers per campaign (Figure 1.B). As can be seen in both figures, the opening of the platform led to a more concentrated distribution of pledges.



A. Sum of pledges per campaign | **B. No. of backers per campaign**

Figure 1. Lorenz curve of the demand. In each figure the red curve represents the distribution before the opening of the platform, and the blue curve represents the distribution after the opening of the platform

Table 5 compares the corresponding Gini coefficients of the variables of interest before versus after the policy change. We find that after the opening of the platform, the Gini coefficient of the pledge distribution increased by 6.5 percent, and the Gini coefficient of the distribution of the number of backers increased by 7.5 percent.

For robustness, we carried out additional comparisons within specific subsets of campaigns. First, we compared the pre- and post-change Lorenz curves and Gini coefficients of only the campaigns that were successful (i.e., reached their funding goals). The results of this comparison were similar to those obtained for the complete dataset: funds and backers became more concentrated after the opening of the platform, as shown in Table 5.

Second, we calculated pre- and post-change Gini coefficients for each separate campaign category. For each category, the Gini coefficient corresponding to each variable of interest increased after the opening of the platform.

Table 5. Gini coefficients of the distributions of the number of backers and the number of pledges, before and after the opening of the market

	Before policy change	After policy change	increase
Gini coefficient - #backers	0.82	0.88	7.5%
Gini coefficient – pledges	0.85	0.90	6.5%
Gini coefficient – pledges of successful campaigns	0.76	0.79	4.2%
Gini coefficient – #backers of successful campaigns	0.73	0.76	3.9%

Third, we carried out an analysis to rule out the possibility that the change in concentration of the demand distribution was attributable solely to a change in campaigns' quality level. To this end, we used propensity score matching to match each pre-change campaign to a post-change campaign of similar quality. The characteristics we took into account to measure the quality of a campaign were whether the campaign includes a video, the log number of words in the description, the number of previous successful campaigns of the owner, the calculated goal, and the campaign's category. We then compared the Gini coefficients of the two matched sets of campaigns (each set comprised 48,312 campaigns), for each variable of interest. We observed that the Gini coefficient corresponding to each variable of interest significantly increased after the opening of the platform.

Forth, to ensure that the change in the concentration of the demand distribution was not attributable to a change in the composition of backers on the platform resulting from the entrance of new backers, we calculated pre- and post-change Gini coefficients (based on the number of backers) for campaigns backed by users who had invested in campaigns both during the year before the opening of the platform and during the year after the opening of the platform. We found that the Gini coefficient increased after the opening of the platform.

Fifth, to ensure that the change in the concentration of the demand distribution was not merely a result of time-related effects, we also calculated Gini coefficients for the period between June 3, 2012 and June 3, 2013. We observed that the Gini coefficient of the sum of pledges during that year-long time period was similar to that of the year preceding the opening the platform (0.85), and the Gini coefficient of the number of backers was slightly higher than that of the year before the opening of the market (0.83 compared to 0.82, suggesting that during the 2012–2013 time period the distribution of backers was slightly less equal than that during the year preceding Kickstarter's policy change). These results suggest that time-related effects cannot account for the change in the concentration of demand. We further applied discontinuity regression to rule out the possibility that time-related effects drove the increase in the number of campaigns entering the market and to verify that this increase was attributable to the event of the policy change.

Taken together, these results provide an initial indication that the distribution of demand after the change was less equal than that before the change and became more concentrated in the head. However, the results do not indicate whether this difference in the distribution of demand is significant. To show significance we fit the amount raised by a given campaign and the campaign's rank (in terms of the sum of pledges it raised) to the following log linear relationship:

$$log\left(AmountPledged_j\right) = \beta_0 + \beta_1 \, log\left(Pledges\ Rank_j\right) + \varepsilon_j \qquad (1)$$

The log linear curve described in Equation (1) is known as the Pareto curve and has been used in the literature to measure distributions of welfare, income, and sales (Brynjolfsson et al. 2011; Pareto 1896). *Pledges* $Rank_j$ is the ordinal ranking of the total amount pledged by campaign *j* (note that in this context, a campaign with a "higher" rank is actually further down in the tail). β_1 measures the extent to which the amount pledged to campaign *j* decreases as the campaign's *Pledges Rank* increases. If the opening of the platform resulted in a long tail effect, then the value of β_1 for post-change campaigns should be less negative (that is, have a lower absolute value) than the value of β_1 for pre-change campaigns, indicating that post-change campaigns with a higher *Pledges Rank* (closer to the tail) are responsible for a higher share of the demand.

We estimated Equation (1) separately for the campaigns before and after the policy change, resulting in Model 1 and Model 2 in Table 6. Both coefficients were significant. The β_1 coefficient of Model 2 was more negative than the β_1 of Model 1, indicating that after the platform opened to more campaigns, the tail became responsible for a **smaller** share of the demand than it had been previously.

To test whether the difference between the values of the coefficients was significant, we added a new dummy variable, '*AfterOpening*', which defines whether an observation corresponds to a campaign launched before or after the opening the platform, and interacted it with the log(*PledgesRank)*. Formally, we estimated the following equation on all the campaigns (before and after the change):

$$log\left(AmountPledged_j\right) = \beta_0 + \beta_1 \, log\left(PledgesRank_j\right) + \beta_2 (AfterOpening) \qquad (2)$$
$$+\beta_3 AfterOpening \times log\left(Pledges\ Rank_j\right) + \varepsilon_j$$

The estimates for Equation (2) are shown in Model 3 in Table 6. The β_3 coefficient of the interaction term is negative and significant, indicating that after the opening of the platform, higher-ranked campaigns had a more negative effect on the amount pledged. That is, the distribution of demand became significantly more concentrated after the opening of the platform.

Table 6. Pareto curve models			
	Model 1: Before opening	Model 2: After opening	Model 3: All
(Intercept)	29.50 (0.08)***	36.04(0.06)***	29.50 (0.08)***
PledgesRank	-2.33 (0.01)***	-3.01 (0.01)***	-2.33 (0.01)***
AfterOpening			6.54*** (0.10)
AfterOpening × Pledges Rank			-0.674*** (0.01)
Adjusted R2	0.65	0.75	0.72
Observations	48,312	83,263	131,575
Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1			

In the same manner, we analyzed the significance of the backers' distribution differences. The results were in the same direction and of similar magnitude and significance.

For robustness, we repeated this procedure and estimated Equations *(1)* and *(2)* for successful campaigns only and reached results with the same direction, magnitude and significance, as shown in Table 7.

Table 7. Pareto curve models for successful campaigns			
	Model 1: Before	Model 2: After	Model 3: All
(Intercept)	20.09 (0.03)***	21.27 (0.04)***	20.09 (0.03)***
PledgesRank	-1.25 (0.003)***	-1.37 (0.004)***	-1.25 (0.004)***
AfterOpening			1.18 (0.04) ***
AfterOpening × Pledges Rank			-0.13 (0.005)***
Adjusted R2	0.901	0.856	0.875
Observations	19886	21768	41654
Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1			

Taken together, these results confirm H1.a and indicate that the distribution of demand after the change was less equal than that before the change, and was more concentrated in the head. Specifically, these results provide a first indication that democratization of the platform (through the removal of entrance barriers) changes the distribution of demand such that a larger share of the money going into the platform is ultimately received by a smaller percentage of campaigns, and a larger share of backers fund a smaller percentage of the campaigns.

As discussed above, these results do not inform us about the particular way in which the distribution of the demand changed as a result of the opening of the platform. Specifically, we can conclude from our findings thus far that a more democratized platform does not lead to a long tail effect; however, we still cannot determine whether it leads to a superstar effect. To this end, we proceed to test H2.

H2: Platform openness and the superstar effect

To delve into the nature of the change to the distribution of funds after the opening the platform, and, specifically, to investigate whether democratization led to a superstar effect, we analyzed both the minimum number and share of campaigns that raised different shares (e.g. 10%, 20%, …) of the total amount of funds. The results are presented in Table 8 and in Figure 2. We can see that, after the opening of the platform, each share of the sum of pledges was raised by a smaller **share** of the campaigns. Importantly, after the opening of the platform, shares smaller than or equal to 70% of the sum of pledges were also raised by smaller **numbers** of campaigns, as compared with the state prior to the policy change. Figure 2 highlights how the difference between the numbers of campaigns before and after opening the market becomes smaller as we examine higher shares of the sum of pledges and is eliminated when reaching a share of 73% of the sum of pledges. We find that the difference between the numbers of campaigns required to raise different shares of funds before and after opening the market is statistically significant (using Kolmogorov-Smirnov test[2]).

Table 8. The number (and share) of campaigns raising different shares of the sum of pledges - one year before and after removing the entrance barriers

Share of the total sum of pledges	# campaigns (%) before	# campaigns (%) after
10%	20 (0.04%)	7 (0.01%)
20%	82 (0.17%)	55 (0.07%)
30%	229 (0.47%)	180 (0.22%)
40%	524 (1.08%)	440 (0.53%)
50%	1,048 (2.17%)	937 (1.13%)
60%	1949 (4.03%)	1851 (2.23%)
70%	3490 (7.22%)	3455 (4.16%)
80%	6206 (12.80%)	6339 (7.63%)
90%	11,577 (23.96%)	12,215 (14.70%)
99%	26,786 (55.44%)	31,271 (37.62%)
100%	48,312 (100%)	83,122 (100%)

Recall that after the opening of the market, the total sum of pledges was 18% higher than before (see Table 2). Thus, the results of this analysis not only show that a smaller number of campaigns was responsible for the same share of funds but also that a smaller number of top-campaigns was responsible for a larger amount of funds (in absolute terms), as shown in Table 9.

[2] To test significance, we separately ordered the campaigns before opening the platform and after by their total pledged amount from top to bottom. We then accumulated for each campaign the sum of pledges up to the current campaign and calculated the respective share of the total sum of pledges. We then used the Kolmogorov-Smirnov test on the two (before and after) distributions of the accumulated sum of pledges.

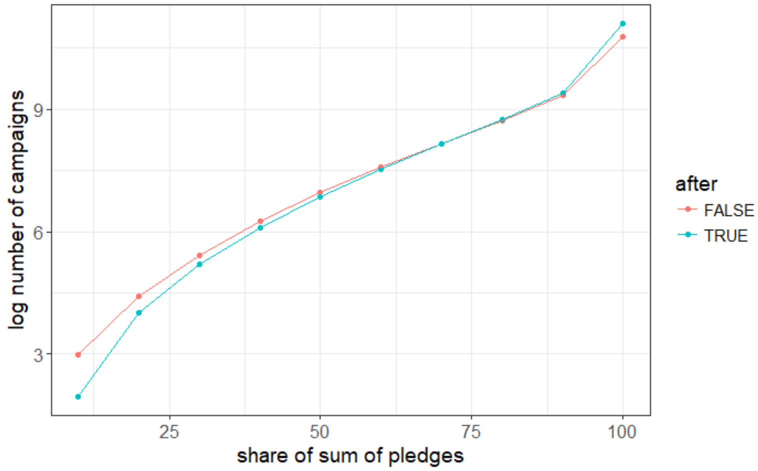


Figure 2. log no. of campaigns that raised different shares of the total sum of pledges, for campaigns before (red) and after (blue) opening the platform

Table 9. Total sum of pledges and share of the total pledges that was raised by the top campaigns, one year before and after opening the platform

Top campaigns	amount pledged (in millions of USD)		share of the total amount pledged	
	Before	After	Before	After
10	34.08	65.08	6.9%	11.1%
50	78.08	112.53	15.7%	19.2%
100	107.95	143.57	21.8%	24.6%
500	195.33	243.27	39.4%	41.6%
1,000	244.49	297.69	49.3%	50.9%
10,000	435.61	509.55	87.8%	87.1%

Taken together, these results show that, after the opening of the platform, the majority of funds were allocated to a smaller number of campaigns, thus providing evidence for the existence of the superstar effect in democratized platforms (H2.a).

To more formally analyze the relationship between the share of the sum of pledges and the number of campaigns that raised them, we followed the method used in H1 for measuring the significance of the differences between the Pareto curves. We used the following procedure:

1. We separated the campaigns into two groups—those launched before the opening of the platform ("before") and those launched after the policy change ("after") and ordered the campaigns in each group according to their total pledged amounts, from top to bottom.
2. For each set of ordered campaigns (before and after) we calculated for each campaign the cumulative sum of pledges up to the current campaign and the respective share of the total sum of pledges (*shareOfAmountPledged*). For example, if the top-most campaign raised $10M, the second campaign raised $9M and the third campaign raised $7M, then the *shareOfAmountPledged* raised by the first campaign (*numOfCampaigns* = 1) is $10M, the *shareOfAmountPledged* raised by the top two campaigns (*numOfCampaigns* = 2) is $19M, and the *shareOfAmountPledged* raised by the top three campaigns (*numOfCampaigns* = 3) is $26M.

3. We combined the before and after datasets and added a dummy variable *AfterOpening* that indicates whether the campaign was initiated before (0) or after (1) the opening of the platform.
4. We then estimated the following equation on the combined dataset

$$\log(numOfCampaigns_i) = \beta_0 + \beta_1 shareOfAmountPledged_i + \beta_2 AfterOpening_i + \beta_3 AfterOpening \times shareOfAmountPledged + \varepsilon_i \quad (3)$$

The results appear in Model 1 in Table 10 and show that *AfterOpening* has a significant negative effect on the number of campaigns that raised a given share of the funds. In other words, the number of projects receiving a given share of the funds decreased following the platform's democratization. However, this effect is moderated by the interaction term: as the share of the amount pledged becomes higher (higher *shareOfAmountPledged* value) the effect of the opening of the platform on the number of campaigns responsible for that share significantly decreases. Thus, our results suggest that in a more democratized market, a smaller number of head-campaigns raise most of the money invested (when considering shares of up to 73% of the total amount pledged).

Table 10. Number of projects vs. share of funds

VARIABLES	Model 1
(Intercept)	2.88*** (0.01)
shareOfAmountPledged	7.48*** (0.01)
AfterOpening	-1.13*** (0.01)
AfterOpening × shareOfAmountPledged	1.52*** (0.02)
Adjusted R2	0.91
Observations	131,575
Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1	

We repeated these analyses for our second variable of interest, examining the relationship between the share of the number of backers and the number of campaigns they supported before versus after the opening of the platform. Results are in the same direction and of similar magnitude and significance to those obtained for the total amounts pledged.

For robustness, we repeated all analyses (both for the shares of funds raised and for the shares of backers) taking into account only successful campaigns, and reached similar results.

To rule out the alternative explanation that any effects observed at the campaign level are due to changes in the composition of the demand side (i.e., after the opening of the platform a different set of backers, who had a preference for head campaigns, entered the platform), we conducted a backer-level analysis, in which we focused on 234,578 serial backers (30% of the backers), who were active as backers on the platform before the opening of the platform and backed more than 10 campaigns (that is, more than the average across the platform, which is 10 campaigns per backer). For these backers we compared the percentage of investments that they pledged to top campaigns before versus after the policy change (the top 10, 50, 100, 500 or 1000 campaigns in terms of funds raised). Our results show that show that the average percentages of serial backers' funds that were pledged to top campaigns increased after the opening of the platform. For example, after the opening of the platform, the average percentage of investment in the top 10 campaigns for those backers increased by 52%, from 4.7% to 7.2%, and the average percentage of investment in the top 50 campaigns increased by 27%, from 10.6 % to 13.4%.

Put together, our results show that, when considering campaigns near the head of the distribution, the opening of the platform resulted in a redistribution of demand, such that a given share of funds or of backers was attributed to a smaller share of campaigns, and, importantly, to a smaller number of campaigns than it was prior to the policy change. Moreover, a given number of top campaigns launched after the policy change was responsible for higher share of the funds compared with the same number of top campaigns launched prior to the change. Thus, our results confirm hypothesis H2.a and show that the peer economy platform investigated herein adheres to the superstar effect.

H3: Heterogeneity analysis

In our final analysis we sought to investigate whether and how the opening of the platform differentially affected the performance (in terms of likelihood to succeed) of head-campaigns and of tail-campaigns. To this end, we used the following procedure. First, as in our previous analyses, we separated the campaigns into “before” and “after” groups. Then, for each group of campaigns, we calculated the 0.25, 0.50, 0.75, 0.95, and 0.995 quantiles based on the total amount pledged. We then matched each campaign to the segment it belongs to: less than the 0.25 quantile, between the 0.25 and 0.50 quantiles, between the 0.50 and 0.75 quantiles, between the 0.75 and 0.95 quantiles, between the 0.95 and 0.995 quantiles and above the 0.995 quantile.

To study the relationship between platform openness, the percentile of the fund distribution, and the campaign’s likelihood to succeed, we estimated the following equation:

$$\begin{aligned} isSuccessful_i = \beta_0 + \beta_1\, after_i + \beta_2\, segment + \beta_3\, after \times segment + \beta_4\, duration_i \\ + \beta_5\, numCreated_i + \beta_6\, hasVideo_i + \beta_7 \log(numWordsInDescription_i) \\ + \beta_8\, category_i \end{aligned} \tag{4}$$

The *after* variable allows us to estimate the baseline effect of opening the platform (after=1), and the interaction between *after* and *segment* measures the additional, segment-specific effect. The results are presented in Table 11.

Table 11. The effect of platform openness on the likelihood to succeed, along different segments of the funds distribution

VARIABLES	**Model 1**
(Intercept)	-0.935 (0.145)***
after	**-2.370 (0.323)*****
segment<Q25	Omitted
segment<Q50	4.111 (0.121)***
segment<Q75	6.046 (0.120)***
segment<Q95	7.417 (0.122)***
segment<Q99	8.742 (0.142)***
segment<Q995	9.863 (0.314)***
segment Q995<	10.337 (0.349)***
after × segment<Q50	**0.280 (0.326)**
after × segment <Q75	**1.095 (0.324)*****
after × segment <Q95	**1.850 (0.325)*****
after × segment <Q99	**2.142 (0.336)*****
after × segment <Q995	**2.257 (0.480)*****
after × segment Q995<	**2.877 (0.553)*****
hasVideo	-0.383 (0.024)***
duration	-0.044 (0.001)***
log(numWordsInDecription)	-0.383 (0.013)***
numCreated	0.160 (0.008)***
AIC	85661.634
Log Likelihood	-42798.817
Deviance	85597.634
Num. obs.	131434

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Category fixed effects are omitted for brevity

As can be observed, among campaigns in the first segment (<Q25), the opening of the platform is associated with a decrease in an individual campaign’s likelihood to succeed. However, as we move towards the higher

segments, this effect becomes smaller. For example, in the second segment, the negative effect of the opening of the platform is smaller by a factor of 1.32 (exp(0.28)) compared with the first segment; that is, in total, the effect decreases by a factor of 0.12 (exp(-.2.37+0.28)). In the last segment (above Q99.5), the effect of the opening of the platform on an individual campaign's likelihood to succeed becomes positive and increases in total by a factor of 1.66 (exp(-2.37+2.877)).

These results support H3.a, by showing that the effect of platform openness on likelihood to succeed is heterogeneous across campaigns located in different positions along the demand distribution. Moreover, we see that the magnitude of the effect monotonically decreases as we move up in the distribution, towards the head. Additionally, our observation that the performance of the head of the distribution (99.5%) improved after the policy change lends further support to H2.a, strengthening our conclusion that opening the platform led to a superstar effect. Specifically, not only did democratization of the platform lead fewer campaigns to receive more of the funds, it also increased the very top campaigns' likelihood to succeed.

Summary and Conclusion

The objective of our work was to study how a platform owner's choice to open, or democratize, a peer economy market (through platform design choices) might affect the distribution of demand on the platform. We drew from the rich "long tail" literature, which suggests that the emergence of (traditional) online commerce has led to shifts in consumption patterns. As discussed above, whereas some studies in the long-tail literature have pointed to a shift in demand from bestsellers to the tail, showing that bestsellers hold a smaller market share online than they do offline, other studies have shown that the well-known "superstar" effect is still in play, leading the consumption-share of bestselling products to grow over time. Our work aimed to resolve this tension in the context of the peer-economy.

Our analysis relied on a natural experiment in the form of a policy change that occurred on Kickstarter.com that resulted in lowering the entry barriers to the platform, thereby opening the market to more players. We observed that this policy change had the following effects on the distribution of demand on the platform:

- The distribution of demand after the change was less equal than that before the change, and was more concentrated in the head (H1.a).
- Considering campaigns near the head of the distribution: Opening the platform led to a reduction both in the percent of campaigns and in the number of campaigns responsible for a given share of the demand (in terms of money invested and the number of backers) (H2.a).
- Opening the platform had a negative average effect on an individual campaign's likelihood to succeed; however, head-campaigns were less negatively affected than tail-campaigns (H3.a).

Our findings indicate that a more democratized peer-economy does not lead to a long-tail effect and, in fact, leads to a superstar effect. These results correspond to previous findings by Elberse and Oberholzer-Gee (2007) and Goel et al. (2010). On the basis of these results we conclude that, counterintuitively, a more democratized peer-economy results in a less even distribution of funds.

Our work offers both theoretical and managerial contributions. From the theoretical perspective we contribute to the IS literature on the tension between the long tail effect and the superstar effect and extend it to the context of the peer-economy, where transactions are conducted between peers (rather than between firms and consumers). While further research is required, our results may provide insights to the choice-overload literature. Our finding that opening the market (and thereby substantially increasing the number of offers available in that market) leads to a superstar effect can potentially be attributed to choice-overload: potential backers now have more campaigns to choose from, leading them to invest in the more popular and well-known ones.

From the managerial perspective, our findings can be translated and applied to managerial decisions regarding the governance of online marketplaces. For example, our observation that demand increased after the platform's transition to an open acceptance policy, but that this demand was concentrated among top-performing campaigns (to a greater extent than it was prior to the policy change), may lead platform managers to consider changes to their platforms' recommendation, word-of-mouth, and filtering mechanisms to better fit campaigns to potential backers.

Our work may also carry implications for other peer-economy sectors other than crowdfunding, including, for example, ridesharing and accommodation sharing. Testing our conjectures in other contexts constitutes an interesting avenue for future work.

Acknowledgements

This research was supported by the ISRAEL SCIENCE FOUNDATION (grant No. 0751507), and the Blavatnik Interdisciplinary Cyber Research Center.

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