Overfunding and Signalling Effects of Herding Behaviour in Crowdfunding*

Svatopluk Kapounek[I]

Zuzana Kučerová [II]

July 2019

Abstract

The paper employs dynamic market-wide herding measure on 117,166 lending-based campaigns on 119 online platforms in 37 countries. Our dynamic herding behaviour measure explores whether lenders follow each other at the whole crowdfunding market, within the groups of top platforms, within the specific category or platform, and within the specific category in the specific platform.

We show that herding behaviour plays an important signalling role to reduce opportunity costs if the auction does not receive enough money bids. Additionally, our threshold models identify significant herding behaviour after funding goals are raised and highlight negative effects of signalling mechanisms which lead to adverse selection at crowdfunding markets.

Keywords: Crowdfunding, P2P lending, overfunding, herding, asymmetric information, signalling

JEL Classification: G21, D26, C55

---

* This research was funded by the Czech Science Foundation via grant No. P403/17-25924S "Comparative Study of Crowdfunding Projects: Business Decision-Making Process, Risks and Regulation".

[I] Department of Finance, Mendel University in Brno, Czech Republic.

Full corresponding address: Mendel University in Brno, Faculty of Business and Economics, Department of Finance, Zemedelska 1, 613 00 Brno, Czech Republic, Phone: +420 545 132 444, Fax: +420 545 132 450, e-mail: kapounek@mendelu.cz

[II] Department of Finance, Mendel University in Brno, Czech Republic, e-mail: zuzana.kucerova@mendelu.cz.

1. Introduction

Lending-based crowdfunding (microloans, peer-to-peer loans, social loans) enables individual lenders (investors, funders) to lend money and individual borrowers (founders, entrepreneurs) to gain money quickly, with low transaction costs through the internet auctions and without a bank intermediation. Each campaign presented at the crowdfunding platform is launched by individual borrower who present specific project for funding through multiple micro loans from individual investors (or lenders). However, there an asymmetric information between the investors and borrowers, especially about project risk, potential return and borrower creditworthiness, which causes adverse selection (Zhang and Liu, 2012). Moreover, there is a risk of opportunity costs if the auction is cancelled for the lack of investors' money bids (each campaign must gain the demanded amount of money).[1]

However, there are no institutions (e.g. banks, rating agencies, registers of failed projects, borrowers' credit history) to reduce the asymmetric information or the risk of opportunity costs at the crowdfunding market. Therefore, potential investors (lenders) have very limited information about the project risks (potential return, borrowers' creditworthiness, and opportunity costs) and only signals reduce the uncertainty which lead the lenders to invest in certain projects.

The signalling mechanism in crowdfunding occurs through the following different channels: (1) materials shared on project website (Ahlers et al., 2015), (2) sharing information and signals by lenders via social networks (Mollick, 2014), and (3) providing information about the number, frequency and the amounts of bids by the lenders (Dholakia and Soltysinski, 2001; Herzenstein et al., 2011). The signalling mechanisms lead to time-varying herding behaviour that changes with the time and raised money after the auction is presented at crowdfunding platform. Dholakia and Soltysinski (2001) show positive effect of the number of bids on herding behaviour after making the first bid,

[1] Platforms mostly operate on "all-or-nothing model" when entrepreneurs have "skin in the game" as every loan auction must receive enough money bids to gain the demanded amount of money and to be successful; otherwise, the auction is cancelled and money is returned to individual lenders. This situation is sometimes defined as "the rule of full funding" (Herzenstein et al., 2011). Several platforms allow the borrowers to close the project successfully even though the collected amount does not reach the target goal. This model is known as keep-it-all model and the borrower must usually pay a higher fee for such possibility (Cumming et al., 2019).

Herzenstein et al. (2011) contribute that herding behaviour increases only to the point at which it has received full funding.

We contribute to this strand of literature and identify continuing herding behaviour of lenders after the goal amount has been raised. The overfunding[2] possibility has a negative impact on other projects as these projects do not raise enough funds (Koch, 2016) and the overfunded projects means higher obligations or margins to the borrower. In that case, the signalling mechanisms cause overfunding which leads to adverse selection at the crowdfunding markets.

In our paper, we assume that lenders reduce uncertainty following each other within the specific market, category or platform. We follow Sias (2004) and adjust dynamic institutional herding measure to online auctions and crowdfunding market specifics. We use a rich dataset of 117,166 lending-based crowdfunding auctions and provide robust evidence of herding behaviour of lenders and campaign overfunding separately at the whole crowdfunding market, within the group of top platforms, within the specific project category or platform, as well as within the project category in the specific platform.

We also control for overall target goal and campaign duration and find that in case of large projects and project with campaign duration between 3 months and 2 years, lenders are risk-averse and prefer lending to projects from relatively richer countries.

The structure of the paper is as follows. Section 2 reviews the literature concerning herding behaviour generally and in peer-to-peer markets. Section 3 introduces data and methods used in the paper. Section 4 provides empirical evidence of herding behaviour and additional effects of goal, GDP per capita and project duration. Section 5 contains robustness analyses and section 6 concludes.

2. Literature Review

The behaviour of people can be assessed using the *social comparison theory* originally proposed by Festinger (1954) who studies social influence processes and some types of competitive behaviour as socio-psychological processes. He formulates that people use a set of standards to evaluate both the reality, when they use objective standards, and themselves (self-evaluation), when they try to compare their behaviour with the behaviour

[2] Once a specific loan gains full funding it is not closed, it can exceed the pre-set goal amount till the end of the funding campaign and other lenders may still enter this auction and contribute and as such the project can be overfunded.

of other people in case of not available standards. Banerjee (1992) characterises *herding behaviour* as behaviour when people are doing what other people are doing rather than using their sets of information (or even though their private information suggests doing something different). Moreover, Bikhchandani, Hirshleifer and Welch (1992) define *information cascades* which explain how social conventions and standards are created, maintained and modified and how these cascades can explain the sudden and large changes in the behaviour of some individuals and the spread of new type of behaviour (herding behaviour). As such, some individuals may provide information or signals for other individuals that tend to follow them.

Some authors distinguish between irrational and rational herding. *Irrational herding* can be characterised as a situation when agents follow the behaviour and decisions of other agents or follow other agents investing to non-risk investments or projects, i.e. they neglect the basic characteristics of an individual project and as such they produce suboptimal decisions (Simonsohn and Ariely, 2008; Zhang and Liu, 2012). *Rational herding* is related to observational learning among agents when they look for information about the economic situation and the creditworthiness of a borrower or may utilise information from other agents, i.e. these rational agents built their decisions on information about the individual project and their decisions need to be unbiased (Banerjee, 1992; Bikhchandani, Hirshleifer and Welch, 1992; Simonsohn and Ariely, 2008; Zhang and Liu, 2012).

There is a growing body of empirical literature on herding behaviour. Schachter *et al.* (1985) study the behaviour of investors on the New York Stock Exchange in two periods after the Second World War and find that their reactions to external events were less sensitive during the stable period than during the unstable period. Investors are thus less prone to follow the behaviour of other investors in stable (bull) markets compared to unstable (bear) markets. Fazio (1990) examines how the consumers' attitudes influence their behaviour and also concludes that they copy the behaviour of other consumers in case they face uncertainty. Dholakia and Soltysinski (2001) examine the hearing behaviour in digital auctions and state that bidders follow the behaviour of other bidders, i.e. bidders initially overlook some listings and they start bidding only after the listing receives its first bid. Simonsohn and Ariely (2008) focus on herding behaviour in case of eBay auctions and identify a bias in the investors' decision-making process resulting in suboptimal decisions as investors neglect factors which are hidden and cannot be easily observed.

Later studies are focused on herding behaviour in the process of the peer-to-peer lending; however, the research is only in its initial phase. Puro et al. (2011) identify bidding strategies in peer-to-peer loan markets and their modifications by lenders as a result of lenders' learning; however, lenders on Prosper.com do not follow any dominant strategy. According to Herzenstein et al. (2011), the higher the number of bids from lenders the higher the probability of bids from other lenders and the strategic lending behaviour is beneficially for lenders. Similarly, Lee and Lee (2012) confirm the important role of information in the lenders' decision-making process and the existence of herding when the number of bids of individuals investors strongly increases when the number of total bids and total amount to be funded rises and approaches 100%. In a related study, Yum, Lee and Chae (2012) conclude that lenders take into account other lenders' behaviour when they lack information about the borrower's creditworthiness but rely on their own judgment when they have enough information from the borrower or the market.

Zhang and Liu (2012) study factors which may characterise the herding behaviour in microloans markets: *unobserved heterogeneity* across data (listings, i.e. loans requests) and *payoff externalities* (or *herd externalities* according to Banerjee, 1992) among lenders. The unobserved heterogeneity concerns listing attributes which can be unobserved by the researcher and may attract lenders, however, the available data do not include them. The payoff externalities occur when the behaviour of one lender depends on the behaviour of other lenders (see the problem of conditional cooperation below). Lenders do not contribute to project with a low probability to achieve a full funding and as a result these listings will not turn into a loan. In this case, lenders will incur opportunity costs of time and investments even though their contributions will be refunded and as a result, lenders have a tendency to prefer well-funded listings or listings with a high probability to materialise into a loan. They confirm the existence of a rational herding in the specific microloan market when lenders study the creditworthiness of a borrower and follow the decision of other lenders. According to Katz and Shapiro (1985), who develop a model of oligopoly to analyse the impact of consumption externalities on competition in markets and the form of the market equilibrium, the existence of a strong reputation for being a market share leader may result in socially correlated lending decisions and the overestimation of the herding effect.

One stream of empirical works studies the herding behaviour experimentally. In the context of irrational herding, some authors study the problem of conditional cooperation of economic subjects who contribute voluntarily to the provision of public goods. Using laboratory experiments, they confirm the importance of *conditional cooperation*, social information and objective standards in the decision of donators when they donate or renew their contributions to fund public goods, i.e. they behave pro-socially (Fischbacher, Gächter and Fehr, 2001; Frey and Meier, 2004; Kocher *et al*., 2008; Croson and Shang, 2008; Neugebauer *et al*., 2009; Fischbacher, Gächter and Quercia, 2012; Martinsson, Pham-Khanh and Villegas-Palacio, 2013). However, these studies are focused mainly on donation-based crowdfunding.

In the era of the Internet and online environment, there is an opportunity to study real-life auctions and behaviour. Another stream of studies thus analyses this phenomenon in non-experimental environment and examine the role of information processing in microloan markets where the signals on borrower's creditworthiness are very limited. Iyer et al. (2011) state that, in peer-to-peer markets, lenders infer the most from standard banking information ("hard", objective, factual, verifiable information), however, they also use non-standard information provided by borrowers ("soft", subjective, private, unverifiable information, like pictures or personal descriptions posted by borrowers) to assess the creditworthiness of borrowers particularly in low credit categories. The relationship between a borrower and a lender of one group is thus similar to the relationship between a bank and its client in case of traditional banking; in both cases, they use soft information. In case of peer-to-peer lending, some soft information may compensate for the lack of hard information and may reduce the information asymmetry present in these markets. In other cases, information asymmetries can exist and lenders use only public information. Sonenshein et al. (2011) state that social accounts can play a role as a source of soft information for lenders and facilitate economic exchanges between lenders and borrowers as they may help increase the borrower's creditworthiness. However, accounts can lead to sub-optimal decisions of lenders because borrowers can shape the information according to the current objective and as such accounts can be negatively interconnected with a loan performance. In this context, Hope and Stiglitz (1990) discuss the problems of imperfect information and imperfect enforcement. As a result, lenders must screen the characteristics of loan applicants and then insure against the risk.

Some researchers study the role of specific information on the behaviour of lenders. Duarte, Siegel and Young (2012) focus on the role of borrower's appearance in the lender's decision making, or more precisely, they study how the photographs of borrowers can influence whether they are trustworthy or not. Authors find that borrowers who are perceived as more trustworthy thanks to their appearance have higher probabilities that their loans will be funded, face better credit grades, more favourable interest rates and lower probabilities of default. Pope and Sydnor (2011) and Ravina (2019) also focus on the borrower's appearance and other aspects, such as race, ethnicity, age, gender or attractiveness and the impact of these aspects on the lender's behaviour. While Pope and Sydnor (2011) argue that there is a statistical discrimination against black people (perceived higher probability of default) and a taste-based discrimination against white people or in favour of black people (both credit rating of the borrower and the risk premium included in the lending interest rate does not reflect the higher probability of default), i.e. that there is a racial discrimination in peer-to-peer loan markets. Larrimore *et al*. (2011) confirm the impact of language features (the word use) on the borrower's creditworthiness and the success to gain full funding using specific linguistic software.

In many cases, lenders are in contact with borrowers or other lenders through online discussion forums; this communication is available to other participants of the specific forum. Sometimes, participants create specific social groups integrating both borrowers and lenders and keep the lines of communication open in order to share information concerning borrowers (e.g. assistance for new lenders, warnings in case of fraudulent practices etc.) and overcome the information asymmetry and adverse selection in lending practices. Muniz and O'Guinn (2001) formulate the term *brand community* as a specialised, non-geographically restricted community with social relations among its members. Carlson, Suter and Brown (2008) distinguish between social and psychological brand communities. *Social brand communities* are groups of people who are organised in a group are engaged in some form of social virtual interaction online, even though they do not know each other personally (i.e. without face-to-face communication). Sometimes, such groups can exist even without any social interactions or group membership and these people only feel a sense of this group or community; in this case, authors define *psychological brand communities* and these people do not have to respect the rules or norms of that community. As such, group membership is an optional feature in some crowdfunding platforms. Lin, Prabhala and Viswanathan (2013) or Freedman and Jin (2017) examine these aspects of assessing the borrowers in microloans markets, such as social relationships, and conclude that the online friendship of borrowers may act as signal of the borrower's creditworthiness as it increases the probability of successful funding, lowers interest rates on funded loans, and is associated with lower ex post default rates. And lower default rates lead to lower interest rates. Berger and Gleisner (2009) examine the role of financial intermediaries (or group leaders) in peer-to-peer lending platforms and find that these intermediaries reduce information asymmetries between borrowers and lenders as they screen the financial situation and the creditworthiness of (mainly less attractive) borrowers. Muniz and O'Guinn (2001) state that this behaviour of the community can be characterised as a *sense of moral responsibility* when community members feel responsibility of obligation to the rest of the community, particularly in times of threat of the community, and this potential threat forces them to take a collective action. According to Everett (2015) or Lin, Prabhala and Viswanathan (2013), when borrowers are members of a social group, the members monitor each other and as a result it prevents moral hazard and adverse selection and the repayment rates are high (or the default risk is low). However, Freedman and Jin (2017) warn against using online social networks as a signal of a borrower's creditworthiness in anonymous transactions because not all social connections (particularly those only from borrowers) guarantee higher financial return to the lender.

3. Data and Methods

Our unique and rich panel dataset contains all crowdfunding platforms scanned by TAB big data analytics (formerly Crowdsurfer) in the period 2014–2017. More specifically, there are 117,166 lending-based auctions/projects/campaigns[3] at 119 crowdfunding platforms in 37 countries from 10jun2014 until 06oct2017 (daily data). The campaigns are divided into 16 categories (Table A1 in the Appendix). Despite the fact that we are not able to identify category of the most campaigns (platforms use different category names in different languages), we can summarize that above-average overfunding exceeding 250% raised funds was identified in categories "Capital Goods", "Heath Care Equipment and Services", "Materials", "Real Estate", "Technology, Hardware and Equipment" and "Transportation".

Our dynamic measure of herding behaviour is based on temporal dependence in demand over adjacent days (Sias, 2004). First, to allow project comparison (especially

[3] We removed all very small projects with goal below 10,000 USD from the sample because these microloans are mostly funded only by friends and relatives of the borrower. We also removed projects which do not show any signs of activity (money raising, goal changes etc.) and outliers over 99th percentile of the collected amount of money to goal (in percentage).

project size) and to avoid currency differences, we calculate daily differences of the raised amount of money to goal of the project *k* during day *t*:

$$Raw\Delta_{k,t} = \frac{raised\ money_{k,t}}{goal_k} - \frac{raised\ money_{k,t-1}}{goal_k} \tag{1}$$

which represents daily accumulation of investments in the specific crowdfunding lending-based project. Second, we follow Sias (2004) and standardize the dependent variable to have zero mean and unit variance. Thus, we define the standardized investments accumulation in the project *k*:

$$\Delta_{k,j,t} = \frac{Raw\Delta_{k,t} - \overline{Raw\Delta_{J,t}}}{\sigma\left(Raw\Delta_{j,t}\right)} \tag{2}$$

where $\overline{Raw\Delta_{J,t}}$ represents the cross-sectional average and $\sigma\left(Raw\Delta_{j,t}\right)$ is the cross-sectional standard deviation across the market fraction *j* during day *t*. Specifically, we divide our data sample into different fractions and standardize accumulation of investment separately in relation to the whole market (all projects in our sample), to the top platforms[4], to the specific project category, to the specific platform, and to the specific category within the specific platform.

Third, we run panel regressions employing fixed-effects estimator[5] to evaluate herding momentum β_1 as the relation between the investment accumulation within the market fraction and the lag of the investment accumulation $\Delta_{k,j,t-1}$ in the project *k* within the specific market fraction *j*, during the previous day *t-1*:

$$\Delta_{k,j,t} = \beta_1 \Delta_{k,j,t-1} + \beta_2 goal_{k,j,t} + \beta_3 gdp_{c,j,t} + \beta_4 duration_{k,j,t} + \mu_{i,j} + \theta_t + \varepsilon_{i,j,t}. \tag{3}$$

We also control for selected project specifics (goal and project duration), and investment demand of the country *c*, where the project is realized (measured by GDP per capita in PPP). Finally, we include project fixed effects $\mu_{i,j}$ related to the specific market fraction, time effects θ_t (yearly dummies reflect changes of funding preferences, advertising effects etc.) and possibly heteroscedastic residual $\varepsilon_{i,j,t}$ (we estimate robust standard errors).

---

[4] We follow and identify top platforms which are considered to be „prominent“ (FSB, 2017): Funding Circle, ThinCats Assetz Capital, Lendy (Saving Stream), AuxMoney, Ppdai, and Marketinvoice.

[5] We don’t expect endogeneity bias. The selected project specifics (goal and duration) are defined by the borrower before the campaign is presented at the platform and crowdfunding projects are too small to affect country wealth (GDP). Fixed effects were confirmed by Hausman test and Variable addition test (Table A4 and Table A5 in the Appendix).

Additionally, we use the interaction terms for the all dependent variables which show changing effects of herding behaviour signals at different fundraising stages. Following Dholakia and Soltysinski (2001) and Herzenstein et al. (2011) we define thresholds at 1%, 20%, 40%, 90%, 100%, and 190% of the collected amount. Using interactions with dummies we also report different effects of goal, duration and investment demand above and below the given thresholds.

We assume that not only herding behaviour signals but also all other information (especially project specifics) are transmitted to lenders within the market fractions only. Therefore, we transform goal, duration and GDP per capita to relative values within the specific fraction j. Thus, we assume that lenders decide about the investment opportunities only within the specific market fraction on which they are focused.

Macroeconomic fundamental (GDP per capita in PPP, yearly frequency) is obtained from the World Bank International Comparison Program database and reflects economic development country specifics and investment demand differences. Descriptive statistics of the all variables are presented in Table A2, the cross-correlation matrix is presented in Table A3 (see Appendix).

4. Results

Table 1 presents the estimated herding momentum (Sias, 2004) within the specific market fractions: in all platforms (1), in top platforms (2), in individual categories across all platforms (3), in individual platforms (4) and in individual categories within individual platforms (5).

Table 1: Basic test for herding

	(1)	(2)	(3)	(4)	(5)
	Market	Top Platforms	Category	Platform	Category within Platform
Herding ($\Delta_{k,t-1}$)	0.201***	-0.015	0.159***	0.201***	0.128***
	(0.006)	(0.015)	(0.029)	(0.027)	(0.017)
Constant	-0.013***	-0.104***	-0.005***	-0.027***	-0.027***
	(0.000)	(0.002)	(0.000)	(0.001)	(0.001)
Observations	2,578,043	11,615	223,329	179,679	72,915
Projects	99,085	2,276	7,175	8,788	5,013
R^2	0.039	0.000	0.025	0.052	0.020
σ_υ	1.103	0.971	1.828	0.700	0.537
σ_ε	0.706	0.877	0.724	0.432	0.450
ρ	0.709	0.551	0.865	0.724	0.587

Note: *, **, and *** denote significance at the 10, 5, and 1 per cent level.
Robust standard errors are reported in parentheses.

Our results confirm the existence of herding phenomenon except for the top platforms which could be explained by both less uncertainty and relatively experienced lenders in the group. These first results point to the fact that lenders are strongly influenced by the behaviour of other lenders when deciding which project is worth lending and it holds for all project across all categories or platforms or both.

In the second step, we extend our analysis by using other explanatory variables such as relative target goal, relative GDP per capita of the project founder home country and the relative duration of the financing campaign (see Table 2). Again, the results confirm herding except for top platforms but also the positive impact of all three added variables on the investment accumulation in the basic model for the whole market (1). However, the impact of duration is negative in case of category (3) and platform (4) models, i.e. relatively younger projects attract more investing (the relative collected amount in time *t* is above the average relative collected amount of the specific model group).

This finding is in contrast with the whole market results in which case the relatively older projects are associated with higher investing (alternatively, we can say collecting). This contrast could be explained by the presence of asymmetric information in the world market of lending-based platforms when investors have only a limited set of information when investing all around the world. However, we obtain opposite results when we take the effect of category (across all platforms) or platform (across all categories) into account as lenders dispose a richer set of information and are well-informed about a specific project when they are focused only on the specific category or platform. As a result, relatively younger projects attract investing more than relatively older projects.

When we focus on the positive impact of the economic level of project founder home country on the investment accumulation, it is clear that it plays the most important role in case of category (3) model when lenders are well-informed about the project in the specific category and incorporate also the information derived from the residence of the project founder and as a result, projects from relatively poorer countries (measured by the relative GDP per capita) are less attractive than the projects from countries with relatively richer countries.

Table 2: Extended models

	(1) Market	(2) Top Platforms	(3) Category	(4) Platform	(5) Category within Platform
Herding ($\Delta_{k,t-1}$)	0.100***	-0.007	0.140***	0.192***	0.131***
	(0.014)	(0.018)	(0.029)	(0.027)	(0.018)
Goal	0.073***	0.108***	0.066***	0.159***	0.242***
	(0.006)	(0.029)	(0.005)	(0.018)	(0.014)
GDP per capita	0.032*	-1.053***	0.765***	-0.220	1.168
	(0.018)	(0.115)	(0.105)	(0.366)	(0.850)
Duration	0.025***	0.020	-0.057***	-0.048***	0.017
	(0.005)	(0.027)	(0.020)	(0.017)	(0.020)
Constant	0.473***	-0.009	0.288***	-0.007	-0.032
	(0.038)	(0.298)	(0.021)	(0.013)	(0.023)
Yearly dummies	yes	yes	yes	yes	yes
Observations	249,794	11,203	216,401	172,705	69,645
Projects	9,502	2,247	6,961	8,578	4,898
R^2	0.013	0.026	0.047	0.064	0.051
σ_υ	1.895	1.026	1.782	0.701	0.548
σ_ε	0.698	0.755	0.714	0.418	0.435
ρ	0.880	0.649	0.862	0.738	0.613

Note: *, **, and *** denote significance at the 10, 5, and 1 per cent level.
Robust standard errors are reported in parentheses.

To separate the impact of specific Chinese platforms, we drop these platforms from our dataset and estimate these four models once again on a limited dataset (see Table A6 in Appendix). The results of the basic model for the world market (1) and results for top platforms (2) are almost identical and differ only slightly in case of models (3), (4) and (5). Therefore, we could state that the data from the Chinese platforms do not distort the results obtained from the main dataset.

In third step, we make a threshold analysis for our estimated model presented in Table 2 according to the collected amount concerning a specific project (see Table 3). Therefore, we divide our dataset into two parts and estimate two individual models: for projects above and below a specific threshold which are defined at the level of 1%, 20%, 40%, 90%, 100% and 190% of collected amount. Our results signal the existence of positive herding mainly in projects with collected amount above the specific threshold and in case of just started project (when the collected amount broke the 1% level) and then in case of fully funded projects (when the level o 100% was reached). According to our results, the positive herding effect remains significant till the level of 190% of target amount and then it stops (the results for the thresholds between 101% and 189% are not presented here and are available upon request). For the projects below the specific threshold, the picture is not so clear, and the evidence of herding is much weaker and even negative in case of projects below the level of 1% of collected amount.

Table 3: Thresholds of collected amount

	(1)	(2)	(3)	(4)	(5)	(6)
			Collected amount thresholds			
	1%	20%	40%	90%	100%	190%
Herding ($\Delta_{k,t-1}$)	0.100***	0.078***	0.048***	0.089***	0.242***	0.089
above threshold	(0.014)	(0.014)	(0.015)	(0.030)	(0.058)	(0.061)
Herding ($\Delta_{k,t-1}$)	-1.556***	-0.049	0.080***	0.084***	0.046***	0.096***
below threshold	(0.127)	(0.032)	(0.018)	(0.013)	(0.013)	(0.014)
Goal	0.008	-0.012	-0.046***	-0.108***	-0.142***	-0.054
above threshold	(0.008)	(0.008)	(0.010)	(0.018)	(0.025)	(0.083)
Goal	0.116***	0.109***	0.106***	0.094***	0.097***	0.075***
below threshold	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
GDP per capita	0.077***	0.057**	0.048	0.105***	0.115**	-1.076***
above threshold	(0.021)	(0.023)	(0.029)	(0.041)	(0.050)	(0.387)
GDP per capita	0.224***	0.033	-0.045	-0.017	0.010	0.025
below threshold	(0.033)	(0.026)	(0.030)	(0.031)	(0.033)	(0.019)
Duration	-0.033***	-0.169***	-0.345***	-0.401***	-0.425***	-1.124***
above threshold	(0.012)	(0.015)	(0.021)	(0.030)	(0.035)	(0.288)
Duration	0.076***	0.062***	0.048***	0.044***	0.047***	0.030***
below threshold	(0.004)	(0.003)	(0.004)	(0.005)	(0.005)	(0.005)
Constant	0.532***	0.630***	0.643***	0.648***	0.680***	0.489***
	(0.041)	(0.040)	(0.037)	(0.037)	(0.039)	(0.039)
Yearly dummies	yes	yes	yes	yes	yes	yes
Observations	249,794	249,794	249,794	249,794	249,794	249,794
Projects	9,502	9,502	9,502	9,502	9,502	9,502
Obs. above thr.	82329	70387	56708	35669	30631	2362
Obs. below thr.	167465	179407	193086	214125	219163	247432
Proj. above thr.	6686	6005	5288	3141	2272	94
Proj. below thr.	3331	4935	6278	8393	8761	9485
R^2	0.022	0.039	0.080	0.070	0.068	0.024
σ_υ	1.843	1.766	1.700	1.758	1.828	1.876
σ_ε	0.695	0.689	0.674	0.677	0.678	0.694
ρ	0.876	0.868	0.864	0.871	0.879	0.880

Note: *, **, and *** denote significance at the 10, 5, and 1 per cent level.
Robust standard errors are reported in parentheses.

To sum these partial results up, lenders follow the behaviour of other lenders and invest their money into projects that show higher activity (measured by the collected sum of money relatively to the average collected money in the market) particularly in case of newly started projects (but no projects with zero collected amount as lenders wait for first bids of other lenders) and fully funded projects breaking the 100% level of target goal (these projects are considered as successful and lenders prefer investing into these projects as they do not face opportunity costs connected with unsuccessful projects when money is returned back to the investors). As such, the overfunding has a negative impact on other projects as these projects do not raise enough funds and could possibly be considered as a specific market failure producing non-optimal results (Koch, 2016).

We also uncovered the opposite impact of target goal, economic level of the project founder home country and campaign duration on the investment accumulation. The goal has a negative impact on the collected amount in case of projects above the threshold of 40%, 90% and 100% and the impact disappears above the threshold of 190% which is also confirmed by Cordova et al. (2015) who states that lender to overfunded projects do not take the goal of the project into account. Conversely, a positive impact in case of projects below the threshold, i.e. less financed projects show relatively more bids (i.e. higher collected amounts) as lenders are prone to lend money to these projects.

The investment accumulation is also positively influenced by the relative economic level in case of projects above the threshold (lenders prefer projects from relatively richer countries, i.e. they are more risk-averse) with the exception of project above 190% of the collected amount when lenders are sure about the success of the financing campaign and tend to speculate and lend money to projects from relatively poorer countries (i.e. they are more risk-seeking). In case of the projects below the threshold, there is almost no impact of this variable except for projects under 1% of collected amount with a positive impact of GDP per capita.

Campaign duration shows similar results as there is a positive relation with the investment accumulation for projects below the threshold, i.e. the rising duration leads to increases in the level of collected amount. However, when projects reach the set threshold of collected amount (project are above the threshold) the relation starts being negative in all cases, i.e. the higher the duration the lower the level of the main indicator. In other words, relatively older and more financed projects significantly limit the level of positive changes of collected amounts when compared with the market average.

To confirm these results using the threshold analysis, we also divide our dataset into separate intervals according to collected amount relatively to the target goal and estimate these individual eight models (see Table A7 in Appendix). Again, these results confirm the existence of positive herding behaviour for the projects with the level of collected amount at the level of more than 100%, i.e. for overfunded projects, and for the just started projects. Conversely, there is a negative herding for projects with collected amount between 1% and 90% and just 100% of collected amount. Moreover, the target goal is significant only in case just funded project (i.e. when collected amount reaches just the level of 100% of target goal) and campaign duration is significant and positive only in intervals for collected amount between 40% and 100% of the target goal.

5. Robustness Analysis

To verify our results, we divide our dataset into five groups according to the project activity duration as a part of our robustness analysis (see Table 4). The project activity (or more precisely, the campaign activity) measures the whole period when there is some bidding activity, not the whole financing campaign (i.e. days without any activity are excluded).

Table 4: Groups by project activity duration

	(1)	(2)	(3)	(4)	(5)
	Groups by duration (days)				
	(0; 30>	(30; 90>	(90; 365>	(365; 730>	(730; ∞)
Herding ($\Delta_{k,t-1}$)	0.068***	0.116***	0.162***	0.293**	1.258**
	(0.017)	(0.033)	(0.029)	(0.130)	(0.485)
Goal	0.139***	0.266***	0.006***	0.005	-0.008
	(0.017)	(0.015)	(0.002)	(0.004)	(0.017)
GDP per capita	0.096	-0.168***	0.129***	0.048***	0.031
	(0.084)	(0.038)	(0.024)	(0.011)	(0.036)
Duration	0.330***	0.012	-0.027***	-0.013	0.111
	(0.021)	(0.012)	(0.004)	(0.020)	(0.114)
Constant	2.495***	0.830***	-0.037**	-0.098***	-0.166
	(0.218)	(0.061)	(0.014)	(0.020)	(0.175)
Yearly dummies	yes	yes	yes	yes	yes
Observations	34,891	15,639	183,235	10,695	5,334
Projects	6,221	605	2,557	82	37
R^2	0.024	0.096	0.033	0.054	0.260
σ_υ	2.342	1.248	0.559	0.949	0.423
σ_ε	1.696	0.853	0.308	0.428	0.559
ρ	0.656	0.682	0.766	0.831	0.364

Note: *, **, and *** denote significance at the 10, 5, and 1 per cent level.
Robust standard errors are reported in parentheses.

Herding behaviour is significantly present in all analysed groups. The variable goal has a positive impact on the main indicator in case of projects with campaign activity no longer than one year; in case of longer activity (higher than 1 year) goal does not play any role and there probably are other determinants influencing the collecting activity. As far GDP per capita is concerned, projects from relatively poorer countries attract lenders when the campaign activity is from 1 to 3 months and conversely, lenders prefer projects with longer campaign activity from relatively richer countries when the activity is between 3 months up to 2 years. This could be explained by the risk-averse behaviour of lenders choosing projects with relatively longer campaigns and thus longer repayment period and higher opportunity costs and risk-seeking and speculative activity of lenders connected with short funding period. As for the variable duration, the results are quite interesting and well-connected with the above mentioned results; for projects with very short campaign duration up to 30 days, the longer duration in time *t* (relatively to the average market duration in time *t*) has a positive impact on collecting activity while for project with long campaign duration between 3 months and 1 year, the longer activity influences the collecting activity negatively. In this context, very short campaign activity thus increases the attractivity of the project for lenders and vice versa, longer campaigns could be potentially riskier and as such, lenders could hesitate and limit lending activity relatively to the market average.

Next, we decompose our dataset into four groups according to the goal amount (see Table 5).

Table 5: Groups by goal

	(1)	(2)	(3)	(4)
	Groups by goal (USD)			
	<10,000; 50,000)	<50,000; 200,000)	<200,000; 500,000)	(500,000; ∞)
Herding ($\Delta_{k,t-1}$)	0.137***	0.081***	0.050**	0.053
	(0.023)	(0.024)	(0.020)	(0.033)
Goal	0.008	0.125***	0.034***	0.165***
	(0.013)	(0.009)	(0.007)	(0.021)
GDP per capita	0.088**	-0.083***	0.082***	-0.067*
	(0.034)	(0.024)	(0.022)	(0.040)
Duration	0.185***	0.026***	0.005	-0.138***
	(0.024)	(0.006)	(0.004)	(0.027)
Constant	0.667***	0.847***	0.167***	0.112***
	(0.104)	(0.063)	(0.046)	(0.020)
Yearly dummies	yes	yes	yes	yes
Observations	33,977	113,639	86,237	15,941
Projects	4,270	3,180	1,670	382
R^2	0.015	0.026	0.012	0.051
σ_υ	1.923	1.765	1.805	2.618
σ_ε	1.473	0.545	0.337	0.775
ρ	0.630	0.913	0.966	0.919

Note: *, **, and *** denote significance at the 10, 5, and 1 per cent level.
Robust standard errors are reported in parentheses.

Again, the herding behaviour remains present but for model (4) with goal amount higher than 500 thousand USD (the group with the largest target goal) as investors to large projects are probably well-informed and do not follow the other investors when deciding about their investments. The results about the positive effect of GDP per capita on the investment accumulation in models (1) and (3) confirm previous results of our basic model. However, the negative coefficient in case of model (2) with lower target goal between 50 and 200 thousand USD could signal the fact that lenders within this largest group of projects are mostly risk-seeking as they prefer investing to smaller projects from relatively poorer countries while lenders within the group of larger projects are more risk-averse and select projects with higher target goal from relatively richer countries and thus they try to avoid speculation as they do not want to face high losses. Results for individual project categories are presented in Table A7 in Appendix.

6. Conclusions

Crowdfunding is a popular form of financing for both households and entrepreneurs which gained increasing importance after the financial crisis characterised by economic downturn and limited lending possibilities. Borrowers can gain money relatively simply and quickly just from lenders without bank intermediation. However, the online environment is quite often full of uncertainty and asymmetric information and as such it can cause that unexperienced and not sophisticated lenders may have a tendency to copy the decisions of other lenders. Therefore, we face the phenomenon of herding behaviour (see Banerjee, 1992).

In our paper, we analysed a unique dataset of 117,166 lending-based crowdfunding projects on 119 online platforms in 37 countries during the period 2014–2017 to examine herding behaviour of lenders and confirmed the conclusions of other authors (e.g. Herzenstein et al., 2011; Zhang and Liu, 2012). Our results verify the existence of herding behaviour in lending-based platforms; it was proved in case of all projects and also in case of models when we controlled for project platform, top platforms, project category and both platform and category. Therefore, lenders can produce significant biases in their decision-making process.

We also identify the presence of campaign overfunding, i.e. that lenders do not stop pledging when a project is fully funded. It means that the herding behaviour of lenders is the strongest particularly in case of projects which accepts additional pledges after reaching the target amount. This finding is in contradiction with that of Herzenstein et al.

(2011) who state that herding effect is diminishing after the project receives full funding partly as a result of decreasing interest rate after target goal is reached and partly as a consequence of keeping community rules when bidding on over-funded loans could be considered to be a violation of these rules. This difference in results could be caused by the different dataset as the author use data only from the Prosper platform while our dataset contains from all platforms and it does not prove this fact and also by the existence of “impatient lender” (bidding even after the 100% target goal is reached) as Herzenstein et al. (2011) argue. However, overfunding led by egoistic herding behaviour of investors was also confirmed by Koch (2016). Similarly to Mollick (2014), there are also sings of herding behaviour after a project is launched (i.e. at the beginning of the funding campaign). These first bids could be explained by the existence of internal social capital (i.e. social ties) in early-stage projects attracting investors (particularly friends and family) expecting the that a project will reach its target goal (Agrawal et al., 2015; Colombo at al., 2015) find. On the contrary, the herding behaviour is even negative when a campaign is stopped just at the level of full funding (100% of the goal target). This U-shape funding pattern is caused by the fact that investors like contributing to projects at the very beginning and then at the end and not in the middle of the financing campaign as stated by Kuppuswamy and Bayus (2018).

Moreover, we control for overall target goal and campaign duration to identify whether the results of our basic models are robust enough. We find that large projects with the target goal between 200 and 500 thousand USD and projects with campaign duration between 3 months and 2 years, lenders prefer lending to projects from relatively richer countries as they are more risk-averse and do not want to face the potential financial losses from default projects.

Finally, we contribute with negative effects of herding behaviour signalling effects which lead to specific crowdfunding project overfunding and adverse selection.

References

Agrawal, A, Catalini, C, Goldfarb, A.. 2015. Crowdfunding: Geography, Social Networks, and the Timing of Investment Decisions. *Journal of Economics and Management Strategy*, vol. 24, no. 2, 253-274.

Banerjee, A.W., 1992. A simple model of herd behaviour. *Quarterly Journal of Economics*, 107 (3), 797-817.

Berger, S.C., Gleisner, F., 2009. Emergence of financial intermediaries in electronic markets: The case of online P2P lending. *Business Research*, 2 (1), 39-65.

Bikhchandani, S., Hirshleifer, D., Welch, I., 1992. A theory of fads, fashion, custom, and cultural changes as information cascades. *Journal of Political Economy*, 100 (5), 992-1026.

Carlson, B.D, Suter, T.A., Brown, T.J., 2008. Social versus psychological brand community: The role of psychological sense of brand community. *Journal of Business Research*, 61 (4), 284-291.

Colombo, M., Franzoni, C., Rossi-Lamastra, C. 2015. Internal Social Capital and the Attraction of Early Contributions in Crowdfunding. *Entrepreneurship Theory and Practice*, 39 (1), 75-100.

Cordova, A., Dolci, J., Gianfrate, G. 2015. The Determinants of Crowdfunding Success: Evidence from Technology Projects. *Procedia – Social and Behavioral Sciences*, 181 (11), 115-124.

Croson, R., Shang, J., 2008. The impact of downward social information on contribution decisions. *Experimental Economics*, 11 (3), 221-233.

Cumming, D. J., Leboeuf, G., Schwienbacher, A., 2019. Crowdfunding models: Keep-It-All vs. All-Or-Nothing. *Financial Management*, 1-30. DOI: https://doi.org/10.1111/fima.12262.

Dholakia, U.M, Soltysinski, K., 2001. Coveted or overlooked? The psychology of bidding for comparable listings in digital auctions. *Marketing Letters*, 12 (3), 225-237.

Duarte, Siegel and Young, 2012. Trust and Credit: The Role of Appearance in Peer-to-peer Lending. *The Review of Financial Studies*, 25 (8), 2455-2484.

Everett, C., 2015. Group Membership, relationship banking and loan default risk: The case of online social lending. *Banking and Finance Review*, 7 (2), 15-54.

Fazio, R.H., 1990. Multiple processes by which attitudes guide behaviour: The MODE model as an integrative framework. *Advances in Experimental Social Psychology*, 23, 75-109.

Festinger, L., 1954. A theory of social comparison processes. *Human relations*, 7 (2), 117-140.

Fischbacher, U., Gächter, S., Fehr, E., 2001. Are people conditionally cooperative? Evidence from a public goods experiment. *Economic Letters*, 71 (3), 397-404.

Fischbacher, U., Gächter, S., Quercia, S., 2012. The behavioural validity of the strategy method in public good experiments. *Journal of Economic Psychology* 33 (August 2012), 897-913.

Freedman, S., Jin, G.Z., 2017. The information value of online social networks: Lessons from peer-to-peer lending. *International Journal of Industrial Organization*, 51 (March 2017), 185-222.

Frey, B., Meier, S., 2004. Social comparisons and pro-social behaviour: testing “conditional cooperation” in a field experiment. *American Economic Review*, 94 (5), 1717-1722.

FSB, 2017. FinTech credit. Market structure, business models and financial stability implicaions. Bank for International Settlements and Financial Stability Board report, May 22, 2017.

Herzenstein, M., Dholakia, U.M., Andrews, R.L., 2011. Strategic herding behaviour in peer-to-peer loan auctions. *Journal of Interactive Marketing*, 25 (1), 27-36.

Hope, K., Stiglitz, J.E., 1990. Imperfect information and rural credit markets: Puzzles and policy perspectives. *The World Bank Economic Review*, 4 (3), 235-250.

Iyer, R., Khwaja, A.I., Luttmer, E.F.P., Shue, K., 2011. Screening in New Credit Markets: Can Individual Lenders Infer Borrower Creditworthiness in Peer-to-Peer Lending? *AFA*

2011 Denver Meetings Paper. Available at SSRN: https://ssrn.com/abstract=1570115 or http://dx.doi.org/10.2139/ssrn.1570115

Katz, M.L., Shapiro, C., 1985. Network externalities, competition and compatibility. *American Economic Review*, 75 (3), 424-440.

Koch, J.-A. 2016. The Phenomenon of Project Overfunding on Online Crowdfunding Platforms – Analyzing the Drivers of Overfunding. In: *Proceedings of the 24th European Conference on Information Systems (ECIS 2016)*, Istanbul, Turkey. Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2808427.

Kocher, M.G., Cherry, T., Kroll, S., Netzer, R.J., Sutter, M., 2008. Conditional cooperation on three continents. *Economisc Letters*, 101 (3), 175-178.

Kuppuswamy, V., Bayus, B. L., 2018. Crowdfunding creative Ideas: The dynamics of project backers. In: Cumming, D., Hornuf, L. (eds.). *The Economics of Crowdfunding: Startups, Portals and Investor Behavior*. Palgrave Macmillan, 151-182.

Larrimore, L., Jiang, L., Larrimore, J., Markowitz, D., Gorski, S., 2011. Peer to peer lending: The relationship between language features, trustworthiness, and persuasion success. *Journal of Applied Communication Research*, 39 (1), 19-37.

Lee, E., Lee, B., 2012. Herding behavior in online P2P lending: An empirical investigation. *Electronic Commerce Research and Applications*, 11 (5), 495-503.

Lin, M., Prabhala, N.R., Viswanathan, S., 2013. Judging borrowers by the company they keep: Friendship networks and information asymmetry in online peer-to-peer lending. *Management Science*, 59 (1), 17-35.

Martinsson, P., Pham-Khanh, N., Villegas-Palacio, C., 2013. Conditional cooperation and disclosure in developing countries. *Journal of Economic Psychology*, 34 (February 2013), 148-155.

Mollick, E. 2014. The Dynamics of Crowdfunding: An Exploratory Study. *Journal of Business Venturing*, 29 (1), 1-16.

Muniz Jr., A.M., O'Guinn, T.C., 2001. Brand community. *Journal of Consumer Research*, 27 (4), 412-432.

Neugebauer, T., Perote, J., Schmidt, U., Loos, M., 2009. Selfish-biased conditional cooperation: On the decline of contributions in repeated public goods experiments. *Journal of Economic Psychology*, 30 (February 2009), 52-60.

Pope, D.G., Sydnor, J. What's in a picture? Evidence of discrimination from prosper.com. *Journal of Human Resources*, 46 (1), 53-92.

Puro, L., Teich, J.E., Wallenius, H., Wallenius, J., 2011. Bidding strategies for real-life small loan auctions. *Decision Support Systems*, 51 (1), 31-41.

Ravina, E., 2019. Love & Loans: The effect of beauty and personal characteristics in credit markets. *SSRN Electronic Journal*, February 2019, DOI: 10.2139/ssrn.1101647.

Sias, R.W., 2004. Institutional Herding. The Review of Financial Studies, 17 (1), 165–206. DOI: 10.1093/rfs/hhg035.

Schachter, S., Hood, D.C., Gerin, W., Andreassen, P., Rennert, M., 1985. Some causes and consequences of dependence and independence in the stock market. *Journal of Economic Behavior and Organization*, 6 (4), 339-357.

Simonsohn, U., Areily, D., 2008. When rational sellers face nonrational buyers: Evidence from herding on eBay. *Management Science*, 54 (9), 1624-1637.

Sonenshein, S., Herzenstein, M., Dholakia, U.M., 2011. How accounts shape lending decisions through fostering perceived trustworthiness. *Organizational Behavior and Human Decision Processes*, 115 (1), 69-84.

Yum, H., Lee, B., Chae, M., 2012. From the wisdom of crowds to my own judgment in microfinance through online peer-to-peer lending platforms. *Electronic Commerce Research and Applications*, 11 (5), 469-483.

Zhang, J., Liu, P., 2012. Rational herding in microloan markets. *Management Science*, 58 (5), 892-912.

Appendix

Table A1: Categories

Category	Number of campaigns	Max. collected amount to goal (%) Mean	St.Dev.	Min.	Max.
Automobiles&Components	95	0.41	0.31	0.00	1.00
CapitalGoods	6 291	0.68	0.43	0.00	5.14
Commercial&ProfessionalServices	151	0.40	0.36	0.00	1.00
ConsumerDurables&Apparel	227	0.47	0.38	0.00	1.22
ConsumerServices	299	0.52	0.40	0.00	1.05
DiversifiedFinancials	509	0.40	0.27	0.00	1.49
Energy	115	0.42	0.39	0.00	1.20
Food&StaplesRetailing	187	0.25	0.35	0.00	1.02
HealthCareEquipment&Services	218	0.37	0.47	0.00	3.33
Materials	60	0.33	0.44	0.00	2.74
Media	125	0.47	0.42	0.00	1.70
RealEstate	2 806	0.28	0.37	0.00	2.88
Retailing	71	0.41	0.36	0.00	1.18
Software&Services	394	0.57	0.37	0.00	1.38
TechnologyHardware&Equipment	1 153	0.15	0.34	0.00	4.22
Transportation	382	0.39	0.50	0.00	4.90
Unknown category	104 083	0.23	0.47	0.00	5.91
All categories	117 166	0.26	0.47	0.00	5.91

Table A2: Descriptive statistics

Variable names[1]	Obs	Mean	Std.Dev.	Quantiles Min	0.25	Mdn	0.75	Max
Collected amount to goal	3068102	0.40	0.67	0.00	0.01	0.13	0.58	5.92
$\Delta_{k,t}$ at market	3019248	0.01	1.02	-0.84	-0.21	-0.17	-0.12	58.97
$\Delta_{k,t}$ at top platforms	20310	0.00	0.98	-1.88	-0.53	-0.23	0.04	31.53
$\Delta_{k,t}$ within category	287793	0.02	1.08	-5.12	-0.09	-0.06	-0.04	42.17
$\Delta_{k,t}$ within platform	264757	-0.02	0.63	-7.71	-0.06	-0.03	-0.02	49.79
$\Delta_{k,t}$ within category in platform	143192	-0.02	0.56	-9.54	-0.05	-0.03	-0.03	37.62
Relative goal	2903412	1.05	25.53	0.00	0.03	0.12	0.31	6502.47
Relative goal at top platforms	21499	1.02	1.21	0.01	0.32	0.68	1.26	36.87
Relative goal within category	293996	1.21	16.59	0.00	0.00	0.01	0.23	1422.05
Relative goal within platform	320181	1.02	0.48	0.00	0.73	0.95	1.20	21.98
Rel.goal within category in platform	293584	1.02	0.42	0.00	0.75	1.00	1.15	13.95
Relative GDP per capita in PPP	331400	1.02	0.37	0.04	0.93	0.94	0.98	3.96
Relative GDP[2] at top platforms	22030	1.00	0.23	0.05	0.99	1.00	1.08	2.67
Relative GDP[2] within category	303620	1.01	0.27	0.03	0.97	0.98	0.99	4.03
Relative GDP[2] within platform	331400	1.00	0.06	0.07	1.00	1.00	1.00	3.54
Rel.GDP[2] within category in platform	303620	1.00	0.02	0.35	1.00	1.00	1.00	2.61
Relative duration in days	3068102	1.00	1.55	0.00	0.16	0.43	1.34	43.50
Relative dur.[3] at top platforms	22030	1.00	2.58	0.00	0.28	0.77	1.25	238.76
Relative dur.[3] within category	303685	1.04	1.42	0.00	0.90	1.03	1.07	225.88
Relative dur.[3] within platform	331465	1.03	0.44	0.00	1.00	1.03	1.07	29.06
Rel.dur.[3] within category in platform	303685	1.03	0.32	0.00	1.00	1.02	1.06	35.10
Duration[3]	3068102	231	277	2	39	108	312	1212

[1] all variables in ratios or indexes before log transformation

[2] GDP per capita in PPP

[3] Duration of campaing in days

Table A3: Descriptive statistics

Variable names[1]	(1)[2]	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
(2) $\Delta_{k,t}$ at market	0.29	1.00																			
(3) $\Delta_{k,t}$ at top platforms	0.27	0.67	1.00																		
(4) $\Delta_{k,t}$ within category	0.08	0.43	0.45	1.00																	
(5) $\Delta_{k,t}$ within platform	0.03	0.38	0.61	0.27	1.00																
(6) $\Delta_{k,t}$ within category in platform	0.04	0.30	0.61	0.31	0.90	1.00															
(7)Relative goal	-0.01	0.00	-0.05	0.05	0.02	0.02	1.00														
(8)Relative goal at top platforms	0.19	0.14	0.12	0.02	-0.04	-0.07	0.36	1.00													
(9)Relative goal within category	0.07	0.02	0.00	0.14	0.00	0.00	0.61	0.27	1.00												
(10)Relative goal within platform	-0.03	-0.01	-0.05	0.00	0.01	0.01	0.08	0.65	0.02	1.00											
(11)Rel.goal within category in platform	-0.03	-0.01	-0.05	-0.01	0.01	0.01	0.02	0.62	0.01	0.89	1.00										
(12)Relative GDP per capita in PPP	0.32	-0.01	-0.13	0.14	0.01	0.01	0.26	-0.04	0.23	0.00	-0.01	1.00									
(13)Relative GDP[3] at top platforms	-0.14	-0.28	-0.29	0.00	0.01	0.00	0.03	-0.12	0.03	0.00	-0.01	0.45	1.00								
(14)Relative GDP[3] within category	0.23	-0.03	-0.04	0.19	0.01	0.01	0.17	-0.08	0.33	0.00	-0.01	0.76	0.24	1.00							
(15)Relative GDP[3] within platform	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.02	0.01	0.01	-0.01	0.11	0.52	0.10	1.00						
(16)Rel.GDP[3] within category in platform	-0.02	0.00	-	0.00	0.00	0.00	0.00	-	0.00	-0.01	-0.01	0.07	-	0.09	0.81	1.00					
(17)Relative duration in days	0.08	-0.09	-0.09	-0.13	-0.09	-0.09	0.00	0.17	-0.01	0.00	0.00	0.09	0.11	0.10	0.00	0.00	1.00				
(18)Relative dur.[4] at top platforms	0.04	-0.03	-0.02	0.00	-0.02	-0.04	0.06	0.08	0.05	0.02	0.01	0.04	0.09	0.00	0.00	-	0.32	1.00			
(19)Relative dur.[4] within category	0.15	-0.07	-0.01	-0.08	-0.08	-0.07	0.02	0.00	0.06	-0.01	-0.01	0.10	0.00	0.15	0.00	0.00	0.45	0.68	1.00		
(20)Relative dur.[4] within platform	0.08	-0.11	-0.05	-0.08	-0.20	-0.17	-0.01	0.07	0.00	0.04	0.02	-0.03	0.00	-0.02	0.00	-0.01	0.32	0.40	0.22	1.00	
(21)Rel.dur.[4] within category in platform	0.04	-0.07	-0.09	-0.06	-0.14	-0.18	-0.01	0.03	0.00	0.01	0.02	-0.04	0.00	-0.03	-0.01	-0.01	0.21	0.34	0.21	0.73	1.00
(22)Duration[4]	0.07	-0.10	-0.09	-0.17	-0.10	-0.07	0.00	0.11	-0.02	0.00	0.00	0.08	0.07	0.08	0.00	0.01	0.64	0.12	0.32	0.24	0.14

[1] all variables in ratios or indexes before log transformation

[2] Collected amount to goal

[3] GDP per capita in PPP

[4] Duration of campaing in days

Table A4: Hausman test

Coefficients	(1) Market	(2) Top Platforms	(3) Category	(4) Platform	(5) Category within Platform
Fixed effects	0,2013	-0,0147	0,1589	0,2008	0,1280
Random effects	0,2420	0,1184	0,2079	0,2202	0,1656
Difference (fe-re)	-0,0407	-0,1331	-0,0489	-0,0195	-0,0376
χ^2	58558.64***	741.56***	7023.25***	1778.63***	1363.07***

Note: *, **, and *** denote significance at the 10, 5, and 1 per cent level.

Table A5: Variable addition test

	(1) Market	(2) Top Platforms	(3) Category	(4) Platform	(5) Category within Platform
Herding ($\Delta_{k,t-1}$)	0.179***	-0.085***	0.126***	0.166***	0.098***
	(0.006)	(0.017)	(0.028)	(0.025)	(0.016)
$\overline{\Delta_{k,t-1}}$	0.802***	1.076***	0.878***	0.796***	0.844***
	(0.008)	(0.022)	(0.033)	(0.027)	(0.023)
Constant	-0.010***	-0.011**	-0.006***	-0.006***	-0.007***
	(0.000)	(0.004)	(0.001)	(0.001)	(0.002)
Observations	2,578,043	11,615	223,329	179,679	72,915
Projects	99,085	2,276	7,175	8,788	5,013
σ_u	0,166	0,000	0,113	0,060	0,000
σ_ε	0,706	0,877	0,724	0,432	0,450
ρ	0,052	0,000	0,024	0,019	0,000

Note: *, **, and *** denote significance at the 10, 5, and 1 per cent level.
Cluster-Robust standard errors are reported in parentheses.

Table A6: Extended models without Chinese platforms

	(1) Market	(2) Top Platforms	(3) Category	(4) Platform	(5) Category within Platform
Herding ($\Delta_{k,t-1}$)	0.103***	-0.007	0.137***	0.292***	0.186***
	(0.014)	(0.018)	(0.028)	(0.022)	(0.016)
Goal	0.076***	0.108***	0.251***	-0.027*	-0.221***
	(0.010)	(0.029)	(0.025)	(0.014)	(0.056)
GDP per capita	0.044**	-1.052***	0.325***	-0.281	1.192
	(0.018)	(0.115)	(0.103)	(0.368)	(0.783)
Duration	0.036***	0.020	-0.086***	-0.068***	-0.016
	(0.012)	(0.027)	(0.022)	(0.015)	(0.020)
Constant	0.425***	-0.008	0.262***	-0.044	-0.139*
	(0.027)	(0.298)	(0.031)	(0.046)	(0.084)
Yearly dummies	yes	yes	yes	yes	yes
Observations	89,812	11,178	62,765	60,400	25,812
Projects	7,310	2,223	4,773	6,402	2,860
R^2	0.010	0.026	0.059	0.088	0.037
σ_υ	1.991	1.024	2.089	0.746	0.635
σ_ε	1.178	0.755	1.341	0.705	0.715
ρ	0.741	0.648	0.708	0.528	0.441

Note: *, **, and *** denote significance at the 10, 5, and 1 per cent level.
Robust standard errors are reported in parentheses.

Table A7: Groups by collected amount

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Groups by collected amount							
	(0%; 1%>	(1%; 20%>	(20%; 40%>	(40%; 90%>	(90%; 100%>	=100%	(100%; 190%>	(190%; ∞)
Herding ($\Delta_{k,t-1}$)	0.139**	-0.086***	-0.035*	-0.058***	-0.014	-0.071***	0.412***	0.447***
	(0.058)	(0.025)	(0.021)	(0.013)	(0.018)	(0.017)	(0.053)	(0.138)
Goal	0.000	-0.001	0.006	0.019	-0.003	0.119***	-0.006	0.027
	(0.002)	(0.005)	(0.011)	(0.015)	(0.047)	(0.006)	(0.009)	(0.043)
GDP per capita	0.040***	0.013	0.074***	0.188***	0.181	-0.027	0.073***	0.037
	(0.012)	(0.021)	(0.028)	(0.046)	(0.144)	(0.043)	(0.015)	(0.066)
Duration	-0.000	-0.009**	-0.015	0.058***	0.134**	0.037***	0.013	0.026
	(0.003)	(0.004)	(0.011)	(0.019)	(0.052)	(0.003)	(0.021)	(0.073)
Constant	-0.162***	-0.106***	-0.001	0.584***	1.524***	0.895***	-0.023	0.556***
	(0.014)	(0.034)	(0.028)	(0.126)	(0.160)	(0.051)	(0.021)	(0.201)
Yearly dummies	yes	yes	yes	yes	yes	yes	yes	yes
Observations	1,794	5,834	5,816	16,377	6,191	177,180	29,953	6,649
Projects	194	687	664	2,171	837	4,211	609	129
R^2	0.046	0.009	0.004	0.006	0.005	0.037	0.068	0.088
σ_{υ}	0.0581	0.353	0.780	1.843	2.276	2.197	1.103	3.108
σ_{ε}	0.0518	0.179	0.424	1.106	1.460	0.438	0.920	1.960
ρ	0.558	0.795	0.772	0.735	0.708	0.962	0.590	0.716

Note: *, **, and *** denote significance at the 10, 5, and 1 per cent level.

Robust standard errors are reported in parentheses.

Table A8: Groups by categories

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Groups by categories							
	Automobiles &	Capital Goods	Commercial &	Consumer	Consumer	Diversified	Energy	Food & Staples
Herding ($\Delta_{k,t-1}$)	-0.037	0.138***	0.015	0.286**	0.238***	0.151***	0.222	0.498***
	(0.124)	(0.025)	(0.079)	(0.119)	(0.087)	(0.042)	(0.134)	(0.080)
Goal	-0.025	0.151***	-0.016	0.232***	0.065**	0.102**	0.016	0.028*
	(0.023)	(0.019)	(0.085)	(0.056)	(0.029)	(0.040)	(0.027)	(0.015)
GDP per capita	-0.172	0.020	0.123	-0.568***	-0.043	0.031	0.005	-0.073
	(0.333)	(0.041)	(0.112)	(0.213)	(0.047)	(0.080)	(0.069)	(0.075)
Duration	-0.007	0.085***	-0.147***	-0.000	0.003	0.198***	0.017	0.013
	(0.081)	(0.026)	(0.048)	(0.050)	(0.027)	(0.027)	(0.034)	(0.015)
Constant	0.413***	0.804***	-0.006	1.412***	0.115**	0.933***	0.116***	0.187*
	(0.124)	(0.105)	(0.352)	(0.311)	(0.047)	(0.073)	(0.031)	(0.105)
Yearly dummies	yes	yes	yes	yes	yes	yes	yes	yes
Observations	421	26,325	2,114	2,698	5,832	2,320	2,336	7,918
Projects	57	2,196	99	131	190	291	84	173
R^2	0.005	0.020	0.019	0.079	0.036	0.038	0.028	0.156
σ_υ	2.725	1.904	1.769	1.963	1.856	2.340	2.070	0.455
σ_ε	0.854	1.564	0.888	0.958	0.781	0.893	0.886	0.448
ρ	0.911	0.597	0.799	0.808	0.850	0.873	0.845	0.508

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Groups by categories							
	Health Care Equipment & Services	Materials	Media	Real Estate	Retailing	Software & Services	Technology Hardware & Equipment	Transportation
Herding ($\Delta_{k,t-1}$)	0.044	0.029	0.236***	-0.101**	0.306	0.017	0.026	0.072
	(0.084)	(0.099)	(0.065)	(0.041)	(0.188)	(0.055)	(0.032)	(0.057)
Goal	0.116**	-0.059	0.190***	0.084***	0.041	0.193*	0.036***	0.123***
	(0.052)	(0.044)	(0.048)	(0.011)	(0.030)	(0.099)	(0.008)	(0.046)
GDP per capita	-0.047	0.175	-0.156**	-0.021	0.146	-0.007	0.072**	0.070
	(0.066)	(0.124)	(0.067)	(0.050)	(0.122)	(0.165)	(0.030)	(0.136)
Duration	0.064	-0.005	-0.073	0.027***	0.071	0.099	0.010***	0.027
	(0.042)	(0.056)	(0.053)	(0.003)	(0.085)	(0.076)	(0.004)	(0.081)
Constant	0.217**	-0.103	0.689***	0.551***	0.191***	1.076***	0.180***	0.567***
	(0.100)	(0.126)	(0.169)	(0.081)	(0.064)	(0.219)	(0.058)	(0.176)
Yearly dummies	yes	yes	yes	yes	yes	yes	yes	yes
Observations	3,320	997	2,731	101,668	1,247	997	66,365	3,051
Projects	146	47	71	2,128	52	96	1,052	274
R^2	0.016	0.013	0.091	0.036	0.062	0.018	0.010	0.016
σ_υ	1.547	2.055	1.059	1.902	1.107	4.260	1.344	1.420
σ_ε	0.885	0.651	0.759	0.319	0.830	1.100	0.284	0.996
ρ	0.753	0.909	0.661	0.973	0.641	0.937	0.957	0.670

Note: *, **, and *** denote significance at the 10, 5, and 1 per cent level.
Robust standard errors are reported in parentheses.