Launching prosocial crowdfunding campaigns: the final countdown

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Abstract

Prosocial crowdfunding has achieved a growing audience by providing a financing source for entrepreneurs in the microfinance space. Using data from Kiva, a leading prosocial crowdfunding platform, we examined whether there is a right time to launch a crowdfunding campaign. This is the first study to unravel the role of temporal patterns in securing funds in emerging markets. Our results indicate a reverse turn-of-the-month effect on the fully funded campaigns. We further identified a "positive winter prosocial effect" and a "positive first-half-of-the-week effect" on successful fundraising. As such, our study highlights relevant similarities between financial markets and crowdfunding.

Keywords: Microfinance; Prosocial lending crowdfunding; Time effects; Calendar anomalies; Kiva.

JEL codes: G21, G40, G41

Introduction

Access to external financing is one of the main challenges faced by new ventures in their early stages. Consequently, many small entrepreneurs are now turning to online crowdfunding platforms, directly appealing to the public for help. Crowdfunding is described as a means through which entrepreneurs put out an open call on an internet platform to secure small contributions from a large crowd of individuals for their new ventures, through donations, lending, equity offerings, and/or rewards (Mollick, 2014). Crowdfunding literature highlights several key successful factors of crowdfunding campaigns, such as venture quality (Ahlers et al., 2015), venture narratives, founder's social networks (Zheng et al., 2014), and project's characteristics (Mollick, 2014).

In peer-to-peer lending, "lenders' goals range from pure for-profit to pro-social" depending on the type of crowdfunding platforms they act (Gonzalez, 2023: 315). In the prosocial crowdfunding, the nature of the decision to lend is both financial and prosocial (i.e., Galak et al., 2011). One the one hand, prosocial lenders are typically guided by psychological factors such as the joy of giving, as well as their perceptions about the impact they have on poverty alleviation (Ly and Mason, 2012). This prosocial behavioral factor (e.g., Loureiro and Gonzalez, 2015) is thus guided by moral and ethical principles to selflessly aid those in need (Spanos, 2018). Indeed, prosocial lending "has flourished (…) and has become a new way to fundraise for philanthropy" (Zhang et al., 2023: 1079) providing a new opportunity that can deeply change the traditional landscape of social responsibility (e.g., Spanos, 2018).

On another hand, literature on online prosocial lending and crowdlending platforms such as Kiva shows that lending to the poor is also a financial decision (e.g., Berns et al., 2020; Yoo et al., 2023) besides the influence of psychological factors. When lending money on Kiva, lenders give up on receiving interest rates (Galak et al., 2011). Furthermore, they expect to get their money back, which can be reused to continue lending (Burtch et al., 2014). This explains why prosocial lenders on Kiva tend to respond more positively to lower-risk projects (Berns et al., 2020). Moreover, charitable giving necessarily depends on individuals' financial wealth and liquidity, and so does prosocial lending.

As referred, lenders' decision-making follows a dual nature (i.e., Galak et al., 2011). Prosocial crowdfunding merges a financial context, which links with capital markets, with a prosocial context, which intertwines psychological factors. This nexus was used to guide this study by applying behavioral finance to crowdfunding markets, in particular prosocial crowdfunding. The confluence of psychological factors and financial rationality in decision-making has been documented for decades by behavioral finance literature, revealing trends of abnormal returns due to time effects and calendar anomalies (hereafter, TECA)[1] in capital markets, mainly associated with liquidity (financial) reasons. In stock markets, investor sentiment also influences financing decisions (Liu et al., 2022) besides financial rationality.

The literature broadly relates investors' sentiment to TECA (e.g., Liu et al., 2022) which influences the supply and demand for funds (Liu, 2015) and, consequently, stocks performance. For example, empirical evidence from stock markets highlights higher returns in January than in other months, which is called the January effect (e.g., Barone, 1990; Rozeff and Kinney, 1976). Moreover, some studies posit relatively larger returns of stocks on Fridays than on Mondays—the weekend effect (e.g., Cross, 1973; Barone, 1990; French, 1980; Urquhart and McGroarty, 2014), as well as on the last days of the month and first few days of the next month—the turn-of-the-month (TOTM) effect (e.g., Ariel, 1987; Barone, 1990; Urquhart and McGroarty, 2014).

In the context of prosocial crowdfunding, there is no return of any kind for the lender, unlike that observed in other forms of crowdfunding (e.g., equity crowdfunding, reward crowdfunding, etc.) (Jancenelle et al., 2018; Berns et al., 2020). Hence, when deciding to support a campaign, each prosocial lender prefers the joy of lending support to poor entrepreneurs to their own financial well-being. Therefore, from a financial point of view, prosocial lenders can be considered as not rational in their decision-making process. Prosocial lenders are driven by social impact and psychological feelings. As both investors and prosocial lenders are driven by psychological factors, one can posit that decision-making regarding investment and prosocial lending may share some patterns that influence the stock market and crowdfunding performance. Moreover, some

[1] An anomaly is a situation where financial markets performs contrary to the notion of the efficient market hypothesis (Fama, 1970).

philanthropists have drawn attention to the (direct and indirect) relationship between capital markets' volatility and the performance of philanthropic campaigns.[2]

To the best of our knowledge, research on the link between TECA and the funding success of prosocial crowdfunding campaigns is scant. Nonetheless, emerging literature has been examining TECA and seasonal effects on other forms of decentralized finance (DeFi), namely on cryptocurrency markets (Kinateder and Papavassiliou, 2021) and reward crowdfunding platforms (Taeuscher et al., 2021), offering evidence of psychological factors guiding the performance of those markets too. Through our study, we look to merge crowdfunding literature and TECA literature to classify lenders' decisions in prosocial crowdfunding. To do so, we assessed if TECA reported in behavioral finance literature persists in prosocial crowdfunding in general terms. If so, we examine how they influence the success of prosocial crowdfunding campaigns. The knowledge about TECA can offer the opportunity to strategically define loan-campaign requests and understand the successful fundraising of financially excluded entrepreneurs from developing and emerging economies. Following this aim, we examine a large sample of crowdfunding campaigns from a global leading prosocial crowdfunding platform – Kiva.

Our study offers several main contributions and implications. First, this study extends the literature on behavioral finance to the context of prosocial crowdfunding microfinance by studying the impact of TECA factors on crowdfunding success for the first time. We applied a composite framework that integrates a cross-disciplinary lens of behavioral finance and prosocial crowdfunding research. Second, we provide practical implications

2 The high volatility of the stock markets registered in 2019–2020 was seen as sign of serious economic troubles raising serious concerns about effects of externality on philanthropy activities, namely on the fundraising, grant making, endowments, and so one (https://www.philanthropy.com/article/how-stock-volatility-could-take-a-swipe-at-charitable-giving-and-grant-making/. Accessed: July 25, 2023)

to the entrepreneurship literature and practitioners by providing insights to entrepreneurs seeking financial capital, helping them achieve successful crowdfunding campaigns by incorporating TECA in their decision-making. Finally, our findings are also relevant for Field Partners; they should consider time patterns to recycle their funding more quickly, and thus be available to fund new entrepreneurs, particularly in poor countries.[3] Implications for scholars and policymakers are addressed in the conclusion section.

Background and research hypotheses

Crowdfunding emerged after the global financial crisis of 2008 when traditional financing dried up and low interest rates in savings channeled lenders to participate in peer-to-peer (P2P) lending crowdfunding (Bruton et al., 2015). The evolution of technology and the subsequent rise of the Internet and the boom of online applications and social media boosted the development of crowdfunding platforms (Block et al., 2018). Through crowdfunding, smaller entrepreneurs who traditionally have had great difficulty in obtaining financial capital can reach anyone in the world who has spare cash to invest and a device with access to the Internet. This phenomenon led to the increasing role of crowdfunding and P2P lending as alternative forms of financing, particularly in the early stages of new ventures (Block et al., 2018), working as a replacement of traditional sources of funding, such as banks. Like cryptocurrency markets, crowdfunding platforms work on a 24/7 basis, contrary to traditional financial markets, including stock markets.

[3] FPs are local organizations (non-profits, microfinance institutions, schools, social enterprises, and NGOs) that administer loans and support borrowers in setting up and launching the campaign. In several cases, field partners also pre-disburse the campaign's amount requested by entrepreneurs, acting as microfinance institutions. If these campaigns are funded from the crowd of lenders, the amount raised is used to reimburse the amount the field partners pre-disbursed. Thus, field partners act as the vertex of a triangular system whose refinancing depends on the success of the campaigns with the lenders. Therefore, a higher and faster success of campaigns means that reimbursement occurs more quickly, therefore allowing field partners to recycle the capital invested to help more and more entrepreneurs in need through pre-disbursements.

This opens a new investment window both for investors and for entrepreneurs looking to raise funds to their ventures.[4]

Prosocial P2P lending crowdfunding is a hybrid type of crowdfunding (Galak et al., 2011) where lenders lend their money, without interest, to crowdfunding campaigns and rely on the entrepreneurs to safeguard microfinance institutions that screen and monitor the micro-loans locally, emphasizing a prosocial agenda of such platforms (Berns et al., 2020). Besides playing an important role in financial inclusion, prosocial crowdfunding and its effects have been associated with the alleviation of poverty and the improvement of social welfare (Gao et al., 2021). The context of prosocial crowdfunding is quite different from other forms of crowdfunding such as equity-based crowdfunding, or even reward-based crowdfunding (Jancenelle et al., 2018). In the latter, social aspects related to philanthropy and behavioral lending are less evident or are at least secondary to financial and reward aspects (Berns et al., 2020). In prosocial platforms such as Kiva, lenders tend to consider not only extrinsic factors but also intrinsic factors such as prosocial motivation to aid those less fortunate (Allison et al., 2015). Prosocial lenders exhibit behaviors aligned with a donations-based logit (Jancenelle et al., 2018). Hence, due to its dual nature (Galak et al., 2011), we argue that prosocial crowdfunding is a unique laboratory for policymakers looking to promote social welfare and well-being in poor and emerging countries by boosting this "new way to fundraise for philanthropy" (Zhang et al., 2023:1079). It is of relevance to note that typically prosocial lenders in Kiva are individuals living and working in developed countries[5] providing interest-free loans

[4] Not only does crowdfunding present itself as a financing alternative, as it can provide demand information and, therefore, generate incentives to entrepreneurs, it also helps to improve product quality and helps investors to decide whether to launch a new product (Liu & Wang, 2018).

[5] Based on data collected data from Kiva's Application Programming Interface on lenders that shared their nationality (https://www.kiva.org/build/data-snapshots)

for entrepreneurs "who, by and large, are located in the developing world" (Burtch et al., 2014:776).

This paper enlarges the state-of-the-art on prosocial crowdfunding success. Crowdfunding literature mainly has examined how personal social networks (e.g., Mollick, 2014; Zheng et al., 2014), and other rhetorical cues (Moradi et al., 2023) and images embedded in borrower's profiles (e.g., Yoo et al., 2022, 2023;) influence fundraising success, through diverse theoretical lens—e.g., cognitive theory (Allison et al., 2015); framing theory (Defazio et al., 2021); and, theory of choice homophily (Greenberg and Mollick, 2017).[6] Some of these theoretical lenses put into question the lender's rationality in a prosocial context. We extend this literature by positing that prosocial lenders follow a calendar mindset. This calendar mindset can be related to a lender's financial capability at a time (as in stock markets) and simultaneously to a higher warm-glow effect (Allison et al., 2013) in some calendar events.

The behavioral finance literature explains the reasons for time effects and calendar anomalies (TECA) in stock market performance by studying the influence of psychological factors, such as heuristics and biases, overconfidence, emotion, and social forces, on the decision making of investors (Bakar and Yi, 2016). In the field of prosocial crowdfunding literature remains silent in the nexus of a calendar mindset and the funding success of campaigns. We contribute to filling this research gap. The premise for investigating the existence of calendar seasonality in the crowdfunding markets is that TECA is behavior-related and might be constrained by time and financial availability and time zones of lenders. Based on broader evidence from traditional financial markets and from emerging literature on DeFi (e.g., Kaiser, 2019; Kinateder and Papavassiliou, 2021; Taeuscher et al., 2021), we posit that some TECA might be unveiled in crowdfunding

[6] For an overview of extant research on the determinants of crowdfunding success in different crowdfunding models, see Deng et al. (2022).

markets.

The turn-of-the-month effect (TOTM)

The TOTM effect– i.e., temporary increase in returns during the last days and the first days of each month– was firstly documented by Ariel (1987) and broadly studied by the stock market literature (e.g., Agrawal and Tandon, 1994). This effect can be attributed to liquidity/financial reasons, with the demand of individual investors increasing due to higher month-end cash flows, such as the payment of salaries, interests, and dividends (Barone, 1990). In the context of crowdfunding markets, one can hypothesize that an influx of money might also occur due to higher cash flows for individual lenders in such periods from payment of salaries, retirement plans, and other sources of income which might increase the lenders' funding ability thus increasing the success of loan campaigns during this period. Consequently, the TOTM seems to open a window in which it is easier to reconcile the financial capabilities of lenders with the joy of giving that drives prosocial lenders' decisions in crowdfunding. Hence, by merging the stock market literature with the warm glow theory (Allison et al., 2013) we formulate the first hypothesis (**H1**) as follows: There is a positive TOTM effect on prosocial crowdfunding campaigns' success.

The month-of-the-year (MOTY) effect and the January effect

Rozeff and Kinney (1976) were the pioneers to identify that stock returns vary depending on the month. The authors suggest a calendar anomaly in which the mean returns on stocks are higher in January than in other months, which can be explained by the "tax-loss selling" and "window dressing" hypotheses. Both hypotheses suggest that investors repurchase the stocks in the new year, creating the January effect reflected in abnormal returns. In the prosocial crowdfunding context, we expect a larger influx of funds at year-end to impact campaign success as in the stock market, because of lenders' extra income, such as employee bonuses and pension funds contributions. Behavioral factors and investor sentiment may also explain, at least partially, the January effect, as the turn of the year is hypothesized as a time of renewed optimism (Ciccone, 2011). The turn of the year usually provides a sense of change. Hence, in the context of prosocial crowdfunding, it might also increase the joy of giving. This argument is also aligned with the warm glow effect.

Other MOTY effects have been documented in stock markets. September has been historically the worst-performing month which can be linked to “postschool holiday effect” (Fang et al., 2018). Further, mean returns of stock for November and December have been reported to be greater than those of the remaining months, while mean returns of stock for March to May are significantly less than those during the other nine months (Patel, 2008). As investors and prosocial lenders might share investment sentiments influencing liquidity, we expect that this calendar mindset leads to differences in crowdfunding success between the months of the year due to an association between liquidity reasons and warm-glow effects. Therefore, we formally stress the following general and exploratory hypothesis (**H2):** The success of prosocial crowdfunding campaigns differs across the months of the year.

The day-of-the-week effect (DOTW) and the weekend effect

The day-of-the-week (DOTW) effect was first identified by Cross (1973) on stock markets. The author observed that stock returns on Monday were significantly lower than on other days of the week, especially when compared with Friday – the so-called weekend effect. Institutional investors may be less active on Mondays as this tends to be a day of strategic planning (Wang and Walker, 2000), and individual investors often make financial decisions over the weekend, being active selling on Mondays (Osborne, 1962). Investor psychology literature on the Blue Monday hypothesis also posits that the investors on Monday may be less optimistic (feel "blue"), and if so, they may be more pessimistic about the outlook for the securities they hold (or are considering buying) and more apt to sell for less (or less apt to buy) on Mondays than on other days (Rystrom and Benson, 1989). Since we expect the crowd to be constituted mainly by individual non-professional investors, we argue that investor psychology may also explain the mood of prosocial lenders in crowdfunding.

Evidence from 24/7 cryptocurrency markets shows generally lower trading volume (as well as lower volatility) over the weekends, which indicates that trading takes place predominantly during weekdays (Kaiser, 2019). In this market, it has been also found a DOTW effect with returns on Mondays significantly higher than those on the other days of the week (Caporale and Plastun, 2019).

Literature on stock markets broadly report positive and negative DOTW effects on returns, depending on the day of the week (e.g., Jaffe and Westerfield, 1985; Ajayi et al., 2004). We also posit that some DOTW effects might also be unveiled in prosocial crowdfunding markets. We test the following general and exploratory hypothesis **(H3):** The success of prosocial crowdfunding campaigns differs across the days of the week.

Empirical design

Data

We collected data from Kiva's Application Programming Interface (https://www.kiva.org/build/data-snapshots). Kiva operates on a 24/7 basis[7] and was the pioneer of zero-interest entrepreneurial lending. Since its inception, Kiva has helped fund approximately 2 million loans, enabling about 2 million lenders to mobilize $1.77 billion

[7] That translates into campaigns exhibiting the possibility to be launched at any hour of the day and on any day of the week. Thus, crowdfunding markets differ from conventional financial markets but operate similar to cryptocurrency markets.

in loans for about 4 million borrowers[8]. Kiva is first-comer in the microfinance crowdfunding field with extensive coverage of poor countries, connecting small entrepreneurs with prosocial lenders around the world who are willing to provide funding in the form of micro-loans (Mollick, 2014) mainly to "underserved individuals globally"[9]. Kiva presents itself as a prosocial lending-based platform, with the mission to expand financial access for all, by offering lenders a chance to help those less fortunate with a loan, with no mechanism for lenders to earn a return on their capital (Berns et al., 2020); thereby it enables people to create opportunities for themselves and their families by becoming entrepreneurs (Moleskis and Canela, 2016). See *"Kiva: how it works?"* in the supplementary online material of this article for more details about this platform.

The data refer to 979,765 crowdfunding campaigns launched on Kiva, from 2006 to 2021, by borrowers from 66 different countries and 15 sectors. Our selection criteria were removing campaigns reporting atypical data on funding time (i.e., campaigns with a duration higher than 30 days, above the limit defined by Kiva) and excluding campaign data promoted by Field Partners (FP) without public information on their financial and social performances. Finally, we exclude campaigns that did not disclose information on the amount pledged by lenders[10]. Table A1, in the supplementary online material, details the sample composition.

Variables

Dependent variables

We use several measures of crowdfunding success to highlight how the funding performance of the campaign was: Funded likelihood (e.g., Ahlers et al., 2015), Pledged

[8] https://www.kiva.org/about/impact (Accessed July 25th, 2023).
[9] https://www.kiva.global/ (Accessed July 25th, 2023).
[10] These exclusion criteria were applied for the full sample of 1,399,340 loan campaigns, thus excluding 419,575 campaigns that did not meet the criteria.

Amount and Pledged Goal (e.g., Duan et al., 2020) and Speed (e.g., Dorfleitner et al., 2021; Gama et al., 2023). *Funded* is a binary variable that takes the value 1 if the loan campaign was fully funded by the crowd, and 0 if does not meet the funding goal. *Pledged Amount* (in U.S. dollars) is the logarithm of the total amount pledged by lenders for each campaign (in USD), funded and not fully funded. *Pledged Goal* is the ratio (in decimal) between the pledged amount and the monetary goal of the campaign.

Independent variables

To account for TECA we use the following variables: TOTM, Month, and Weekday. *TOTM* captures the period around the turn of every month. In line with previous research in stock markets (e.g., Agrawal and Tandon, 1994; Sharma and Narayan, 2014) we define *TOTM* as a binary variable that takes the value "1" if the crowdfunding campaign was launched in the time window between the last day of the month and the first three days of the next month, taking the value "0" otherwise. Inspired by this literature, we rely on a set of twelve binary variables for each Month of the year (January to December) to test the *MOTY* effect in the prosocial crowdfunding context. Similarly, to explore a possible *DOTW* effect or even a weekend effect on crowdfunding success, we rely on a set of seven binary variables for each Weekday (Sunday to Saturday) (Caporale and Plastun, 2019).

Control Variables

First, we controlled for the gender effect documented in the crowdfunding literature (e.g., Defazio et al., 2021) using a binary variable *Female* coded as "1" for campaigns led by females (or majority by females in the case of group lending), and coded as "0" for campaigns led by males (or majority by males). Crowdfunding research has provided evidence that the structure of the crowdfunding campaign can influence its outcomes (Mollick, 2014). For this reason, we controlled for the *Project size* (in USD) (Duan et al.,

2020) and for *Project duration* (in days) (Ahlers et al., 2015). We also control for the *Repayment schedule* (Berns et al., 2020). The Repayment schedule is a binary variable coded as “1” if the repayment is made on a regular monthly basis, and “0” otherwise. Finally, we control for FPs’ risk and success. *FP’ Rating* is rated by Kiva and indicates how likely loans through a given FP are to be repaid (Allison et al., 2015). This variable ranges between 1 (high risk) to 5 (low risk). *Default rate* is the ratio of the amount of ended loans that failed to be repaid by the amount of ended loans by FP. *FP's Delinquency* rate is the ratio of late payments’ amount to the total outstanding principal balance Kiva has with the FP.

Table 1 provides the definition of the variables and the descriptive statistics. The correlation matrix for continuous covariates, reported in Table A2, in the supplementary online appendix, does not reveal high pair correlation values thus not suggesting multicollinearity problems.

*****Insert Table 1*****

Results

Table 2[11] reports the estimations for *Funded* likelihood, using the Probit model. Tables 3 and 4 report the estimations for *Pledged Amount* and *Pledged Goal*, respectively, using the OLS model. Columns I report the results for the TOTM effect, individually. Columns II and III show the MOTY and DOTW effects, by months and weekdays, respectively, on crowdfunding success. All estimations include control variables and controls for *Year*, *Sector*, and *Country* fixed effects. Information on the full table with the control variables is available upon request.

*****Insert Tables 2–4*****

11 Since for many countries and years the percentage of funded campaigns is 100% (see Table A1, Panels A and C, in supplementary online material), the number of observations included in the estimation model for *Funded* was reduced to 971,945 due to perfect collinearity.

Our results reveal TECA in the prosocial lending crowdfunding. Results show that the TOTM coefficient (Column I) is significantly negative across all model specifications at a 1% statistical significance level, for Funded likelihood (Table 2), Pledged Amount (Table 3) and Pledged Goal (Table 5). This evidence is contrary to Hypothesis H1. TOTM's effect on prosocial campaigns impacts crowdfunding success in prosocial crowdfunding. Campaigns launched during the TOTM period are less likely to be fully funded until the expected end date and characterized by having lower total pledged amounts. Hence, contrary to evidence from stock markets' literature, we identify a reverse TOTM effect in prosocial crowdfunding.

Our findings provide evidence of MOTY effects on prosocial crowdfunding success in line with Hypothesis H2. We show that crowdfunding campaigns launched between December and March (Columns II.1-3, II.12) report better performances measured by Funded likelihood, Pledged Amount and Pledged Goal. In contrast, prosocial crowdfunding campaigns launched between May and October (Columns II.5-10) are negatively linked to the funding campaign's success. The April and November effects (Columns II.4 and II.11, respectively) in the success of campaigns are mixed. This suggests that April and November are months of transition between cycles of greater and lesser success.

Our results also report positive and statistically significant coefficients for Monday and Tuesday (Columns III.2-3). Campaigns launched on Sundays (Columns III.1) receive funding more quickly and have a higher pledged goal ratio achieved. The coefficients of Wednesday and Thursday (Column III.4-5) are negative and statistically significant except for Pledged Amount. The evidence on the effects of Fridays and Saturdays is mixed across success metrics. This may suggest that these two days mark the transition from a negative cycle (Wednesday-Thursday) to a positive success cycle (Sunday-

Tuesday). Our results, thus provide evidence that campaigns launched from Sundays to Tuesdays report an overall better performance than those launched from Wednesdays to Saturdays. These results confirm a DOTW effect on prosocial lending campaigns impacting crowdfunding success, in line with Hypothesis H3. We check the robustness and the validity of these results in the following section. Then, we discuss our findings in detail.

Robustness checks

Success metrics

To check if our main results are driven by the choice of crowdfunding success metrics, we run our models for three alternative dependent variables broadly used by literature: *Amount Funded*, number of *Lender* (Duan et al., 2020; Gama et al., 2023), and funding *Speed* (e.g., Dorfleitner et al., 2021). The *Amount Funded* (in U.S. dollars) is the total of funds collected in successful campaigns invested in the project, (in logarithm form). The number of *Lenders* that contributed to a given project (in logarithm form) is an important measure of success as borrowers seek to attract many lenders to facilitate access to financing. The funding *Speed* is the logarithm of 1,000 divided by the funding time[12] (expressed in days) (as in Dorfleitner et al., 2021). *Speed* is the rate at which full funding was received via the crowd, i.e., how fast the crowdfunding campaign reached its funding target; thus, how fast it achieved success, assuming that campaigns funded faster were favored by lenders. All these variables assume the value of zero for non-fully funded campaigns to capture the context of Kiva that follows an "All-or-Nothing" model (Defazio et al., 2021). The results are reported in Tables A3-A5 in supplementary online material.[13] Overall, the results confirm prior evidence of a reverse TOTM reported in

[12] Funding time is defined by the number of days between the moment the campaign was launched and the moment it gets fully funded.
[13] Descriptive statistics of each dependent variable are reported at the bottom of each table, respectively.

Tables 2-4. Additionally, we show a positive (negative) association between December-March (May-November) and each of these alternative success metrics, which is in line with our baseline results. The results on the DOTW effect are also consistent with those reported in Tables 2-4. These estimations confirm that our results are not driven by the choice of success metrics thus ensuring the robustness of our findings.

Aggregated effects

Based on the evidence of MOTY and DOTW effects we now run our models using an alternative criterion by aggregating the months into binary variables. *MOTY (binary)* equals 1 if the campaign was launched from December to March, and 0 if otherwise. *DOTW (binary)* equals 1 if the campaign was launched from Sunday to Tuesday, and 0 if otherwise. Table A6 (and Figure 1), in the supplementary online material, reports the results. The results strongly align with previous reported findings. There is a negative TOTM effect on prosocial lending campaigns impacting crowdfunding success. Campaigns launched from December to March and from Sunday to Tuesday perform better than campaigns launched from April to November and from Wednesday to Saturday, respectively.

Validity of coefficient (in)quality assumption

To check the assumption of effects' (un)equality between each month of the year and days of the week we regress each dependent variable on the full set of calendar binary variables (excluding the intercept from the model to avoid perfect collinearity between regressors). As we exclude the intercept, the coefficients of each binary variable represent how different from zero each of those binary variables is. The results are reported in Tables A7-A8 in supplementary online material. The Wald-test and the F-test reported at the bottom of those tables reject the null hypotheses of equality of the coefficients of the set of 12 (months) binary variables as well as of the 7 (weekdays) binary variables as we hypothesized.

Sample Size and Overrepresentation

In behavioral sciences, large sample sizes might produce a bias in the estimations, namely by increasing enormously the likelihood of finding a statistically significant result (Khalilzadeh and Tasci, 2017) which might lead to inferential errors. Additionally, funded campaigns represent 93% of observations in our sample. To test if our results are driven by sample size[14] and by overrepresentation of fully funded campaigns[15], we randomly generated a subsample from our data set imposing a two-third partition on funding success distribution, thus generating a subsample with 278,496 observations, including 208,872 fully funded campaigns (75%) and 69,624 non-funded campaigns (25%). Table A9, in supplementary online material, reports the descriptive statistics of this subsample. This random subsample provides an unbiased assessment that TECA influences the success of prosocial lending campaigns. The results, reported in Table A10, in supplementary online material, are in line with those reported in Table A6, thus confirming the robustness of our results.

Supply side effects

The funding success rate may be high or low because of the TECA on the demand side, but it could also be because of the number of competing campaigns available in each fundraising period[16]. Funding success could also be driven by the number of lenders actively investing in the platform in that period. Hence, to control the supply side, namely the competition between projects, we used the ratio between active projects and active lenders in each period, for each campaign (competition). The results, reported in Tables A11–A16 (supplementary online material), confirm the robustness of our main findings.

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[14] The statistically significance test is influenced by sample size. If the sample size is very large, virtually any population difference will result in statistical significance. On the other hand, the smaller the sample size, the larger must be the population differences to achieve statistical significance (Lindley, 2000).

[15] Overrepresentation biases in statistical inferences and forecasts is also a concern, also in the field of finance, leading some researchers to run empirical models based on trial random subsamples (e.g., Duarte et al., 2018).

[16] We acknowledge an anonymous referee for this contribution.

These estimations also reveal that campaigns launched on Saturdays (we previously identified as a transition day of the week to a positive success cycle; Tables 2–4 and Tables A3-A5 in supplementary online material) report higher success across all success metrics, thus enlarging the greater success cycle for the period Saturday–Tuesday. The results also show that the competition is relevant when explaining the success. The stronger the project competition (i.e., the number of projects funded by active lenders on the platform), the lower the likelihood of a project being fully funded, the lower the amount invested and pledged by lenders, as well as the speed and the number of lenders engaged by each campaign.

Discussion

Taeuscher et al. (2021) recognized that seasonal effects seemingly influence crowdfunding outcomes. We are the first to explicitly address the time and calendar effects on prosocial crowdfunding where lenders are driven by social concerns and by the motive of helping others rather than by financial returns. We expected an influx of funds into the prosocial crowdfunding market during the turn of the month was expected due to assumed higher availability of lenders' cash flows at month-end, resulting from the payment of salaries and extra income, similar to the stock market. However, we documented a reverse turn-of-the-month (TOTM) effect in the prosocial crowdfunding market. Campaigns launched during the 4 days of the turn of the month have poorer crowdfunding success, being less likely to be successfully funded. We recognize that differences in the nature between financial markets and prosocial crowdfunding markets might drive these results that are, to some extent, contrary to our expectations, but with feasible explanations. In prosocial crowdfunding, monetary gains might not be a priority of lenders when it comes to their income allocation as they lend on an interest-free crowdfunding platform. To an extent, prosocial lenders may only decide to lend to a project after they have fulfilled their primary financial needs and investment goals. Moreover, there might be less awareness among lenders about new campaigns launched during this period, which may lead to lower inflows. Because we were unable to collect data on lenders' investment priorities, we left this as a potential research avenue for crowdfunding scholars.

Some of our findings regarding the month-of-the-year (MOTY) effect are partially in line with what has already been found in the stock market literature. We identified a January effect with this month being positively and significantly linked to the campaigns' success. This result can be explained by two main reasons. 1) Liquidity: in January, working individuals supposedly have more spare money due to the year-end bonuses and subsidies they receive; 2) the turn of the year gives people a sense of a clean start and an opportunity to change, and, in general, individuals are more optimistic and in a good spirit. Accordingly, prosocial lenders may try to make good on a New Year's resolution, by committing to contribute in some way to social causes and trying to make a good small change in the world. The joy of giving that drives prosocial lenders is in line with the warm glow effect (Allison et al., 2013).

The most interesting and puzzling finding of this study is that there is a clear distinction between the seasons of the year and their effects on crowdfunding success– which we called "*positive winter prosocial effect*". Most Kiva lenders are from North America, with the U.S. being the country with most lenders, and Europe[17]. In these two continents, the winter season starts in December and lasts until March. Our results point toward a significantly positive influence of the winter season on the funding success of a prosocial crowdfunding campaign. In other words, campaigns launched during the summer and surrounding milder months in the spring and autumn seasons have worse funding success,

[17] https://www.tableaudor.com/kiva-lenders (Accessed Jul. 25th, 2023).

thus suggesting that the lender's behavior may be weather-induced and/or dependent on time availability. As such, we suggest that the study of weather and crowdfunding success can be a fruitful research avenue. Usually, working individuals take their long vacations during summers or in milder months, a period during which they may be more engaged in outdoor activities. As this is typically a period of relaxation for people, they naturally are more disconnected, spending less time on their phones and the internet, therefore not having much time nor availability to explore the different prosocial projects to find the ones they most identify with. Furthermore, this is the time of the year when they spend more money on holidays, traveling, and everything involving activities of leisure. For this reason, personal spending might be their priority, and as such, they tend to be more financially tight.

We also provide evidence of day-of-the-week (DOTW) effects. In general, crowdfunding success is higher if the campaigns are launched between Saturdays and Tuesdays. We associated these findings with some effect of the weekend on the influx of lenders and their funds into the prosocial crowdfunding market. For most individuals, the weekends are days off work; as such, as the weekend approaches, people start to make plans and estimate their spending. So, before the weekend, people are more interested in saving money for planned and unplanned weekend spending. This might explain why crowdfunding campaigns launched during the last weekdays have lower chances of getting fully funded, raising higher amounts of funding, engaging with more lenders, and having their campaigns funded more quickly. After the weekend, individuals know how much of their spare money they can direct toward lending on prosocial crowdfunding platforms, increasing lender's engagement with new campaigns. Accordingly, campaigns launched at the beginning of the week are fully funded faster and present higher success levels than those launched on Wednesdays and Thursdays.

Concluding remarks

Crowdfunding is a recent phenomenon that has observed a rapid rise. As it represents a novel way for entrepreneurs to raise capital for a variety of projects (Mollick, 2014) across a wide range of sectors, the knowledge about the critical factors influencing crowdfunding campaign success interests entrepreneurs. Using data collected from Kiva, we examined the effects of the turn-of-the-month period, the 12 months of the year, and the 7 days of the week, on prosocial crowdfunding success outcomes. We offer consistent evidence of TECA on prosocial campaigns impacting crowdfunding success. Overall, we conclude that campaigns perform the worst and are less likely to succeed if launched during the 4-day window of the turn of the month (the reverse TOTM effect), as well as in summer and mild months—from the perspective of the northern hemisphere, where there is a greater concentration of lenders (*negative summer prosocial effect*), from Wednesdays to Fridays (the *negative second half of the week effect*). The assessment of these effects is robust in our additional analyses.

This study offers a significant theoretical contribution and relevant implications for scholars, microentrepreneurs, microfinance institutions, and policymakers. First, this study is the first to show the "positive winter prosocial effect" versus the "negative summer prosocial effect", as well as the **"**positive half-of-the-week effect". This work contributes to the theory building in the field of behavioral and entrepreneurial finance in the context of prosocial crowdfunding microfinance. The field of behavioral finance, in which lenders' sentiment is considered highly relevant, has received little attention in the crowdfunding literature so far.

Second, the focus on prosocial crowdfunding is also a valuable laboratory for scholars trying to expand knowledge boundaries in corporate, behavioral, and entrepreneurial finance by testing the limits of financial rationality on lending decisions. Hence, the evidence of TECA on crowdfunding we provide we this study also has implications for scholars. We recommend scholars account for potential time patterns and seasonality, as well as best practices in crowdfunding success, at least accounting for time-fixed effects, such as day of the week, month, and year (e.g., Kuppuswamy and Bayus, 2017), when examining capital influxes. Empirical approaches to other corporate markets guided by philanthropic concerns may examine if TECA effects persist and how they relate to philanthropes' sentiment. Third, for microentrepreneurs we offer insights regarding best practices for market timing to launch prosocial campaigns tailored to underprivileged entrepreneurs, mainly from poor and emerging countries. This might be valuable to entrepreneurs seeking financial capital so they can maximize the success of their campaigns by incorporating time patterns in their decision-making.

Fourth, these insights might also be relevant to microfinance institutions (i.e., field partners). Field partners are fundamental actors of prosocial crowdfunding. In addition to helping entrepreneurs to build up their campaigns, field partners also pre-disburse the campaign's amount for some entrepreneurs acting as the vertex of a triangular system whose refinancing depends on the success of the campaigns with the lenders. Therefore, the higher the success of campaigns, the greater the ability of field partners to extend their services to the entrepreneurial ecosystem in poor and emerging countries. By helping entrepreneurs maximize funding success, our evidence helps field partners obtain refunds faster, thus facilitating funding to new borrowers. It will also help crowdfunding platforms to run more efficient business models or even choose to introduce timing in new platform designs and changes in their websites. Therefore, based on this new evidence on campaigns' funding success, this study contributes to enhancing the success of prosocial crowdfunding platforms that provide a relevant service in overcoming various societal challenges in socioeconomically backward settings in developing countries, namely by promoting the mitigation of poverty, financial exclusion, and social inequalities.

For policymakers in developing countries, the evidence of a calendar mindset should guide public policy measures to encourage the raising of funds for campaigns launched in periods during which the conditions for success are bleak, namely between April and November. One of the most relevant target groups of prosocial crowdfunding is rural entrepreneurs. The cold winter coupled with rainy periods makes entrepreneurs involved in rural activities particularly vulnerable. This may reduce household income and increase the need for funds during a period of a lower propensity of prosocial lenders to provide loans. In the southern hemisphere, policymakers should seek to compensate for this lower propensity during challenging contexts. The literature has proved the positive effect of entrepreneurship on rural poverty (e.g., Naminse et al., 2019) and shows that financial inclusion in the digital economy era effectively increases household well-being in emerging countries (e.g., Du et al., 2022). Therefore, policymakers should not ignore their role in promoting alternative ways of financial inclusion to counter the "negative summer effects" in poor countries (from the northern hemisphere point of view). These recommendations will be helpful to mitigate the challenges of access to capital from traditional sources faced by microentrepreneurs in developing countries, particularly for those at the bottom of the economic pyramid which tend to be weakly integrated into the global economy (Yamalakonda et al., 2023). In turn, policy actions aligned with these recommendations will contribute to reduce income asymmetries among worldwide geographies. Finally, this study may have a spill-over effect on innovation, namely on green innovation, boosted by decentralized finance instruments in those countries, as it occurs for listed companies due to the flourishing of digital finance instruments (Kong et al., 2022).

We recommend caution before generalizing our findings to other crowdfunding contexts. Kiva represents a unique segment of the crowdfunding universe, that is, prosocial crowdfunding. Although we adopted a wide range of success metrics reported in the literature on different crowdfunding settings besides those following an "All-or-Nothing" model as Kiva, one avenue to extend the literature on TECA in crowdfunding is to explore whether and how these time and calendar effects affect crowdfunding success on other types of crowdfunding, including platforms based on a "keep-it-all" model. It also seems relevant to study crowdfunding schemes offering returns to lenders, a context more closely related to traditional financial markets, which is different from the interest-free loan context of Kiva. We suggest two additional future research avenues. First, we suggest other types of crowdfunding platforms that might provide investor-level data to crowdfunding scholars for them to study time patterns and herding effects in the campaign's progress to secure funding. Second, future research should examine whether time patterns and calendar anomalies exist even for projects exhibiting low-quality signals and for new ventures with unobserved private information on their credit risk. Due to data limitations, we could not address these relevant aspects.

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List of Tables

Table 1. Variables definition and descriptive Statistics (N=979,765 observations)

		Mean	Median	SD	Min	Max
Dependent variables						
Funded	Equals 1 if the campaign was successfully funded, equals 0 otherwise.	0.93	1.00	0.26	0.00	1.00
Pledged Amount	Total amount pledged by lenders for each campaign (in USD), funded and not fully funded.	687.00	450.00	744.47	0.00	10,100.00
Pledged Goal	Ratio between the pledged amount and the campaign goal.	0.96	1.00	0.16	0.00	1.13
Independent variables						
TOTM	Equals 1 if the campaign was launched on the last day of the month and the first three days of the month, equals 0 otherwise.	0.11	0.00	0.31	0.00	1.00
Month				0		
January	Set of 12 binary variables for each month (January, …, December).	0.08	0.00	0.28	0.00	1.00
February		0.09	0.00	0.28	0.00	1.00
March		0.09	0.00	0.29	0.00	1.00
April		0.08	0.00	0.27	0.00	1.00
May		0.08	0.00	0.27	0.00	1.00
June		0.08	0.00	0.27	0.00	1.00
July		0.08	0.00	0.27	0.00	1.00
August		0.08	0.00	0.27	0.00	1.00
September		0.08	0.00	0.27	0.00	1.00
October		0.08	0.00	0.28	0.00	1.00
November		0.08	0.00	0.27	0.00	1.00
December		0.09	0.00	0.28	0.00	1.00
Weekday						
Sunday	Set of 7 binary variables for each day of the week (Sunday, …, Saturday).	0.02	0.00	0.15	0.00	1.00
Monday		0.18	0.00	0.38	0.00	1.00
Tuesday		0.19	0.00	0.39	0.00	1.00
Wednesday		0.19	0.00	0.40	0.00	1.00
Thursday		0.20	0.00	0.40	0.00	1.00
Friday		0.18	0.00	0.39	0.00	1.00
Saturday		0.03	0.00	0.18	0.00	1.00
Control variables						
Loan-Borrower						
Female	Equals 1 if female entrepreneur or group of majority females, 0 otherwise.	0.74	1.00	0.44	0.00	1.00
Project size	Monetary goal of the campaign (in U.S. dollars).	738.90	500.00	796.62	25.00	13,050.00
Project maturity	Maturity of the campaign (in days).	13.40	14.00	7.14	2.00	145.00
Repayment Schedule	Equals 1 if the repayment is made in monthly basis, equals 0 otherwise.	0.83	1.00	0.37	0.00	1.00
Field Partner						
Rating	Kiva-assessed risk level of a field partner (1=high risk, ..., 5= low risk).	2.83	3.00	0.86	1.00	4.00
Default	Kiva-assessed default ratio of the amount of ended loans that failed to repay by amount of ended loans by field partner (in %).	1.23	0.38	2.76	0.00	31.89
Delinquency	Kiva-assessed delinquency ratio is the ratio between the amount in late payments by the total outstanding principal balance Kiva has with the field partner (in %).	30.29	15.14	35.30	0.00	100.00

Table 2. Dependent Variable: *Funded* (binary); Method: Probit

	Column I	Column II											
	I	**II.1**	**II.2**	**II.3**	**II.4**	**II.5**	**II.6**	**II.7**	**II.8**	**II.9**	**II.10**	**II.11**	**II.12**
Time effects	*TOTM*	*Jan.*	*Feb.*	*Mar.*	*Apr.*	*May*	*Jun.*	*Jul.*	*Aug.*	*Sep.*	*Oct.*	*Nov.*	*Dec.*
Independent variables													
TOTM *(binary)*	-0.138***	-0.135***	-0.140***	-0.140***	-0.138***	-0.141***	-0.137***	-0.133***	-0.137***	-0.138***	-0.134***	-0.137***	-0.131***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Month *(binary)*		0.167***	0.555***	0.324***	-0.009	-0.153***	-0.101***	-0.278***	-0.059***	-0.269***	-0.199***	0.042***	0.239***
		(0.009)	(0.011)	(0.010)	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.008)	(0.009)	(0.010)
Control variables	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
Fixed effects	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
Intercept	2.512***	2.498***	2.456***	2.473***	2.513***	2.533***	2.523***	2.540***	2.518***	2.548***	2.505***	2.512***	2.511***
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
Observations	971,945	971,945	971,945	971,945	971,945	971,945	971,945	971,945	971,945	971,945	971,945	971,945	971,945
Pseudo R^2	0.343	0.343	0.348	0.345	0.343	0.343	0.343	0.345	0.343	0.345	0.344	0.343	0.344

	Column III						
	III.1	**III.2**	**III.3**	**III.4**	**III.5**	**III.6**	**III.7**
Time effects	*Sun.*	*Mon.*	*Tues.*	*Wed.*	*Thur.*	*Frid.*	*Sat.*
TOTM *(binary)*	-0.138***	-0.137***	-0.138***	-0.137***	-0.138***	-0.138***	-0.138***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Weekday *(binary)*	-0.011	0.046***	0.029***	-0.033***	-0.041***	0.013**	-0.020
	(0.017)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.014)
Control variables	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
Fixed effects	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
Intercept	2.513***	2.506***	2.508***	2.518***	2.521***	2.509***	2.513***
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
Observations	971,945	971,945	971,945	971,945	971,945	971,945	971,945
Pseudo R^2	0.343	0.343	0.343	0.343	0.343	0.343	0.343

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. For variables definition see Table 1. All estimations include control variables (Loan-borrower: *Female*, *Project Size*, *Project maturity*, *Repayment Schedule*; Field Partner: *Rating*, *Default*, *Delinquency*) and controls for Fixed effects (Year, Sector, Country). The estimations for covariates are not reported but available upon request.

Table 3. Dependent Variable: ***Pledged Amount (measured by log(1+Pledged Amount)); Method: OLS***

	Column I	**Column II**											
	I	**II.1**	**II.2**	**II.3**	**II.4**	**II.5**	**II.6**	**II.7**	**II.8**	**II.9**	**II.10**	**II.11**	**II.12**
Time effects	*TOTM*	*Jan.*	*Feb.*	*Mar.*	*Apr.*	*May*	*Jun.*	*Jul.*	*Aug.*	*Sep.*	*Oct.*	*Nov.*	*Dec.*
Independent variables													
TOTM *(binary)*	-0.012***	-0.012***	-0.012***	-0.013***	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***	-0.011***	-0.012***	-0.012***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Month *(binary)*		0.049***	0.065***	0.045***	0.010***	-0.001	-0.000	-0.058***	-0.023***	-0.065***	-0.045***	-0.015***	0.028***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Control variables	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
Fixed effects	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
Intercept	6.327***	6.325***	6.327***	6.327***	6.327***	6.327***	6.327***	6.326***	6.329***	6.332***	6.326***	6.331***	6.311***
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.039)	(0.040)	(0.040)	(0.040)
Observations	979,765	979,765	979,765	979,765	979,765	979,765	979,765	979,765	979,765	979,765	979,765	979,765	979,765
R^2	0.685	0.686	0.686	0.686	0.685	0.685	0.685	0.686	0.686	0.686	0.686	0.686	0.686

	Column III						
	III.1	**III.2**	**III.3**	**III.4**	**III.5**	**III.6**	**III.7**
Time effects	*Sun.*	*Mon.*	*Tues.*	*Wed.*	*Thur.*	*Frid.*	*Sat.*
TOTM *(binary)*	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Weekday *(binary)*	0.005	0.015***	0.006***	-0.002	-0.013***	-0.003**	-0.010***
	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
Control variables	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
Fixed effects	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
Intercept	6.327***	6.327***	6.326***	6.327***	6.331***	6.328***	6.330***
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
Observations	979,765	979,765	979,765	979,765	979,765	979,765	979,765
R^2	0.685	0.686	0.685	0.685	0.686	0.685	0.685

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. For variables definition see Table 1. All estimations include control variables (Loan-borrower: *Female*, *Project Size*, *Project maturity*, *Repayment Schedule*; Field Partner: *Rating*, *Default*, *Delinquency*) and controls for Fixed effects (Year, Sector, Country). The estimations for covariates are not reported but available upon request.

Table 4. Dependent Variable: *Pledged Goal (ratio, as decimal); Method: OLS*

	Column I	Column II											
	I	**II.1**	**II.2**	**II.3**	**II.4**	**II.5**	**II.6**	**II.7**	**II.8**	**II.9**	**II.10**	**II.11**	**II.12**
Time effects	*TOTM*	*Jan.*	*Feb.*	*Mar.*	*Apr.*	*May*	*Jun.*	*Jul.*	*Aug.*	*Sep.*	*Oct.*	*Nov.*	*Dec.*
Independent variables													
TOTM *(binary)*	-0.008***	-0.008***	-0.008***	-0.009***	-0.008***	-0.009***	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Month *(binary)*		0.010***	0.023***	0.015***	-0.002***	-0.010***	-0.005***	-0.020***	-0.002***	-0.014***	-0.012***	0.002***	0.013***
		(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Control variables	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
Fixed effects	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
Intercept	1.099***	1.098***	1.099***	1.099***	1.099***	1.099***	1.099***	1.098***	1.099***	1.100***	1.098***	1.098***	1.091***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Observations	979,765	979,765	979,765	979,765	979,765	979,765	979,765	979,765	979,765	979,765	979,765	979,765	979,765
R^2	0.148	0.148	0.149	0.148	0.148	0.148	0.148	0.149	0.148	0.148	0.148	0.148	0.148

	Column III						
	III.1	**III.2**	**III.3**	**III.4**	**III.5**	**III.6**	**III.7**
Time effects	*Sun.*	*Mon.*	*Tues.*	*Wed.*	*Thur.*	*Frid.*	*Sat.*
TOTM *(binary)*	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Weekday *(binary)*	0.003**	0.003***	0.001***	-0.002***	-0.004***	0.001**	0.002*
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Control variables	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
Fixed effects	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*	*Included*
Intercept	1.099***	1.099***	1.098***	1.099***	1.100***	1.098***	1.098***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Observations	979,765	979,765	979,765	979,765	979,765	979,765	979,765
R^2	0.148	0.148	0.148	0.148	0.148	0.148	0.148

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. For variables definition see Table 1. All estimations include control variables (Loan-borrower: *Female*, *Project Size*, *Project maturity*, *Repayment Schedule*; Field Partner: *Rating*, *Default*, *Delinquency*) and controls for Fixed effects (Year, Sector, Country). The estimations for covariates are not reported but available upon request.