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Overfunding and Signaling Effects of Herding Behavior in Crowdfunding*

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Abstract

The paper employs a dynamic market-wide herding behavior measure of 117,166 lending-based campaigns in 119 online platforms in 37 countries that explores whether lenders follow each other in 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 behavior plays an important signaling role in reducing opportunity costs if the auction does not receive enough monetary bids. Additionally, our threshold models identify significant herding behavior after funding goals are raised and highlight the controversial effects of signaling mechanisms on adverse selection in crowdfunding markets.

Keywords: Asymmetric information, crowdfunding, herding behavior, overfunding, peer-to-peer lending, signaling

JEL Classification: C55, D26, G21

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1. Introduction

Lending-based crowdfunding (microloans, peer-to-peer loans) enables individual lenders (investors, funders) to lend money and individual borrowers (founders, entrepreneurs) to gain money quickly, with low transaction costs through internet auctions and without bank intermediation. Each campaign presented at the crowdfunding platform is launched by an individual borrower who presents a specific project for funding through multiple micro loans from individual lenders. Iyer et al. (2011) state that, in peer-to-peer markets, lenders infer the most from standard banking information ("hard"); however, they also use non-standard information provided by borrowers ("soft") to assess the creditworthiness of borrowers, particularly in low credit categories. Therefore, they face a problem of asymmetric information between lenders and borrowers, especially concerning project risk, potential return and borrower creditworthiness, which causes adverse selection (Zhang and Liu, 2012). Wang et al. (2015) define nine basic types of risks connected with peer-to-peer lending, with insufficient credit checking as one of them. Moreover, there is a risk of opportunity costs if the auction is cancelled for a lack of lenders' monetary bids (each campaign must gain the demanded amount of money).[1]

However, the online environment is characterized by mostly anonymous communication, without face-to-face contact and with rising pressure and uncertainty after the last financial crisis and economic downturn. In crowdfunding markets, there are no institutions (e.g., banks, rating agencies, registers of failed projects, and detailed borrowers' credit history) to reduce the asymmetric information and prevent adverse selection or the risk of opportunity costs. Therefore, potential lenders have a very limited set of information about the project risks (potential return, borrowers' creditworthiness, and opportunity costs), and only certain signals from borrowers help reduce the uncertainty in this online environment, which motivates lenders to invest in certain projects. Moreover, these signals must be accompanied by the trust of online

[1] Platforms mostly operate on "all-or-nothing model" when entrepreneurs have "skin in the game" as every loan auction must receive enough monetary 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 this possibility (Cumming et al., 2019).

community members, which encourages lenders to follow the decisions of other lenders (Akerlof, 1970; Wohlgemuth et al., 2016).

The signaling mechanism is also present in crowdfunding and occurs through the following different channels: (1) sharing materials by borrowers on project websites (Ahlers et al., 2015); (2) sharing information and signals by lenders in the form of comments on projects' pages or lenders' forums via social networks (Mollick, 2014); and (3) providing information about the number, frequency and the amounts of bids of lenders publicized by crowdfunding platforms (Dholakia and Soltysinski, 2001; Herzenstein et al., 2011). The third channel should enable investors to limit information asymmetry and adverse selection; they receive these signals – the investors' or campaigns' records – provided by platforms and follow the behavior of other investors when they see the set of information about a specific crowdfunding project (Wohlgemuth et al., 2016). Online lending platforms thus provide big data, which may limit the information asymmetry between lenders and borrowers and reduce both the search and signaling costs (Yan et al., 2015). As such, the signaling mechanism influences trust and limits uncertainty (Akerlof, 1970), and it causes time-varying herding behavior in crowdfunding that changes over time and with the level of raised money after the auction is launched. Dholakia and Soltysinski (2001) show the positive effect of the number of bids on herding behavior after making the first bid. Herzenstein et al. (2011) add that herding behavior increases only to the point at which it has received full funding. However, once a specific project gains full funding, the financing campaign is not closed, the raised sum of money can exceed the pre-set goal amount, and other lenders may still enter this auction and contribute; as such, the project can be overfunded. Therefore, the overfunding possibility could have a negative impact on other projects because these projects do not raise enough funds during the campaign (Koch, 2016), and the overfunded projects mean higher borrower obligations to return higher amounts, including margins to lenders.

In our paper, we assume the existence of the third type of signaling channel described above, which enables lenders to reduce uncertainty by increasing transparency within the specific market, category or platform; otherwise, they will follow each other. We follow Sias (2004) and adjust the dynamic herding behavior measure to the environment of online auctions and crowdfunding market specifics. We use a rich dataset on 117,166 lending-based crowdfunding auctions and provide robust evidence of herding behavior of lenders and campaign overfunding separately for the whole crowdfunding market, within the group of top platforms, within the specific project category or platform, and within the project category in the specific platform. We also control for the overall target goal and campaign duration and find that in the case of large projects and projects with a campaign duration between 3 months and 2 years, lenders are risk-averse and prefer lending to projects from relatively richer countries.

We aim to contribute to this strand of empirical research in several points. First, we study the dynamic herding behavior in lending-based platforms and prove that it exists both at the beginning end of the crowdfunding campaign, i.e., we confirm the U-shaped funding pattern (Kuppuswamy and Bayus, 2018). Second, we emphasize the phenomenon of campaign overfunding, i.e., that lenders do not stop bidding when 100% of the goal amount is reached but continue far above this level (Koch, 2016). We show that this phenomenon can be explained by the existence of herding behavior and argue that the herding behavior of lenders is the strongest, particularly in the case of projects that accept additional pledges after reaching the target amount. Third, we focus on the problem of increased adverse selection in crowdfunding markets, which could be fueled by the herding behavior of lenders in situations when they face asymmetric information and uncertainty. We prove that the signaling mechanism (when investors have public information about the funding progress of any project) supports the herding behavior and the occurrence of overfunding, and, as such, signals surprisingly fuel (not eliminate) additional adverse selection in the crowdfunding markets. Fourth, our results are confirmed using a vast dataset from 119 lending-based platforms around the world; this dataset contains data not only for platforms from regions such as the US or the EU but also platforms from Australia, China, Japan or Russia. Thus, our paper offers unique results of cross-country analyses compared to other authors who have focused primarily on individual platforms or regions (e.g., Kuppuswamy and Bayus, 2018; Lee and Lee, 2012; Yum et al., 2012; Herzenstein et al., 2011; Puro et al., 2011).

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

2. Literature Review

Many decisions of economic agents (individuals, companies or governments) are made with insufficient information (mainly private information, as public information is accessible without any obstacles), i.e., agents face the problem of information asymmetry when one agent possesses a different set of information than another agent facing only a limited set of information. As a result, agents with insufficient information may produce non-optimal decisions. The problem of information asymmetry was described by Akerlof (1970) when he illustrated the problem of quality differences and uncertainty using the example of automobile market; he emphasized the role of trust and informal unwritten guaranties, which can limit uncertainty in markets. This adverse selection may also be partly mitigated by sending signals from one agent (sender, signaler) to another agent (receiver) concerning the characteristics of the individual, company, product, etc.

Spence (1973) is among the first researchers to mention the concept of signaling theory with application to job markets. He is followed by Ross (1977), who develops the incentive-signaling model that explains the relationship between managerial incentives and signaling in the financial market. However, the production of signals could be accompanied by a certain level of costs, and some signalers have better conditions to absorb these costs than others (Spence, 1973; Bird and Smith, 2005; Connelly et al., 2011). According to Westphal and Zajac (2001), some signalers finally do not meet the signals initially send to receivers. i.e., there are some discrepancies between former and actual plans. Over time, the theory was applied in many economic, financial, managerial or business research studies. For a comprehensive review of the literature on signaling theory, see (Connelly et al., 2011).

Some authors study the role of trust in the online economic environment, which suffers from a lack of face-to-face contact and communication, which is also the case for crowdfunding. Some authors distinguish between traditional offline and new online trust and state that consumers and businesses in peer-to-peer markets prefer doing business with agents connected with the most trusted Web sites or social networks (for a detailed review of this topic, see Shankar et al., 2002). Wohlgemuth et al. (2016) study the social trading and behavior of investors copying the investment decisions of other traders who they do not know but whom they trust; they find that weak signals of trustworthiness may cause traders to copy the behavior of other traders. Both globalization and internalization processes also influence the development of models of trust in which international and cross-cultural dimensions also play an important role (Schoorman et al., 2005).

The behavior 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 behavior as socio-psychological processes. He formulates that people use a set of standards to evaluate both reality when they use objective standards and themselves (self-evaluation) when they try to compare their behavior with the behavior of other people when there are no standards.[2] Banerjee (1992) characterizes herding behavior as behavior in which people do what other people are doing rather than using their own sets of information (or even though their private information suggests doing something different). Moreover, Bikhchandani, Hirshleifer and Welch (1992) define information cascades to explain how social conventions and standards are created, maintained and modified and how these cascades can explain the sudden and large changes in the behavior of some individuals and the spread of new types of behavior (herding behavior). As such, some individuals may provide information or signals to other individuals who tend to follow them.

Some authors distinguish between irrational and rational herding. Irrational herding can be characterized as a situation when agents follow the behavior and decisions of other agents or follow other agents investing in non-risk investments or projects, i.e., they neglect the basic characteristics of an individual project and thus 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 utilize 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).

[2] Schachter et al. (1985) state that two types of variables influence the degree of psychological dependence of people. The first includes when situations or circumstances change, when people face unexpected events or when people find that they made bad decisions. Second, there are intrapersonal variables in which people differ in the extent to which they have a tendency to be influenced by the decisions of other people. The authors state that people who are educated, self-confident or experts in a specific area will probably rely on themselves and not follow the opinions or behaviors of others.

There is a growing body of empirical literature on herding behavior. Schachter et al. (1985) study the behavior 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 behavior of other investors in stable (bull) markets compared to unstable (bear) markets. Fazio (1990) examines how consumers' attitudes influence their behavior and concludes that they copy the behavior of other consumers in case they face uncertainty. Dholakia and Soltysinski (2001) examine hearing behavior in digital auctions and state that bidders follow the behavior 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 behavior in the case of eBay auctions and identify a bias in the investors' decision-making process, resulting in suboptimal decisions as investors neglect factors that are hidden and cannot be easily observed.

Later studies have focused on herding behavior in the process of peer-to-peer lending; however, this 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), as the number of bids from lenders on the Prosper platform increases, the higher the probability of bids from other lenders and the strategic lending behavior becomes more beneficial for lenders. Similarly, Lee and Lee (2012) confirm the important role of information in the lenders' decision-making process and the existence of herding on the Popfunding platform (placed in Korea), as the number of bids of individual lenders strongly increases when the number of total bids and total amount to be funded rises and approaches 100%. In a related study, Yum et al. (2012) conclude that lenders on the Prosper platform take into account other lenders' behavior 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. Evidence of herding is confirmed by Zhang and Chen (2017) in the case of the Chinese P2P lending platform Renrendai.

Zhang and Liu (2012) study factors that may characterize the herding behavior in microloan markets: unobserved heterogeneity across data (listings, i.e., loan requests) and payoff externalities (or herd externalities according to Banerjee, 1992) among lenders. The unobserved heterogeneity concerns listing attributes that can be unobserved by the researcher and may attract lenders; however, the available data do not include them. The payoff externalities occur when the behavior of one lender depends on the behavior of other lenders (see the problem of conditional cooperation below). Lenders do not contribute to projects with a low probability of achieving 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; as a result, lenders have a tendency to prefer well-funded listings or listings with a high probability to materialize into a loan. They confirm the existence of 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 analyze 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.

3. Data and Methods

Our unique and rich panel dataset contains all crowdfunding platforms scanned by TAB big data analytics (formerly Crowdsurfer) in the 2014–2017 period. More specifically, there are 117,166 lending-based auctions/projects/campaigns[3] on 119 crowdfunding platforms in 37 countries from June 10, 2014, to October 6, 2017 (daily data). The campaigns are divided into 16 categories (Table A1 in the Appendix). Despite the fact that we are not able to identify the category of most campaigns (platforms use different category names in different languages), we can summarize that above-average overfunding – that is, raised funds exceeding 250% of the target – was identified in the "Capital Goods", "Heath Care Equipment and Services", "Materials", "Real Estate", "Technology, Hardware and Equipment" and "Transportation" categories.

Our dynamic measure of herding behavior is based on temporal dependence in demand over adjacent days (Sias, 2004). First, to allow project comparison (especially project size) and to avoid currency differences, we calculate daily differences in the raised amount of money to the goal of campaign *i* during day *t*:

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

$$Raw\Delta_{i,t} = \frac{raised\ money_{i,t}}{goal_i} - \frac{raised\ money_{i,t-1}}{goal_i} \quad (1).$$

Thus, our measure is based on the success rate of campaign funding (raised money to goal), especially differences in the success rate that illustrate an increasing or decreasing rate of capital accumulation in the specific crowdfunding lending-based campaign. Second, we follow Sias (2004) and standardize the dependent variable to have a zero mean and unit variance. Thus, we define the standardized *capital accumulation* in project *i* as follows:

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

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 market fraction *j* during day *t*. Specifically, we divide our data sample into different fractions and standardize the accumulation of capital 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. In other words, our measure $\Delta_{i,j,t}$ represents the relative capital accumulation rate within the specific market fraction.

We suppose that herding behavior occurs when the capital accumulation rate in past causes exceeding capital accumulation in specific campaigns (relative to other campaigns in the market fraction), although there may be other motives for such behavior. Thus, our empirical strategy is based on the estimation of the dynamic herding measure effect. We run panel regressions employing a fixed-effects estimator[5] to estimate herding effect β_1 as the relation between the capital accumulation rate within the market fraction and the lag of the capital accumulation $\Delta_{i,j,t-1}$ in the campaign *i* within the specific market fraction *j* during the previous day *t-1*:

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

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

[5] We do not expect endogeneity bias. The selected project specifics (goal and duration) are defined by the borrower before the campaign is presented in 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).

We also control for selected project specifics (goal and campaign duration[6]) and the relative economic level of the project founder's home country c, where the project is realized (measured by GDP per capita in PPP). Finally, we include project fixed effects $\mu_{i,j}$, time effects θ_t (yearly dummies reflect changes of funding preferences, advertising effects, etc.) and possibly heteroscedastic residual $\varepsilon_{i,j,t}$ (robust standard errors).

Additionally, we use the interaction terms for all dependent variables that show changing effects of herding behavior 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 capital demand above and below the given thresholds.

We assume that not only herding behavior signals but also all other types of 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 fundamentals (GDP per capita in PPP, yearly frequency) are obtained from the World Bank International Comparison Program database and reflect economic development country specifics and capital demand differences. Descriptive statistics for all variables are presented in Table A2, and 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). Our first results confirm the existence of a 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

[6] Goal and duration are announced before the campaign is launched. Duration is fixed and considered as a strictly exogenous variable. Goals are slightly updated, especially when the campaign does not attract investors, but we consider insignificant changes that cannot affect causality between the variables.

the fact that lenders are strongly influenced by the behavior of other lenders and follow them when deciding which project is worth lending, and it holds for all projects across all categories or platforms or both.

Table 1: Basic test for herding

	(1) Market	(2) Top Platforms	(3) Category	(4) Platform	(5) 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.

In the second step, we extend our analysis by using project specifics (such as the relative target goal and the relative duration of the financing campaign) and the relative economic level measured by the relative GDP per capita of the project founder's home country (see Table 2). Again, the results confirm herding behavior, except for top platforms, as well as the positive impact of all three added explanatory variables on the capital accumulation in the basic model for the whole market (1). However, the impact of duration is negative in the case of category (3) and platform (4) models, i.e., relatively younger campaigns 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 positive results for the whole market model, in which case, the relatively older campaigns are associated with higher investing (alternatively, we can say collecting in the case of crowdfunding projects).

This contrast could be explained by the presence of asymmetric information and uncertainty in the world market of lending-based crowdfunding, which is characterized by the existence of many platforms when investors have only a limited set of information about projects all around the world and they likely look for a certain signal to cope with a lack of information. However, we obtain opposing results when we take the effect of the category (across all platforms) or platform (across all categories) into account because lenders dispose of 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 campaigns attract investing more than relatively older campaigns, and the effect of information asymmetry may disappear.

When we focus on the positive impact of the economic level of the project founder's home country on capital accumulation, it is clear that this level plays an important role in the case of the category (3) model when lenders are well informed about the project in the specific category and incorporate information derived from the residence of the project founder. As a result, projects from relatively poorer countries are less attractive than projects from relatively richer countries (as measured by the relative GDP per capita). However, the situation is opposite in the case of the top platforms (2) model, i.e., lenders probably perceive guaranties produced by top platforms as a signal of trust in the projects offered, do not follow the other lenders (the indicator of herding is insignificant) and accept the potential higher risk connected to projects from poorer countries. These findings also confirm the results of Akerlof (1970), who define the role of guaranties as signals leading to less uncertainty.

Table 2: Extended models

	(1)	(2)	(3)	(4)	(5)
	Market	Top Platforms	Category	Platform	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 the 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 Table 2, we obtain an unexpectedly positive effect of the goal on capital accumulation. This result could be influenced by a huge number of projects with a low collected amount in our basic data sample. Therefore, we provide detailed results in the third step of our analysis, where we present thresholds of collected amount during the campaign concerning a specific project (see Table 3). We interact the regressors with dummies that are defined at the level of 1%, 20%, 40%, 90%, 100% and 190% of the collected amount. Our results indicate the existence of positive herding mainly in projects with collected amounts above the specific threshold and in cases of projects that have recently begun (when the collected amount broke the 1% level) and then in cases of fully funded projects (when the 100% level was reached). According to our results, the positive herding effect remains significant until 190% of the target amount is reached and then stops (the results for the thresholds between 100% and 190% are not presented here and are available upon request).

Lenders facing uncertainty and asymmetric information imitate the behavior of other lenders and invest their money into projects that show higher activity (measured by the collected sum of money relative to the average collected money in the market), particularly in the case of newly started campaigns (but no campaigns with zero collected amount as lenders wait for first bids of other lenders) and fully funded projects breaking the 100% level of the target goal (these projects are considered successful and lenders prefer investing in these projects because they do not face opportunity costs connected with unsuccessful projects when the project did not attain the goal amount and money is returned to the investors). As such, overfunding has a negative impact on other projects because it limits financial sources in the market, and other projects do not raise enough funds. The overfunding could be considered as a specific market failure producing non-optimal results.

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.

We also uncover in more detail the impact of the target goal, economic level of the project founder's home country and campaign duration on capital accumulation. In contrast to Table 2, we explain the robust impact of the target goal on capital accumulation. The goal has a negative impact on the collected amount in the case of projects above the thresholds of 40%, 90% and 100%, and the impact disappears above the threshold of 190%. This finding is also confirmed by Cordova et al. (2015), who state that lenders to overfunded projects are not very interested in the goal level of the project (i.e., whether the project is small or large). Conversely, a positive impact for case of projects below the threshold, i.e., less financed projects have relatively more bids (i.e., higher collected amounts) because lenders are prone to lend money to these projects.

Capital accumulation is also positively influenced by the relative economic level in the 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.

Campaign duration shows similar results because relatively older and more financed campaigns significantly limit the level of the rise of capital accumulation when compared to the market average. There is a positive relation with the capital accumulation for projects below the threshold; however, when projects reach the set threshold of the collected amount, the relation begins to be negative in all cases.

To confirm these results using the threshold analysis, we also divide our dataset into separate intervals according to the collected amount relative to the target goal and estimate these individual models (see Table A7 in Appendix). Again, these results confirm the existence of positive herding behavior for projects with the collected amount at a level higher than 100%, i.e., for overfunded projects and for campaigns that just started. Conversely, there is negative herding for projects with collected amounts between 1% and 90% and at the level of 100% of the collected amount. Our results therefore confirm the existence of the U-shaped funding pattern characterized by Kuppuswamy and Bayus (2018). Moreover, the target goal is significant only in the case of recently funded projects (i.e., when the collected amount just reaches 100% of the target goal) and the campaign duration is significant and positive only in intervals for collected amounts 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 campaign activity duration as a part of our robustness analysis (see Table 4). 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 campaign 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 behavior is significantly present in all analyzed groups, which are divided according to the whole campaign duration. Regarding GDP per capita, projects from relatively poorer countries attract lenders when the campaign activity is from 1 to 3 months; conversely, lenders prefer projects with longer campaign activity from relatively richer countries when the activity is between 3 months and 2 years. For the variable duration, the results are quite interesting and well connected with the previous assumptions; for projects with very short campaign durations up to 30 days, the longer duration in time *t* (relative to the average market duration in time *t*) has a positive impact on collection activity, while for projects with long campaign durations between 3 months and 1 year, the longer activity negatively influences the collection activity. In this context, very short campaign activity thus increases the attractiveness of the project for lenders; vice versa, longer campaigns could be riskier, and as such, lenders could hesitate and limit lending activity relative to the market average.

Table 5: Groups by founders' countries

	(1) Europe	(2) China	(3) US, CA, NZ, AU, JP	(4) Others
Herding ($\Delta_{k,t-1}$)	0.118***	-0.426***	0.086***	0.026
	(0.016)	(0.101)	(0.030)	(0.027)
Goal	0.107***	0.071***	-0.001	0.166***
	(0.012)	(0.007)	(0.014)	(0.040)
GDP per capita	-0.005	0.015	0.107	0.075
	(0.019)	(0.067)	(0.128)	(0.057)
Duration	-0.005	0.019***	0.328***	0.172***
	(0.013)	(0.001)	(0.036)	(0.021)
Constant	0.335***	0.425***	1.046*	1.020***
	(0.027)	(0.058)	(0.586)	(0.118)
Yearly dummies	yes	yes	yes	yes
Observations	70,367	162,210	12,221	4,997
Projects	4,424	2,806	1,668	605
R^2	0.014	0.117	0.023	0.025
σ_υ	1.691	2.594	2.082	1.966
σ_ε	1.177	0.169	1.293	0.773
ρ	0.673	0.996	0.722	0.866

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

Finally, we estimate individual models for four groups according to the founders' countries: (1) Europe; (2) China; (3) the United States, Canada, New Zealand, Australia and Japan; and (4) other countries. Our results confirm positive herding behavior in the case of the first and third groups, i.e., for projects where the founder comes from either a European country or other developed countries included in the third group. However, there is a negative and significant value of the regression coefficient in the case of projects from China; these results indicate that new pledges from lenders all over the world to projects of Chinese founders do not provoke additional pledges in the following period, and as such, these new pledges may serve as a negative signal for other lenders.

6. Conclusions

Crowdfunding is a popular form of financing for both households and entrepreneurs that gained increasing importance after the financial crisis, which was characterized by an economic downturn and limited lending possibilities. Borrowers can gain money relatively simply and quickly from lenders without bank intermediation. However, the online environment is quite often full of uncertainty and asymmetric information. It can result in situations in which inexperienced and unsophisticated lenders may have a tendency to follow the decisions of other lenders. Therefore, we face the phenomenon of herding behavior (see Banerjee, 1992).

In our paper, we analyzed a unique dataset of 117,166 lending-based crowdfunding projects on 119 online platforms in 37 countries during the 2014-2017 period to examine herding behavior of lenders and confirmed the conclusions of other authors (e.g., Herzenstein et al., 2011; Zhang and Liu, 2012). Our results confirm the robust evidence of herding behavior in lending-based platforms. Moreover, we conclude that lenders follow other lenders in the whole market as well as in the market fraction specified by platforms and project categories.

We also identify the presence of campaign overfunding, i.e., that lenders do not stop pledging when a project is fully funded, which means that the herding behavior of lenders is the strongest, particularly in the case of projects that accept additional pledges after reaching the target amount. This finding contradicts that of Herzenstein et al. (2011), who state that the herding effect diminishes after the project receives full funding partly as a result of the decreasing interest rate after the 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. The difference in results could be caused by the different datasets used, as the author uses data only from the Prosper platform, while our dataset contains data from all platforms; it could also be caused by the existence of an "impatient lender" (bidding even after 100% of the target goal is reached), as Herzenstein et al. (2011) argue. However, overfunding led by the egoistic herding behavior of investors was also confirmed by Koch (2016). Similar to Mollick (2014), there are also signs of herding behavior after a campaign 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 that a project will reach its target goal (Agrawal et al., 2015; Colombo at al., 2015). In contrast, the herding behavior is even negative when a campaign is stopped just at the level of full funding (when 100% of the goal target is reached). This U-shaped funding pattern is caused by the fact that investors contribute to projects immediately after the campaign is launched and closely before the end of the announced period, which was also proved by Kuppuswamy and Bayus (2018).

Moreover, we performed several robustness checks and controlled for the overall target goal and campaign duration to verify whether the results of our basic models are robust enough. We found that in the case of projects with a campaign duration between 3 months and 2 years, lenders prefer lending to projects from relatively richer countries because they are more risk-averse and do not want to face the potential financial losses from default projects. Then, we divided our dataset into four sub-samples according to founders' country groups and confirmed a significant occurrence of positive herding behavior in Europe and the region comprising the US, Canada, New Zealand, Australia and Japan.

In our paper, we focused on the signaling mechanism when crowdfunding platforms provide information about the number, frequency and the amounts of bids of lenders and found that this signaling supported the herding behavior of crowdfunding lenders and the occurrence of overfunding practices. As a result, these signals do not eliminate additional adverse selection in the crowdfunding markets, as expected.

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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
Capital Goods	6 291	0.68	0.43	0.00	5.14
Commercial & Professional Services	151	0.40	0.36	0.00	1.00
Consumer Durables & Apparel	227	0.47	0.38	0.00	1.22
Consumer Services	299	0.52	0.40	0.00	1.05
Diversified Financials	509	0.40	0.27	0.00	1.49
Energy	115	0.42	0.39	0.00	1.20
Food & Staples Retailing	187	0.25	0.35	0.00	1.02
Health Care Equipment & 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
Real Estate	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
Technology Hardware & 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 campaign 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_υ	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)	(2)	(3)	(4)	(5)
	Market	Top Platforms	Category	Platform	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.