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Do time effects impact crowdfunding performance in prosocial peer-to-peer lending crowdfunding? Evidence from multi-country crowdfunding platform Kiva

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Abstract

In the last decade, online crowdfunded microfinance and peer-to-peer (P2P) lending have become trendy forms of alternative funding as they provide financial opportunities for small entrepreneurs, who lack access to traditional financing tools, alleviating poverty and improving social welfare. Thus, research on prosocial P2P lending crowdfunding have been capturing a growing audience concerned to maximize the funding success of digital loan campaigns through the Internet. Using the crowdfunding platform Kiva, we study the relationship between time patterns and the successful funding of crowdfunding campaigns in the prosocial P2P lending crowdfunding context. Drawing from the stock market (and cryptocurrency market) literature, we identify specific time frames where crowdlenders are most prone to lend money, unravelling time patterns in prosocial crowdfunding markets that can benefit entrepreneurs' crowdfunding campaigns. Our results show a reverse turn-of-the-month (TOTM) effect on P2P crowdfunding performance. Additionally, our findings suggest a positive winter and a negative summer prosocial effects on the campaign's performance. We detect a significant positive January effect in the prosocial crowdfunding market, similar to the stock market literature. Further, we identify a positive Tuesday effect and a negative Thursday effect, alongside with a positive beginning-week-days effect and a negative last-weekdays effect in the context of prosocial P2P lending crowdfunding.

Keywords: Prosocial P2P lending crowdfunding; Determinants of campaign' success; Seasonal effects; time patterns; Kiva.

Table of contents

List of figures

List of tables

1. Introduction

The access to external financing is one of the main challenges faced by start-ups and new ventures in early stages (N. Berger & F. Udell, 1998). Several reasons might explain this funding gap, but the severe information asymmetries and agency costs that new ventures face are two of the most relevant (Leboeuf & Schwienbacher, 2018). Consequently, many entrepreneurs are turning to online crowdfunding platforms, directly appealing to the general public for help (hereafter, the crowd), as a way to obtain funding for their innovative projects (Kuppuswamy & Bayus, 2018).

Crowdfunding contributes to potentially narrowing the funding gap for young and small businesses, helping to overcome the lack of funding by offering new financing opportunities (Hervé & Schwienbacher, 2018; Macht & Weatherston, 2014), thus promoting financial inclusion (Jenik, Lyman, & Nava, 2017), while alleviating poverty and improving social welfare (Gao et al., 2021).

Conventionally, crowdfunding is described as a means of financing entrepreneurs and their new ventures through an open call on an Internet platform by receiving small contributions from a large crowd of individuals through donations, lending, equity offerings and/or rewards (Mollick, 2014). Considering these four main types of crowdfunding, this study analyzes the prosocial peer-to-peer (P2P) lending crowdfunding context, a hybrid type of crowdfunding with features of both donation and lending crowdfunding. In prosocial P2P lending crowdfunding the debt is provided without interest, where lenders provide micro loans to small entrepreneurs emphasizing a prosocial agenda of microfinance, while usually intermediated by field partners (i.e., local microfinance institutions) that supervise the micro loans in each country (Berns et al., 2020). Thus, the burden of debt to the entrepreneurs is smaller since the interest rates of these crowdfunding loans are zero.

Although both crowdfunding and online P2P lending are recent phenomena, the determinants of campaigns' success have been thoroughly studied in the last decade. Crowdfunding literature highlights several key successful factors, such as venture quality (Ahlers et al., 2015), venture's narratives (Moss et al., 2015), founder's social networks (Kromidha & Robson, 2016; Lukkarinen et al., 2016; Mollick, 2014; Moutinho & Leite, 2013; Zheng et al., 2014) and project's characteristics, like campaign duration and funding target amount (Forbes & Schaefer, 2017; Lukkarinen et al., 2016; Mollick, 2014). However, to the best of our knowledge, the research on the link between time effects and the funding success of crowdfunding campaigns is, at least, scant. The knowledge about time effects (i.e., time patterns) and their impact on campaign success outcomes can be a powerful tool for those seeking to get financial support though crowdfunding. Especially in the context of prosocial P2P lending crowdfunding, time patterns can offer the opportunity to strategically define loan requests and get a successful fundraising to the financially excluded and more disadvantaged entrepreneurs. Drawn by this research gap, this study explores seasonality, time patterns and whether behavioural biases exist in funding decisions of the crowd of lenders on prosocial P2P lending crowdfunding. To fill this void, we answer the following research question: *whether and how calendar effects impact crowdfunding performance in prosocial P2P lending crowdfunding during the last decade?*

For decades, anomalies in financial markets have been documented and studied, particularly calendar anomalies. There is evidence that stock markets produces higher returns in January than in other months – the so-called January effect (e.g., Barone, 1990; Keim, 1983; Reinganum, 1983; Rozeff & Kinney, 1976). Furthermore, some studies posits relatively large returns of stocks on Fridays compared to those on Mondays – the weekend effect (e.g., Al-Khazali & Mirzaei, 2017; Barone, 1990; Cross, 1973; French, 1980; Urquhart & McGroarty, 2014). Likewise, it's been observed higher returns in the last few days and firsts days of each month – the turn-of-the-month effect (e.g., Al-Khazali & Mirzaei, 2017; Ariel, 1987; Barone, 1990; Lakonishok & Smidt, 1988; McConnell & Xu, 2008; Urquhart & McGroarty, 2014). This building evidence on calendar anomalies supports claims that financial markets are not rational, in a financial perspective, questioning the Efficient Market Hypothesis (Latif et al., 2011). Therefore, calendar anomalies are great opportunities for investors to profit from mispricing, as they can develop strategies aimed at exploiting these anomalies. Extending this literature, this study seeks to understand if there are time patterns in the prosocial crowdfunding market, a hybrid context of dual nature: financial and prosocial (Galak et al., 2011). Thus, our motivation goes beyond the financial scope of investors return (since crowdlenders do not receive any interest for the funding granted in the prosocial context) to further understand the success of prosocial P2P lending crowdfunding campaigns.

To answer our research question, we examine a large sample of crowdfunding campaigns from one of the global leading prosocial crowdfunding platforms: Kiva. Kiva follows an "All-or-Nothing" model, where a successfully funded campaign occurs when the level of contributions reaches the set financial goal; on the contrary, if the set goal is not reached, the raised amounts must be fully returned to the crowd of lenders, and therefore the campaign is not successful.

Based on several crowdfunding performance measures (*Funded* likelihood, *Amount* funded, number of *Lenders*, and the funding *Speed*), we show evidence that there is a reverse turn-of-the-month (TOTM) effect and a positive January effect in the crowdfunding performance of prosocial P2P lending crowdfunding. Further, we found that the seasons of the year are influential determinants of crowdfunding success, with the predominance of a positive winter and negative summer prosocial effects, with winter (summer) season being the best (worst) season to raise financial capital from the crowd. We also detected differences in campaigns' success outcomes depending on the day of the week – the positive Tuesday and negative Thursday effects – and at the same time we show that at the beginning of the week campaigns are fully funded at a faster pace, while at the end of the week they take a longer time to be fully funded – the positive beginning-week-days effect and the negative last-weekdays effect.

This study offers four main contributions. First, using a composite framework that integrates a cross-disciplinary lens of behavioural finance, entrepreneurship and prosocial P2P lending crowdfunding research, this study extends literature on behavioural finance to the context of prosocial crowdfunding microfinance by studying calendar effects on crowdfunding performance. Second, this research contributes to crowdfunding literature by exploring a determinant of crowdfunding success. Third, it also adds to the entrepreneurship literature and to practitioners by providing insights to entrepreneurs seeking for financial capital, helping them achieve successful crowdfunding campaigns by incorporating seasonality and time patterns in their decision-making. Fourth, through the contributions we provide on funding success factors in prosocial crowdfunding, this study contributes to promote prosocial crowdfunding and to mitigate economic and social inequalities that entrepreneurs face particularly in poor settings.

The remainder of this study is organized as follows. Section 2 presents the theoretical background on crowdfunding success. Section 3 reviews the literature on calendar anomalies and develops the research hypotheses. Section 4 describes the lending process on Kiva crowdfunding platform. Section 5 describes the empirical design. Section 6 reports the results discussed in section 7. Section 8 concludes.

2. Background

2.1. Crowdfunding

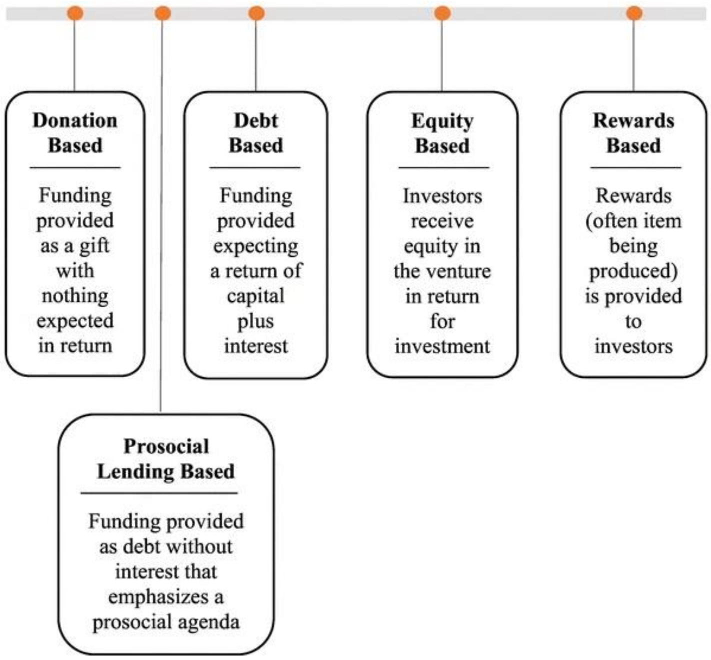
In recent years, the evolution of information technology and the digitalization of society with growing presence of the internet allowed the development of collective online finance marketplaces, widening the available possibilities for individuals to obtain financing. This phenomenon led to the increasing role of crowdfunding and P2P lending as alternative forms of financing (Kuti & Madarász, 2014), particularly in the early stages of new ventures (Block et al., 2018; Bruton et al., 2015; Lehner et al., 2015), working as a replacement of traditional sources of funding, such as banks (Berger & Gleisner, 2009).

Internet-based prosocial crowdfunding is a merger of the concepts of crowdsourcing and microfinance (Bradford, 2012; Mollick, 2014), being crowdsourcing "an online, distributed problem-solving and production model that leverages the collective intelligence of online communities to serve specific organizational goals" (Brabham, 2013: page xix), while the purpose of microfinance is to provide funding to those excluded from the conventional financing from credit institutions (Aghion et al., 2007).

Crowdfunding can be defined as the efforts by entrepreneurs and entrepreneurial organizations to fund their ventures by pooling small contributions from a large number of individuals (the "crowd"), usually done via or with the help of the internet and utilizing their social networks, without standard financial intermediaries (Buysere et al., 2012; Mollick, 2014). Through crowdfunding, smaller entrepreneurs who traditionally have had great difficulty in obtaining financial capital are able to reach anyone in the world who has spare cash to invest and a device with access to the Internet (Bradford, 2012).

When examining crowdfunding activities, we can distinguish four different crowdfunding models (represented in figure 1): donation-based, lending-based, equity-based, and reward-based crowdfunding, differing on the type of return offered to the crowd of lenders. Prosocial P2P lending crowdfunding is an hybrid type of crowdfunding where lenders lend their money, without interest, to crowdfunding campaigns, emphasizing a prosocial agenda, and rely on the entrepreneurs by the safeguard of microfinance institutions that screen and monitor the micro loans locally (Berns et al., 2020).

Figure 1. Spectrum of the various types of crowdfunding (Berns et al., 2020)



Originally, crowdfunding gained prominence with the financing of artists or creative projects (A. Agrawal et al., 2014) and its emergence can be attributed to some key factors and events. One event was the 2007/2008 economic-financial crisis that had an impact on both start-ups, micro and small firms. As a reaction to the economic-financial crisis, the regulation of financial institutions (with a strong focus on banks) was intensified, restraining the amount of funding micro and small firms as well as start-ups - characterised for having uncertain and risky business models - could obtain through banks for their ventures (Block et al., 2018). Additionally, with the global crisis, the public lost confidence in the financial system, particularly in the banking sector leading people to turn to other financing alternatives (Jenik, Lyman, & Nava, 2017). Crowdfunding emerged after the global crisis, when traditional financing dried up and low interest rates in savings channelled lenders to participate in P2P lending crowdfunding (Bruton et al., 2015). The increased technology opportunities also played an important role in the exponential growth of the crowdfunding markets. Because crowdfunding platforms were only made available through the Internet and via mobile phones and other devices, the evolution of technology and the subsequent rise of the Internet and boom of online applications and social media allowed the creation of crowdfunding and the development of crowdfunding platforms (Block et al., 2018; Jenik, Lyman, & Nava, 2017).

Besides playing an important role in financial inclusion, by improving borrowers access to credit (Jenik, Lyman, & Nava, 2017) and in giving opportunities to organizations that lack easy access to banks, angel investors, and venture capitalists (Brown et al., 2017), prosocial crowdfunding and its effects have been associated with the alleviation of poverty and improvement of social welfare (Gao et al., 2021), helping people living in underdeveloped countries to improve their quality of life (Navarro et al., 2018).

Crowdfunding can also be considered a marketing tool, serving as a way to promote a new product / service, boost brand image (Brown et al., 2017), and to build a fan base (Gerber & Hui, 2013). Furthermore, it allows entrepreneurs to obtain feedback from investors and get their ideas validated before they enter into the market (Rossi, 2014). Therefore, it is a mean to test marketability (Valanciene & Jegeleviciute, 2013), and can even be used as a mean to price determination in uncertain circumstances (Belleflamme et al., 2010).

The funding mechanisms consist in having entrepreneurs (i.e., borrowers) receiving a loan through an open call on the crowdfunding platform, where they post the details about the project and the pledge amount. Potential investors (i.e., lenders) go through the projects and campaigns and support - by providing funds - the ones they most identify with and find more attractive (Kuti & Madarász, 2014). Contrary to traditional financial intermediaries, crowdfunding platforms do not borrow or lend money on their own account. Their intermediary role is simply to match borrowers and lenders, by providing information about the projects and some other functionalities (Hooghiemstra & Buysere, 2016). Crowdfunding platforms can operate on a "Keep-it-All" model, where even if the fundraising goal was not met the borrower can keep the entire amount raised, or on a "All-or-Nothing" model, in which the borrowers keeps nothing unless the goal is achieved, that is, all contributions are returned to the lenders in case of a partially funded campaign (Cumming et al., 2014).

2.2. Success factors in crowdfunding

Crowdfunding literature identifies factors that could potentially have a significant impact on the success outcomes of the crowdfunding campaign. To what concerns the project's characteristics, there is a group of scholars who offer strong evidence that keeping the funding goal (i.e., project size) as low as possible increases the chances of a crowdfunding campaign being successfully funded (Forbes & Schaefer, 2017; Mollick, 2014; Zheng et al., 2014). The reasoning behind is that lower funding goals mean that the percentage funded increases more per pledge, and lenders are more inclined to contribute to a campaign with a high percentage funded as opposed to a high amount funded. As such, by attracting more lenders, the likelihood of funding success becomes greater (Forbes & Schaefer, 2017). However, other scholars have reached different findings, suggesting that larger funding targets are preferable in equity and debt-based crowdfunding as it gives investors a feeling of security by knowing that their investments will only go through if a sufficiently number of investors believe in and financially support the project (Hakenes & Schlegel, 2014). Larger sums may also be attractive to equity investors considering that larger amounts of funds collected enable firms to take more substantial measures towards growth and increase in value (Lukkarinen et al., 2016). The project's duration, representing the duration of the crowdfunding campaign, has also been identified as to potentially have an impact on the outcomes of the crowdfunding campaigns. It has been positively related to the success of campaigns as longer durations imply that the crowdfunding campaigns are open to receive funding for longer, increasing the likelihood of the contributions adding up to the amount requested by the entrepreneur (Cordova et al., 2015). However, longer durations can be understood as a sign of lack of confidence from entrepreneurs, having a negative impact on the funding of the campaign (Mollick, 2014). Furthermore, shorter durations may encourage prospective investors to act fast, rather than postponing the investment decision, and besides this, shorter campaigns may convey a message of decisiveness and ability to deliver (Lukkarinen et al., 2016).

A thoroughly description of the project, where important information such as development timelines, and business plans is provided, it can help project creators reach the more risk-averse investors, by being transparent with the use of their funds (Forbes & Schaefer, 2017). Moreover, the likelihood of success, i.e. reaching the funding goal, increase when there is provision of financials (e.g. financial information, such as historical or forecasted revenue and profit figures) (Lukkarinen et al., 2016), the campaign has well-structed ideas, and the technical characteristics of the products are in detail (Moutinho & Leite, 2013), highlighting the relevancy of the understandability of a firm's concept or product offering (Lukkarinen et al., 2016).

The entrepreneur's personal social networks also play an important role in the success of crowdfunding campaigns (Lukkarinen et al., 2016; Mollick, 2014; Zheng et al., 2014), with borrowers that expose their projects in their own social networks presenting a greater pledge/backer ratio, and the greater the number of the borrower's network, the greater the pledge/backer ratio (Kromidha & Robson, 2016). Moreover, geographical distance also plays a role, with local investors investing relatively early, and at the start of funding. This geographic effect is driven by investors who are likely to have a personal connection with the entrepreneur (such as "family and friends") (A. K. Agrawal et al., 2011).

Despite the vast array of empirical evidence on the success factors of crowdfunding, grounded on various theoretical frameworks (e.g., framing and signalling theories, social responsibility theory, etc.), the literature remains silent regarding the role of market efficiency in the nexus of calendar effects and funding success of campaigns.

3. Calendar anomalies and hypotheses development

The Efficient Market Hypothesis (EMH) postulated by Fama (1970) states that a market where security prices fully reflect all available information is an efficient market. One implication of the EMH is that it is not possible to "beat the market" consistently, meaning that no market participant is able to systematically obtain a return above the market since market prices should only react to new information. In efficient markets, the price of securities is close to their fundamental values because of either the rational investors or the arbitragers' buy and sell action of underpriced or overpriced stocks (Yalçın, 2010).

Notwithstanding, individuals do not always make the decisions they are expected to make, and markets do not reliably behave as they are expected to behave, therefore, people are not always rational, and markets are not always efficient (Chaudhary, 2013). The field of behavioural finance explains the reasons why, by investigating the cognitive factors and emotional biases that impact the decision-making process of investors (individuals, groups and organizations) (Ricciardi & Simon, 2001).

Furthermore, the EMH cannot explain the observed market anomalies - unusual occurrences or abnormalities in smooth pattern - in the stock markets (Latif et al., 2011). One example of the anomalies that are found to contradict and defy the EHM are calendar anomalies, that imply that the market behaves differently depending on the hours of the day, days of the week, various times of the month and year (Nasir et al., 2017).

However, crowdfunding literature has provided scant attention to time patterns and calendar effects, such as the turn-of-the-month (TOTM) effect, the month-of-the-year (MOTY) effect, and the day-of-the-week (DOTW) effect. The motivation of this study is to contribute to fill the void on this research gap.

As transactions in the crowdfunding market take place continuously, with the possibility to launch campaigns and make investments 24/7 from anywhere in the world, in contrast to financial markets which are closed over the weekend, the crowdfunding market is not a perfectly comparable environment to study the calendar effects that are found in the stock market. However, seasonality and time patterns have been a subject of investigation in other financial alternative markets, including in those markets where trades occur at any hour of the day and any day of the week, namely in the cryptocurrency markets (Haferkorn & Quintana Diaz, 2015; Kaiser, 2019; Kinateder & Papavassiliou, 2021; Long et al., 2020).

The premise for investigating the existence of seasonality in the crowdfunding markets is that calendar effects are behavioral-related, and also might be constraint by time-availability and time zones of investors. Our premise is that crowdfunding performance is likely to be time-dependent, based on broader evidence from traditional financial markets, it can be expected that some type of calendar effects might be unveil in crowdfunding markets, through our study. Indeed, in crowdfunding it has already been found that weather-induced moods influence lenders' contributions (Shafi & Mohammadi, 2020), and also that some months experience better results in terms of project's likelihood of success compared to others (Zoricak & Stofa, 2016).

Drawn by stock market literature and the lens of calendar anomalies, and drawn by the crowdfunding literature and the success determinants of campaigns, to answer our research question, we formulate the first general hypothesis:

Hypothesis 1: Calendar effects on P2P lending campaigns impact crowdfunding performance in prosocial crowdfunding.

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

The turn-of-the-month effect (TOTM) represents the temporary increase in stock returns during the last days and the first days of each month, that is, during the turn of the month interval. This phenomenon was first documented by Ariel (1987) when studying the U.S. stock prices in the 1963-1981 period. This author found a positive mean return for stocks only for days immediately before and during the first half of calendar months. Other authors also posit a TOTM effect, specifically documenting the anomaly in the very last trading day of the month and the first three days of the following month (A. Agrawal & Tandon, 1994; Kunkel et al., 2003; Lakonishok & Smidt, 1988). Scholars also presented evidence that TOTM effect varies during different market conditions (Singh et al., 2020), and that its effects are dependent on the sector to which firms belong to and on the firms' size (Sharma & Narayan, 2014).

The abnormally high positive returns at the turn of the month have been connected to clustered information, namely from important macroeconomic news announcements (Nikkinen et al., 2007) and good earnings announcement releases (Penman, 1987). The "window dressing" hypothesis is also a well-accepted justification for the TOTM effect, stating that during the turn of the month period institutional investors rebalance their portfolios with the sale loss-making stocks and purchase of profit-making stocks to boost the performance indicators that are generally published at the end of the month (Barone, 1990; Thaler, 1987).

The existence of the TOTM effect can also be attributed to liquidity 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; Ogden, 1990). In this period, as there is a greater amount of cash held by individual and institutional investors, there is more demand of stocks. Consequently, the stock prices increase, becoming more profitably during the turn of the month days than in non-turn of the month days (Vidal & Vidal-García, 2022).

Since there are higher month-end cash flows for individual investors in stock markets, one can hypothesize that these findings might also occur in crowdfunding markets given the prosocial nature of this type of crowdfunding and the importance of the core values of the project to backers (Belleflamme et al., 2014). With payment of salaries, retirements and income lenders have more available cash flows that might increase funding success during this period. We thus formulate the following hypothesis to study the potential existence of the TOTM effect in prosocial crowdfunding:

Hypothesis 2: TOTM effect on P2P lending campaigns impact crowdfunding performance in prosocial crowdfunding.

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

Rozeff & Kinney (1976) were the firsts to identify that stock returns vary depending on the month of the year. More precisely, the authors detected a January effect, a calendar anomaly in which the mean returns on stocks are higher in January than in other months. This seasonal effect seems to be more evident for small capitalization firms, with smaller stocks outperforming larger ones (Haug & Hirschey, 2006; Keim, 1983; Reinganum, 1983).

In the literature, several reasons for this January effect are presented, with the "tax-loss selling" and "window dressing" hypotheses being the primary explanations, both suggesting that these investors repurchase the stocks in the new year, creating the abnormal returns observed in January. The rationale for the "tax-loss selling" hypothesis resides in the fact that at the end of the financial year investors rebalance their portfolios for fiscal reasons, proceeding with the sale their loss-making shares in December in order to reduce the tax burden (Barone, 1990; Chen & Singal, 2004; Moller & Zilca, 2008).

The evidence in support of the "tax-loss selling" hypothesis is also consistent with the "window dressing" hypothesis. This theory suggests that investors sell the securities that they do not want to include in their annual accounts at the end of the year in order to improve the performance of their investment portfolios and present a more acceptable portfolio of stocks to fund holders in their year-end reports (Barone, 1990; Lakonishok et al., 1991).

The justifications for the January effect presented above do not accommodate in the prosocial crowdfunding framework. However, some other reasons widely accepted in the financial markets literature are applicable in the context of this study, driving us to hypothesize the January effect in the context of prosocial P2P lending crowdfunding. One of those reasons concern the larger influx of funds at year-end, as a result of employee bonuses and the funding of pension fund contributions. The higher liquidity of investors at the end of the year leads them to buy more stocks at the beginning the new year (Ligon, 1997). Furthermore, behavioural explanations and investor sentiment may explain, at least partially, the January effect, as the turn of the year is hypothesized as a time of renewed optimist and as an opportunity for change. Many people (including investors) may have a renewed sense of optimism and optimistic expectations regarding their investments (Ciccone, 2011).

Besides the January and December effect, other MOTY effect have been documented. September has been historically the worst performing month for stocks returns (Siegel, 2014), with some scholars linking this September effect with a "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 the month March to May have been found to be significantly less than those during the other nine months (Patel, 2008).

In reward-based crowdfunding, while studying the relationship between the month when a project starts and funding success, February has been identified as the month with better results, and the summer months of June and July the months with worst results (Zoricak & Stofa, 2016).

Based on all of evidence presented for different months, we built the following hypothesis to encapsulate the MOTY effect in the prosocial crowdfunding context:

Hypothesis 3: MOTY effect on P2P lending campaigns impact crowdfunding performance in prosocial crowdfunding.

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

The day-of-the-week (DOTW) effect was firstly identified by Cross (1973), when 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. To such a great extent, Monday returns are dominated by returns of other weekdays, and Friday returns dominate returns of other weekdays (Al-Khazali & Mirzaei, 2017; Urquhart & McGroarty, 2014). It has also been documented that while the average return for the other four days of the week is positive, the average for Monday is significantly negative (French, 1980). Another findings include that the largest falls in stock prices occur in the first two days of the week and are more pronounced on Tuesday, and there is an high rate of change in stock prices on Friday, before the weekend closure (Barone, 1990).

The main justifications for the phenomenon of the DOTW effect on the stock market are that institutional investors may be less active on Mondays as this tends to be a day of strategic planning (Wang & Walker, 2000), and individual investors often make financial decisions over the weekend, being active selling on Mondays (Osborne, 1962). An alternative explanation presented in stock market literature is the tendency of firms to delay the announcement of bad news until the weekend and after Friday's market closing, to avoid market disruption (French, 1980). In the light of investor psychology literature, there is the "Blue Monday hypothesis" which states 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 & Benson, 1989).

In the cryptocurrency markets, even though it is possible to trade on the seven days of the week, there is generally lower trading volume (as well as lower volatility) over the weekends, which indicates that trading takes place predominantly during weekdays (Kaiser, 2019). Regarding one of the most well-known digital currencies, Bitcoin, it has been found a DOTW effect with returns on Mondays significantly higher than those on the other days of the week (Aharon & Qadan, 2019; Caporale & Plastun, 2019).

Inspired by this literature, we formulate the following hypothesis:

> **Hypothesis 4:** DOTW effect on P2P lending campaigns impact crowdfunding performance in prosocial crowdfunding.

4. Kiva: prosocial P2P lending crowdfunding platform

To test our hypotheses we rely on Kiva, a leading online prosocial P2P lending platform and first comer in the microfinance crowdfunding field (Marakkath & Attuel-mendes, 2015). Founded in 2005 in San Francisco, Kiva is an international non-profit organization that connects small entrepreneurs with lenders around the world who are willing to provide funding in the form of micro loans (Mollick, 2014) mainly to "underserved individuals globally"[1].

Since its inception, Kiva has helped fund a total of 1,985,638 loans, enabling about 2 million lenders to mobilize $1.77 billion in loans for about 4 million borrowers[2]. Kiva presents itself as a prosocial lending-based platform, with the mission to expand financial access for all, by offering lenders a change 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 & Canela, 2016).

In Kiva, loans are facilitated through two lending models: direct and partner loans. In direct loans, the campaigns are prepared and posted on the platform directly by the borrower, who also raise funds directly through a digital account. In the case of partner loans, those processes are conducted by a field partner that acts as an intermediary, supporting borrowers, namely in setting up and launching the campaign. Field partners are local organizations (non-profits, microfinance institutions (MFI), schools, social enterprises, and NGO's) that provide a few services, such as training and financial literacy classes, and administer loans. Often, the field partners disburse the loans to the entrepreneurs even before the crowdfunding campaign is posted on the Kiva website, giving them a head start in their entrepreneurial venture. Thereby, Kiva's field partners are responsible for evaluating the loan application, and eventually for pre-disbursing (partially or totally) the loans and collecting repayments.

From the moment each entrepreneur's loan request is posted on Kiva, potential lenders can browse the requests and contribute to each one in any amount from $25 to the full amount of the loan, not being possible to continue raising capital after the funding goal is reached. In terms of campaign durations, all loan requests are posted on Kiva until they

[1] https://www.kiva.global/ (Accessed June 23, 2022).
[2] https://www.kiva.org/about/impact (Accessed June 23, 2022).

are fully funded, and typically for a fixed time window of 30 days. Ultimately the decision regarding the campaign's duration is left to the discretion of entrepreneurs. If during the duration of the campaign the loan request is fulfilled, Kiva forwards the money raised from the crowd to the field partners, as repayment of the loan. This way, individual lenders become creditors for the part of the loan they funded.

If field partners give borrowers access to credit prior to posting their loan request on Kiva, borrowers are not affected if the crowdfunding campaign is not fully funded. In that case, if the campaign does not succeed (that is, the financial goal is not attained within the fundraising period), all the money raised must be returned to the lenders (following an "All-or-Nothing" model), so the funding of borrowers is exclusively made by the field partner.

Kiva was the pioneer of zero-interest entrepreneurial lending (Hartley, 2010), in the sense that lenders on Kiva do not receive interest from the loans they support, nor does Kiva collect any interest from the loans it helps providing. Nevertheless, borrowers need to pay some interest to Kiva's local field partners, as there are many expenses in providing small loans in developing markets. In spite of that, these are lower interest rates than the microfinance industry averages (Marakkath & Attuel-mendes, 2015). Hence, when a loan is repaid, lenders receive their share of the principal while the field partners keep the interest. It is worth mentioning that in the crowdfunding market, online crowdfunding platforms, such as Kiva, operate on a 24/7 basis. That translates into campaigns having the possibility to be launched at any hour of the day, and in any day of the week, being open to receive funding likewise. Thus, crowdfunding markets differentiate from conventional financial markets, and function similar to cryptocurrency markets.

Different from other P2P lending platforms, in which lending is mainly for profit, in Kiva the lender's behaviour is driven by prosocial concerns[3]. The social agenda of Kiva is part of what makes the platform successful, giving exposure to diverse fields of entrepreneurship, from green to female ventures, or even targeting monetary support to higher education. Indeed, on digital platforms, it is assumed that people are more inclined to provide support to projects with a social benefit, with significant ethical implications for the common good, than to those with different orientations (Defazio et al., 2021). Hence, lending decisions are usually grounded on the story of the borrowers, or on the loan's

[3] Lenders on Kiva not only expect to help someone in need, but can also get their money back (at 0% interest) which is proven true by the 96.3% repayment rate of Kiva, across all of its loan (https://www.kiva.org/about/due-diligence/risk) (Accessed June 23, 2022)

purpose (Zhao et al., 2017). We rely on Kiva to better understand the prosocial lender's behaviours, namely their influences and biases, that drives them to invest in social projects.

5. Empirical design

5.1. Data and Sample

We collected data from Kiva' Application Programming Interface (https://www.kiva.org/build/data-snapshots) on 2,182,072 crowdfunding campaigns, including both direct and partner loans, from 2006 to 2021, launched by borrowers from 89 different countries, and 15 sectors. Then, we removed campaigns reporting atypical data on funding time (i.e., campaigns with a duration higher than 30 days, meaning above the limit defined by Kiva), and we proceeded with the removal of some outliers from the sample, by dropping the observations above the 99th percentile from our continuous variables. Finally, to avoid computation problems due to the large sample, we conducted a sample randomization reducing our sample test to 10% of full observations (using the command *sample* from Stata 17.0). Therefore, our sample test includes 177,093 campaigns from 2006 to 2021.

Table A1, in appendix, details the sample composition. Our dataset is constituted by 177,093 crowdfunding campaigns categorized in 15 different sectors, mainly in agriculture (45,130 campaigns), food (39,538) and retail (32,826). However, the highest percentage of successfully funded campaigns are from the those in manufacturing (99.79%), arts (99.22%) and education (98.74%) sectors. Most campaigns come from the Philippines (23.23%), Kenya (10.72%) and Cambodia (5.19%). The larger demand for projects' financing though Kiva occurs in 2017 (10.88%), 2018 (10.86%) and 2019 (10.20%).

5.2. Variables

Table 1 provides variables definition.

Table 1. Variables Definition

Variable	Description
Dependent variables	
Funded	Equals 1 if the campaign was fully funded, equals 0 otherwise
Amount	Total amount in U.S. dollars (plus 1) of the fully funded campaign, in logarithm form
Lenders	Total number of lenders (plus 1) of the fully funded campaign, in logarithm form
Speed	The logarithm of 1,000 divided by the funding time measured in days
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
Month	Set of 12 binary variables for each month (January,…, December)
Week Day	Set of 7 binary variables for each day of the week (Sunday,…, Saturday)
Control variables	
Female	Equals 1 if female entrepreneur or majority-female group, 0 otherwise
Ln (project size)	Funding goal of the campaign (in U.S. dollars), in logarithm form
Ln (project duration)	Duration of the campaign (in days), in logarithm form
Repayment Schedule	Equals 1 if the repayment is made in a monthly basis, equals 0 otherwise
Direct Loan	Equals 1 if the loan campaign was launched by the borrower, equals 0 if it was launched by a Field Partner
Year	Year of the post date of the loan campaign
Sector	Sector of the loan campaign
Country	Country of the borrower

Dependent variables

In line with standard practices in crowdfunding literature, we use different measures of crowdfunding performance to highlight different aspects of success and popularity of a funding campaign: *Funded*, *Amount*, *Lenders*, and *Speed*.

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 (Ahlers et al., 2015; Shneor & Vik, 2020) . The *Amount* is the logarithmic transformation of the amount funded in U.S. dollars (plus 1), representing the funds collected in successful campaigns invested in the project (Ahlers et al., 2015; Duan et al., 2020). Since Kiva follows an "All-or-Nothing" model, campaigns that do not reach the requested amount are unsuccessful, thus in that case this variable takes the value zero. Furthermore, we use the logarithmic transformation of the number of *Lenders* (plus 1) that contributed to a given project (Ahlers et al., 2015; Duan et al., 2020), assuming the value zero for unsuccessfully funded crowdfunding campaign. The number of *Lenders* is an important measure of success as borrowers seek to attract a large number of lenders (Vismara, 2016) to facilitate access to financing. Additionally, it enables to quantify the lender's engagement in the crowdfunding project. Having a high number of lenders backing the project translates into a higher validation from the crowd of the project's idea and of the crowdfunding campaign. However, prosocial crowdfunding provides micro loans to small entrepreneurs, therefore the average number of lenders will be naturally smaller than in other types of crowdfunding. For example, it is in reward-based crowdfunding where typically there is a higher number of individuals backing up the projects (e.g., Kuppuswamy & Bayus, 2017; Devaraj & Patel, 2016)

Finally, *Speed* represents the rate at which full funding was received via the crowd, i.e., how fast the crowdfunding campaign reached its target, and therefore how fast it achieved success, assuming that campaigns funded faster were favoured by lenders (Ly & Mason, 2012). *Speed* uses the number of days between the moment the campaign was launched and the moment it was fully funded (i.e., the funding time). The funding *Speed*, was calculated as 1,000 divided by the funding time (expressed in days), and its values were logarithmized (i.e., log (1,000/ funding time)), in line with prior research (e.g., Dorfleitner et al., 2021; Gama et al., 2021). Again, for unsuccessfully funded loans, speed is set to be zero as their funding time is infinite.

Independent variables

The calendar time hypothesis states that the stock market behaves differently at different hours of the day, on different days of the week, and at various times of the month and year (Rossi, 2015). The main time patterns observed in the stock markets worldwide are the turn-of-the-month effect, the January effect and the day-of-the-week effect. With the aim to identify if those type of time patterns or alternative ones exist in prosocial P2P lending crowdfunding and if it influences the campaign's performance, this study focuses on the analysis of the time of the month, months and week days where crowdfunding campaigns are more likely to be successfully funded, as it may also provide insights of favourable market timing to launch campaigns. To this end, we defined a set of three independent variables, to account for the three seasonal effects: *TOTM* (binary variable to capture the TOTM effect), *Month* (a set of 12 binary variables to capture the MOTY effect), and *Week Day* (a set of 7 binary variables to capture the DOTW effect).

TOTM captures the period around the turn of every month. When studying the TOTM effect, the time window of focus is between the last trading day of each month, and the first three trading days of the next month (-1 to 3) (Sharma & Narayan, 2014). In fact, when the turn of the month interval considered is wider, researchers of the stock market anomalies found the TOTM effect to be particularly more statistically significant during this 4-day turn of the month period (e.g., Agrawal & Tandon, 1994; Kunkel et al., 2003;

Lakonishok & Smidt, 1988). Therefore, we consider a four-day time frame to test for the TOTM effect in prosocial P2P lending crowdfunding starting with the last day of the prior month. As previously mentioned, contrary to stock markets, crowdfunding platforms operate in a continuous funding cycle, thus every day is a potential funding day. As such, 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 following month, taking the value "0" otherwise.

Inspired by capital markets literature (e.g., Onyuma, 2008), we rely on a set of twelve binary variables for each *Month* of the year (*January*, …, *December*) to test the MOTY effect in the context of crowdfunding; each binary variable assuming the value of "1" for crowdfunding campaigns posted in that month of the year, and the value of "0" otherwise. Similarly, to explore a possible DOTW effect or even a weekend effect on the prosocial P2P lending crowdfunding performance, we rely on a set of seven binary variables for each *Week Day* (*Sunday*, …, *Saturday*) each one taking the value "1" for crowdfunding campaigns launched in that day of the week, and "0" otherwise (Basher & Sadorsky, 2006; Caporale & Plastun, 2019).

Control Variables

Our choice of control variables has been motivated by prior research on the antecedents on crowdfunding campaigns performance. First, we controlled for the gender of borrowers as in the crowdfunding literature differences in the ability of females versus males to raise funds have been documented, with females being more likely to successfully crowdfund their projects (Borrero-Domínguez et al., 2020; Greenberg & Mollick, 2017). To control for gender effect, we used the 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).

Moreover, crowdfunding research has provided evidence that the structure of the crowdfunding campaign can influence the outcomes of said campaign (Mollick, 2014). For this reason, we controlled for some project characteristics. Specifically, we controlled for the *Project size* (Ahlers et al., 2015; Duan et al., 2020) – the target amount of money that borrowers asked the crowd for in their crowdfunding campaigns, in logarithm form (plus 1) – and for *Project duration* (Ahlers et al., 2015; Mollick, 2014) – the logarithm of the target campaign duration in days. The duration was calculated as the number of days between the date when the campaign was launched and the planned date for the campaign to end, independently if it was fully funded before the end date, and with an upper limit of 30 days.

Additionally, we set the control variable *Repayment schedule*, which refers to the periodicity of the loan repayment for the borrower to pay back to the lenders (Berns et al., 2020). The repayment schedule of the loan can be monthly, bullet (once at the end of the loan term), or whatever most accurately reflects the way that the entrepreneur will be making repayments. We controlled for the *Repayment schedule* with a dummy variable coded "1" if the repayment schedule is monthly, and "0" otherwise. Finally, to control the effects of lending models (i.e., direct loans *versus* partner loans) on campaigns performance, extensively approached on section 4, we rely on the variable *Direct loan,* a binary variable coded "1" for those campaigns asking for a direct loan, and "0" when crowdfunding were intermediated through a field partner.

5.3. Descriptive statistics

Table 2 reports the descriptive statistics of the variables employed in this study. The summary statistics are based on the random sample of 177,093 observations, of which 167,596 prosocial crowdfunding campaigns were successfully funded (i.e., 94.6%). Borrowers attracted, on average, 10 lenders per campaign, summing up to the amount of about 320 U.S. dollars. The average speed at which campaigns get fully funded is of 4.88, corresponding to an average funding time of about 8 days. The majority of our sample is constituted by crowdfunding campaigns launched by female entrepreneurs (or majority of group female), averaging 79.4%. On average, projects have a size of 464 U.S. dollars and have a duration, of 10 days. The correlation matrix for continuous covariates, reported in Table A2 in appendix, does not reveal high pair correlation values thus not suggesting multicollinearity problems.

Table 2. Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Dependent variables					
Funded	177,093	0.946	0.225	0	1
Amount	177,093	5.770	1.611	0	8.552
Lenders	177,093	2.437	1.036	0	5.361
Speed	177,093	4.880	1.606	0	12.870
Independent variables					
TOTM	177,093	0.110	0.313	0	1
Month *(set of binary variables)*					
January	177,093	0.077	0.267	0	1
February	177,093	0.085	0.279	0	1
March	177,093	0.092	0.288	0	1
April	177,093	0.078	0.268	0	1
May	177,093	0.081	0.273	0	1
June	177,093	0.080	0.272	0	1
July	177,093	0.081	0.273	0	1
August	177,093	0.081	0.273	0	1
September	177,093	0.087	0.282	0	1
October	177,093	0.089	0.285	0	1
November	177,093	0.085	0.279	0	1
December	177,093	0.082	0.275	0	1
Week Day *(set of binary variables)*					
Sunday	177,093	0.027	0.163	0	1
Monday	177,093	0.178	0.383	0	1
Tuesday	177,093	0.191	0.393	0	1
Wednesday	177,093	0.191	0.393	0	1
Thursday	177,093	0.193	0.394	0	1
Friday	177,093	0.179	0.384	0	1
Saturday	177,093	0.041	0.199	0	1
Control variables					
Female	177,093	0.794	0.404	0	1
Ln(project size)	177,093	6.142	0.883	3.219	11.513
Ln(project duration)	177,093	2.432	0.437	0	4.977
Repayment Schedule	177,093	0.868	0.339	0	1
Direct Loan	177,093	0.006	0.078	0	1

5.4. Model

To test the research hypotheses for the binary variable *Funded* we employ a Probit regression model, as follows:

$$\Pr(\text{Funded} = 1 | \text{X}) = \phi(\beta_{0i} + \beta_{1i} TOTM + \sum_{m=2}^{14} \beta_{mi}\, Month_m + \sum_{w=15}^{21} \beta_{wi}\, Week\ Day_w + \sum_{k=22}^{26} \beta_{ki}\, \text{Z}) \quad \text{eq (1)}$$

where *Pr* denotes probability i^{th} campaign be fully funded based on *X* covariates, and ϕ is the Cumulative Distribution Function of the standard normal distribution; *m* denotes each calendar month and *w* each week day; *Z* is the vector of control variables.

To test the calendar effects on the *Amount* funded, number of *Lenders*, and funding *Speed* we estimate the following Ordinary Least Squares (OLS) regression model:

$$Amount, Lenders, Speed = \beta_{0i} + \beta_{1i} TOTM + \sum_{m=2}^{14} \beta_{mi}\, Month_m + \sum_{w=15}^{21} \beta_{wi}\, Week\ Day_w + \sum_{k=22}^{26} \beta_{ki}\, \text{Z} + \varepsilon_{\text{i}} \quad \text{eq (2)}$$

where ε denotes the error term.

6. Results

6.1. Univariate analysis

To offer a preliminary overview of the potential time patterns in the performance of prosocial P2P lending crowdfunding, we employ a univariate analysis of differences in means and in samples' distribution of the crowdfunding success. To do so, we run a T-test (a parametric test for mean differences) and a Wilcoxon rank-sum test (non-parametric test for sample distribution analysis) based on time effects. The results, reported in Tables A3-A6, in appendix, reject the null hypothesis of those tests[4] (p-value <0.10) for TOTM effect, as well as for several months and week days effects, thus suggesting that those time patterns impact the performance of P2P lending crowdfunding when measured by *Funded* likelihood (Table A3), *Amount* funded (Table A4), number of *Lenders* (Table A5), and funding *Speed* (Table A6). This evidence aligns with our research hypotheses.

6.2. Multivariate analysis

Tables 3[5], 4, 5 and 6 report the estimations for *Funded* likelihood using the probit model as well as the estimations for *Amount* funded, number of *Lenders,* and funding *Speed,* respectively, using the OLS. Column I reports the results for the TOTM effect. Columns II and III show the MOTY and DOTW effects on crowdfunding success, respectively. All estimations control for *Sector, Country* and *Year* fixed effects to capture any sector-, country- and year-unobserved heterogeneities that could affect crowdfunding performance outcomes.

Potential multicollinearity problems may affect the reliability of coefficient estimations and thus bias our results. To determine the possible existence of multicollinearity issues, we calculated the variance inflation factors (VIFs) for the independent variables, and control variables in all four model specifications have a maximum VIF of 1.1. Since they are below the critical value of 5, multicollinearity is not an issue in our results (Kutner et al., 2005).

[4] T-test null hypothesis: The difference in group means is zero; Wilcoxon rank-sum test null hypothesis: The two groups have the same distribution.

[5] Since for many countries the percentage of funded campaigns is 100% (see Table A1, Panel B), the number of observations included in the estimation model for funded was reduced to 165,839. The difference (11,254 obs.) corresponds to the number of financed projects in those countries.

Table 3. Dependent Variable: *Funded (0/1)*; 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**
	TOTM	*Jan.*	*Feb.*	*Mar.*	*Apr.*	*May*	*Jun.*	*Jul.*	*Aug.*	*Sep.*
Independent variables										
TOTM	-0.172***	-0.169***	-0.173***	-0.171***	-0.172***	-0.176***	-0.172***	-0.166***	-0.171***	-0.172***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Month		0.177***	0.573***	0.363***	-0.041*	-0.197***	-0.208***	-0.338***	-0.080***	-0.063***
		(0.026)	(0.032)	(0.028)	(0.024)	(0.022)	(0.023)	(0.022)	(0.025)	(0.024)
Week Day										
Control variables										
Female	0.935***	0.936***	0.945***	0.935***	0.935***	0.935***	0.935***	0.940***	0.935***	0.935***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Ln (project size)	-0.919***	-0.920***	-0.921***	-0.920***	-0.919***	-0.920***	-0.920***	-0.921***	-0.919***	-0.919***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Ln (project duration)	-1.073***	-1.074***	-1.073***	-1.073***	-1.074***	-1.074***	-1.074***	-1.075***	-1.073***	-1.074***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Repayment Schedule	-0.082***	-0.079***	-0.076***	-0.078***	-0.082***	-0.082***	-0.080***	-0.077***	-0.080***	-0.080***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Direct Loan	-0.846***	-0.841***	-0.843***	-0.856***	-0.845***	-0.841***	-0.839***	-0.842***	-0.844***	-0.845***
	(0.128)	(0.128)	(0.128)	(0.127)	(0.128)	(0.128)	(0.127)	(0.129)	(0.128)	(0.128)
Fixed effects										
Sector	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Country	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Year	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Intercept	11.156***	11.154***	11.065***	11.121***	11.161***	11.186***	11.197***	11.196***	11.161***	11.162***
	(0.171)	(0.171)	(0.169)	(0.171)	(0.171)	(0.171)	(0.171)	(0.170)	(0.171)	(0.171)
Number of observations	165,839	165,839	165,839	165,839	165,839	165,839	165,839	165,839	165,839	165,839
LR Chi2	31,563.30**	31,610.03***	31,942.24***	31,747.54***	31,566.02***	31,638.84***	31,641.55***	31,771.78***	31,573.61***	31,569.75***
Pseudo R2	0.434	0.434	0.439	0.436	0.434	0.435	0.435	0.437	0.434	0.434
VIF (excluding Fixed effects)										
Máx.	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10
Mean	1.05	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04
Min.	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3. Dependent Variable: *Funded (0/1)*; Method: Probit (continued)

	Column II			Column III						
	II.10 *Oct.*	**II.11** *Nov.*	**II.12** *Dec.*	**III.1** *Sun.*	**III.2** *Mon.*	**III.3** *Tues.*	**III.4** *Wed.*	**III.5** *Thur.*	**III.6** *Frid.*	**III.7** *Sat.*
Independent variables										
TOTM	-0.167***	-0.171***	-0.166***	-0.172***	-0.172***	-0.172***	-0.172***	-0.172***	-0.172***	-0.172***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Month	-0.198***	0.071***	0.252***							
	(0.022)	(0.026)	(0.027)							
Week Day				-0.053	0.022	0.052***	-0.008	-0.052***	0.000	0.000
				(0.046)	(0.018)	(0.018)	(0.017)	(0.017)	(0.018)	(0.036)
Control variables										
Female	0.937***	0.935***	0.937***	0.935***	0.935***	0.935***	0.935***	0.935***	0.935***	0.935***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Ln (project size)	-0.920***	-0.919***	-0.921***	-0.919***	-0.919***	-0.919***	-0.919***	-0.919***	-0.919***	-0.919***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Ln (project duration)	-1.074***	-1.074***	-1.076***	-1.073***	-1.073***	-1.073***	-1.073***	-1.073***	-1.073***	-1.073***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Repayment Schedule	-0.080***	-0.082***	-0.075***	-0.082***	-0.081***	-0.082***	-0.081***	-0.081***	-0.082***	-0.082***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Direct Loan	-0.860***	-0.846***	-0.837***	-0.843***	-0.845***	-0.847***	-0.846***	-0.849***	-0.846***	-0.846***
	(0.127)	(0.128)	(0.127)	(0.128)	(0.128)	(0.127)	(0.128)	(0.127)	(0.128)	(0.128)
Fixed effects										
Sector	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Country	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Year	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Intercept	11.185***	11.159***	11.184***	11.157***	11.151***	11.148***	11.157***	11.165***	11.156***	11.156***
	(0.171)	(0.171)	(0.171)	(0.170)	(0.171)	(0.171)	(0.171)	(0.171)	(0.171)	(0.171)
Number of observations	165,839	165,839	165,839	165,839	165,839	165,839	165,839	165,839	165,839	165,839
LR Chi2	31,634.09***	31,570.71***	31,656.26***	31,564.81***	31,564.82***	31,571.98***	31,563.54***	31,572.54***	31,563.30***	31,563.30***
Pseudo R2	0.435	0.434	0.435	0.434	0.434	0.434	0.434	0.434	0.434	0.434
VIF (excluding Fixed effects)										
Máx.	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10
Mean	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04
Min.	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4. Dependent Variable: *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**
	TOTM	*Jan.*	*Feb.*	*Mar.*	*Apr.*	*May*	*Jun.*	*Jul.*	*Aug.*	*Sep.*
Independent variables										
TOTM	-0.089***	-0.087***	-0.089***	-0.090***	-0.089***	-0.090***	-0.089***	-0.088***	-0.088***	-0.089***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Month		0.091***	0.235***	0.162***	-0.008	-0.100***	-0.091***	-0.202***	-0.051***	-0.045***
		(0.013)	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Week Day										
Control variables										
Female	0.619***	0.619***	0.619***	0.618***	0.619***	0.619***	0.619***	0.620***	0.619***	0.619***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Ln (project size)	0.571***	0.570***	0.570***	0.570***	0.571***	0.571***	0.571***	0.570***	0.570***	0.570***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Ln (project duration)	-0.601***	-0.601***	-0.601***	-0.600***	-0.601***	-0.600***	-0.600***	-0.600***	-0.601***	-0.601***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Repayment Schedule	-0.046***	-0.045***	-0.045***	-0.046***	-0.046***	-0.046***	-0.045***	-0.045***	-0.045***	-0.045***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Direct Loan	-0.818***	-0.816***	-0.816***	-0.821***	-0.818***	-0.816***	-0.816***	-0.818***	-0.816***	-0.818***
	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)
Fixed effects										
Sector	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Country	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Year	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Intercept	4.074***	4.076***	4.076***	4.062***	4.076***	4.082***	4.072***	4.080***	4.073***	4.076***
	(0.150)	(0.150)	(0.149)	(0.149)	(0.150)	(0.150)	(0.150)	(0.149)	(0.150)	(0.150)
Number of observations	177,093	177,093	177,093	177,093	177,093	177,093	177,093	177,093	177,093	177,093
R-squared	0.219	0.220	0.221	0.220	0.219	0.220	0.220	0.221	0.220	0.220
F-test	404.59***	401.86***	405.21***	403.28***	401.33***	402.00***	401.88***	404.08***	401.50***	401.47***
VIF (excluding Fixed effects)										
Máx.	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10
Mean	1.05	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04
Min.	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4. Dependent Variable: *Amount*; Method: OLS (continued)

	Column II			Column III						
	II.10	**II.11**	**II.12**	**III.1**	**III.2**	**III.3**	**III.4**	**III.5**	**III.6**	**III.7**
	Oct.	*Nov.*	*Dec.*	*Sun.*	*Mon.*	*Tues.*	*Wed.*	*Thur.*	*Frid.*	*Sat.*
Independent variables										
TOTM	-0.088***	-0.089***	-0.088***	-0.089***	-0.089***	-0.089***	-0.089***	-0.089***	-0.089***	-0.089***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Month	-0.114***	0.005	0.105***							
	(0.012)	(0.012)	(0.012)							
Week Day				-0.012	0.016*	0.026***	-0.005	-0.030***	-0.005	0.002
				(0.021)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.017)
Control variables										
Female	0.619***	0.619***	0.619***	0.619***	0.619***	0.619***	0.619***	0.619***	0.619***	0.619***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Ln (project size)	0.570***	0.571***	0.570***	0.571***	0.571***	0.570***	0.571***	0.571***	0.571***	0.571***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Ln (project duration)	-0.601***	-0.601***	-0.601***	-0.601***	-0.601***	-0.601***	-0.601***	-0.601***	-0.601***	-0.601***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Repayment Schedule	-0.046***	-0.046***	-0.044***	-0.046***	-0.046***	-0.046***	-0.046***	-0.046***	-0.046***	-0.046***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Direct Loan	-0.819***	-0.818***	-0.812***	-0.818***	-0.817***	-0.818***	-0.818***	-0.819***	-0.818***	-0.818***
	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)
Fixed effects										
Sector	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Country	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Year	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Intercept	4.090***	4.073***	4.045***	4.078***	4.071***	4.068***	4.075***	4.080***	4.074***	4.074***
	(0.150)	(0.150)	(0.150)	(0.150)	(0.150)	(0.150)	(0.150)	(0.150)	(0.150)	(0.150)
Number of observations	177,093	177,093	177,093	177,093	177,093	177,093	177,093	177,093	177,093	177,093
R-squared	0.220	0.219	0.220	0.219	0.220	0.220	0.219	0.220	0.219	0.219
F-test	402.29***	401.33***	402.07***	401.33***	401.36***	401.42***	401.33***	401.46***	401.33***	401.33***
VIF (excluding Fixed effects)										
Máx.	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10
Mean	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04
Min.	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5. Dependent Variable: *Lenders*; 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**
	TOTM	*Jan.*	*Feb.*	*Mar.*	*Apr.*	*May*	*Jun.*	*Jul.*	*Aug.*	*Sep.*
Independent variables										
TOTM	-0.058***	-0.057***	-0.058***	-0.058***	-0.058***	-0.058***	-0.058***	-0.057***	-0.058***	-0.058***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Month		0.068***	0.129***	0.064***	0.003	-0.047***	-0.052***	-0.125***	-0.019***	-0.020***
		(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Week Day										
Control variables										
Female	0.302***	0.302***	0.302***	0.302***	0.302***	0.302***	0.302***	0.303***	0.302***	0.302***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Ln (project size)	0.556***	0.556***	0.556***	0.556***	0.556***	0.556***	0.556***	0.556***	0.556***	0.556***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Ln (project duration)	-0.078***	-0.078***	-0.078***	-0.077***	-0.078***	-0.077***	-0.077***	-0.077***	-0.078***	-0.078***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Repayment Schedule	-0.076***	-0.076***	-0.076***	-0.076***	-0.076***	-0.076***	-0.076***	-0.076***	-0.076***	-0.076***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Direct Loan	-0.011	-0.010	-0.010	-0.013	-0.011	-0.010	-0.010	-0.011	-0.010	-0.011
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
Fixed effects										
Sector	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Country	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Year	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Intercept	-0.869***	-0.868***	-0.868***	-0.874***	-0.870***	-0.866***	-0.871***	-0.866***	-0.870***	-0.869***
	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)
Number of observations	177,093	177,093	177,093	177,093	177,093	177,093	177,093	177,093	177,093	177,093
R-squared	0.373	0.373	0.374	0.373	0.373	0.373	0.373	0.374	0.373	0.373
F-test	855.20***	849.40***	852.67***	849.45***	848.30***	848.86***	848.98***	852.23***	848.40***	848.41***
VIF (excluding Fixed effects)										
Máx.	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10
Mean	1.05	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04
Min.	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5. Dependent Variable: *Lenders*; Method: OLS (continued)

	Column II			Column III						
	II.10 *Oct.*	**II.11** *Nov.*	**II.12** *Dec.*	**III.1** *Sun.*	**III.2** *Mon.*	**III.3** *Tues.*	**III.4** *Wed.*	**III.5** *Thur.*	**III.6** *Frid.*	**III.7** *Sat.*
Independent variables										
TOTM	-0.057***	-0.058***	-0.058***	-0.058***	-0.058***	-0.058***	-0.058***	-0.058***	-0.058***	-0.058***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Month	-0.057***	-0.002	0.056***							
	(0.007)	(0.007)	(0.007)							
Week Day				-0.010	0.008	0.017***	-0.002	-0.016***	-0.003	-0.009
				(0.012)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.010)
Control variables										
Female	0.302***	0.302***	0.302***	0.302***	0.302***	0.302***	0.302***	0.302***	0.302***	0.302***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Ln (project size)	0.556***	0.556***	0.556***	0.556***	0.556***	0.556***	0.556***	0.556***	0.556***	0.556***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Ln (project duration)	-0.078***	-0.078***	-0.078***	-0.078***	-0.078***	-0.077***	-0.078***	-0.078***	-0.078***	-0.078***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Repayment Schedule	-0.076***	-0.076***	-0.075***	-0.076***	-0.076***	-0.076***	-0.076***	-0.076***	-0.076***	-0.076***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Direct Loan	-0.012	-0.011	-0.008	-0.011	-0.011	-0.011	-0.011	-0.012	-0.011	-0.011
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
Fixed effects										
Sector	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Country	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Year	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Intercept	-0.862***	-0.869***	-0.885***	-0.867***	-0.871***	-0.873***	-0.869***	-0.867***	-0.870***	-0.869***
	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)
Number of observations	177,093	177,093	177,093	177,093	177,093	177,093	177,093	177,093	177,093	177,093
R-squared	0.373	0.373	0.373	0.373	0.373	0.373	0.373	0.373	0.373	0.373
F-test	849.21***	848.30***	849.09***	848.31***	848.33***	848.45***	848.30***	848.43***	848.31***	848.31***
VIF (excluding Fixed effects)										
Máx.	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10
Mean	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04
Min.	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6. Dependent Variable: *Speed*; 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**
	TOTM	*Jan.*	*Feb.*	*Mar.*	*Apr.*	*May*	*Jun.*	*Jul.*	*Aug.*	*Sep.*
Independent variables										
TOTM	-0.132***	-0.119***	-0.132***	-0.134***	-0.131***	-0.133***	-0.132***	-0.130***	-0.130***	-0.131***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Month		0.722***	0.260***	0.223***	-0.095***	-0.084***	-0.192***	-0.321***	-0.204***	-0.161***
		(0.012)	(0.012)	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Week Day										
Control variables										
Female	0.657***	0.659***	0.657***	0.656***	0.657***	0.657***	0.656***	0.659***	0.658***	0.657***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Ln (project size)	-0.570***	-0.576***	-0.571***	-0.570***	-0.569***	-0.569***	-0.570***	-0.571***	-0.571***	-0.570***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Ln (project duration)	-0.681***	-0.682***	-0.682***	-0.680***	-0.681***	-0.681***	-0.680***	-0.680***	-0.680***	-0.683***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Repayment Schedule	-0.102***	-0.097***	-0.101***	-0.102***	-0.102***	-0.102***	-0.100***	-0.100***	-0.100***	-0.099***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Direct Loan	-1.354***	-1.341***	-1.352***	-1.359***	-1.353***	-1.352***	-1.350***	-1.354***	-1.346***	-1.356***
	(0.058)	(0.057)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)
Fixed effects										
Sector	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Country	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Year	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Intercept	10.213***	10.225***	10.216***	10.197***	10.234***	10.220***	10.209***	10.223***	10.210***	10.220***
	(0.144)	(0.142)	(0.143)	(0.144)	(0.144)	(0.144)	(0.144)	(0.143)	(0.144)	(0.144)
Number of observations	177,093	177,093	177,093	177,093	177,093	177,093	177,093	177,093	177,093	177,093
R-squared	0.276	0.290	0.278	0.277	0.276	0.276	0.277	0.279	0.277	0.277
F-test	547.81***	582.97***	548.93***	547.75***	544.07***	543.94***	546.25***	551.49***	546.64***	545.55***
VIF (excluding Fixed effects)										
Máx.	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10
Mean	1.05	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04
Min.	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6. Dependent Variable: *Speed*; Method: OLS (continued)

	Column II			**Column III**						
	II.10	**II.11**	**II.12**	**III.1**	**III.2**	**III.3**	**III.4**	**III.5**	**III.6**	**III.7**
	Oct.	*Nov.*	*Dec.*	*Sun.*	*Mon.*	*Tues.*	*Wed.*	*Thur.*	*Frid.*	*Sat.*
Independent variables										
TOTM	-0.130***	-0.134***	-0.131***	-0.132***	-0.130***	-0.133***	-0.132***	-0.131***	-0.133***	-0.132***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Month	-0.200***	-0.118***	0.198***							
	(0.011)	(0.012)	(0.012)							
Week Day				0.084***	0.181***	0.104***	-0.042***	-0.113***	-0.142***	0.003
				(0.020)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.016)
Control variables										
Female	0.657***	0.658***	0.658***	0.657***	0.657***	0.657***	0.657***	0.657***	0.657***	0.657***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Ln (project size)	-0.571***	-0.571***	-0.570***	-0.570***	-0.570***	-0.570***	-0.570***	-0.570***	-0.570***	-0.570***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Ln (project duration)	-0.682***	-0.681***	-0.681***	-0.681***	-0.681***	-0.680***	-0.681***	-0.682***	-0.681***	-0.681***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Repayment Schedule	-0.102***	-0.102***	-0.098***	-0.101***	-0.103***	-0.102***	-0.101***	-0.101***	-0.103***	-0.102***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Direct Loan	-1.355***	-1.356***	-1.342***	-1.357***	-1.345***	-1.355***	-1.354***	-1.358***	-1.357***	-1.354***
	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)
Fixed effects										
Sector	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Country	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Year	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Intercept	10.241***	10.238***	10.159***	10.191***	10.175***	10.190***	10.219***	10.233***	10.210***	10.213***
	(0.144)	(0.144)	(0.144)	(0.144)	(0.144)	(0.144)	(0.144)	(0.144)	(0.144)	(0.144)
Number of observations	177,093	177,093	177,093	177,093	177,093	177,093	177,093	177,093	177,093	177,093
R-squared	0.277	0.276	0.277	0.276	0.278	0.276	0.276	0.277	0.277	0.276
F-test	546.83***	544.53***	546.46***	543.57***	548.43***	545.16***	543.67***	545.48***	546.49***	543.39***
VIF (excluding Fixed effects)										
Máx.	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10
Mean	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04
Min.	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Results show that the TOTM coefficient (Columns I) is significantly negative across all model specifications at 1% statistical significance level, for *Funded* likelihood (Table 3, p-value <0.01), *Amount* funded (Table 4, p-value <0.01), number of *Lenders* (Table 5 p-value <0.01), and funding *Speed* (Table 6, p-value <0.01), in support of Hypothesis 2. TOTM effect on P2P lending campaigns impact crowdfunding performance in prosocial crowdfunding. Our findings suggest that campaigns launched during the turn of the month period are less likely to be fully funded until maturity; these campaigns are characterized for having lower funding amounts, getting less lenders, and being funded slowly. Therefore, instead of the expected positive TOTM effect, we identify a reverse TOTM effect in the prosocial P2P lending crowdfunding negatively impacting the campaign's performance.

Further, our findings demonstrate that a MOTY effect on P2P lending campaigns impact crowdfunding performance in prosocial crowdfunding, in line with Hypothesis 3. Crowdfunding campaigns launched in January (Columns II.1), February (Columns II.2), March (Columns II.3) and December (Columns II.12) reports better performances when measured by *Funded* likelihood (Table 3, p-value < 0.01), *Amount* funded (Table 4, p-value <0.01), number of *Lenders* (Table 5, p-value <0.01), and funding *Speed* (Table 6, p-value <0.01). In contrast, prosocial crowdfunding campaigns launched in May (Columns II.5), June (Columns II.6), July (Columns II.7), August (Columns II.8), September (Columns II.9) and October (Columns II.10) are negatively linked to funding campaign's performance, in all of our four models (Table 3-6, p-value <0.01). We did not find any statistically significant April (Columns II.4) or November (Columns II.11) effects on *Amount* funded (Table 4, p-value >0.1) and number of *lenders* (Table 5, p-value >0.1). However, November is positively related with *Funded* likelihood (Table 3, p-value <0.01), but negatively related with for funding *Speed* (Table 6, p-value <0.01). Thus, crowdfunding campaigns launched in November are more likely to get to the funding target before maturity but are funded at a slow rate. To what concerns to April, the estimated negative coefficients in both *Funded* (Table 3, p-value <0.1), and *Speed* (Table 6, p-value <0.01) models show that crowdfunding campaigns launched in this month have a lower probability of getting full funding, and the goal amount is reached at a slower pace.

Regarding the DOTW effect, our results report positive and statistically significant coefficients for Tuesday (Columns III.3) across all measures of crowdfunding success – *Funded* likelihood (Table 3, p-value <0.01), *Amount* funded (Table 4, p-value <0.01), number of *Lenders* (Table 5, p-value <0.01), and funding *Speed* (Table 6, p-value <0.01), providing us the information that on this particular day of the week crowdfunding campaigns present an overall good performance. The Thursday coefficients (Columns III.5), on the other hand, is significantly negative for *Funded* likelihood (Table 3, p-value <0.01), *Amount* funded (Table 4, p-value <0.01), number of *Lenders* (Table 5, p-value <0.01), and funding *Speed* (Table 6, p-value <0.01). These results reveal that crowdfunding campaigns launched on this day of the week, in general, have a poorer performance in all dimensions of success considered in this study. The results reveal that the remaining week days only influence the funding *Speed*, not having any statistically significant impact on *Funded* likelihood, on the number of *Lenders* nor on *Amount* funded. The evidences shows a positive relationship between campaign launched in the first half of the week (i.e., Sunday – Columns III.1, Monday– Columns III.2, and Tuesday– Columns III.3) and the funding *Speed*, whereas the second half of the week, excluding Saturday, (i.e. Wednesday– Columns III.4, Thursday– Columns III.5, and Friday– Columns III.6), the coefficients for these variables are negative and significant (Table 6, p-value<0.01). Overall, these results confirm a DOTW effect on P2P lending campaigns impacting crowdfunding performance in prosocial crowdfunding, thus supporting our Hypothesis 4.

Our results, thus reveal that calendar effects in the prosocial P2P lending crowdfunding exist and do impact the performance of crowdfunding campaigns, thus supporting Hypothesis 1. These results provide entrepreneurs in prosocial P2P lending crowdfunding with valuable information regarding the periods of time where the likelihood of campaign's success is higher (or lower).

When examining the results for the control variables, females are more likely to be successful in crowdfunding on Kiva platform, which is in line with the crowdfunding literature (e.g., (Borrero-Domínguez et al., 2020; Greenberg & Mollick, 2017). Projects with greater size tend to have lower *Funded* likelihood and lower funding *Speed*, as expected, due to the higher funding goal of the campaigns, and get larger *Amount* funded and a higher number of *Lenders*. Projects with shorter campaigns' duration are more likely to be *Funded*, achieve higher *Amount* funded, get backed by a large pool of *Lenders,* and get full funding at a higher *Speed*. As opposed to monthly loan repayments, when the repayment schedule is irregular, projects have a higher probability of being fully *Funded* and a significant and positive association with the remaining crowdfunding performance measures (i.e., *Amount*, *Lenders* and *Speed*). And lastly, entrepreneurs tend to have more successful crowdfunding performance (i.e., *Funded* likelihood, *Amount* and *Speed*) in prosocial crowdfunding if they resort to field partners loans instead of direct loans.

7. Discussion

Motivated by the work of Taeuscher et al. (2021), where it is "further recognized that there exist seasonal effects that seemingly influence crowd funding outcomes", we aimed to expand the study of seasonality and calendar effects to prosocial crowdfunding. This study demonstrates that time patterns and calendar effects are present in the prosocial crowdfunding market, as drivers of crowdfunding performance, having the power to influence the funding success outcomes of crowdfunding campaigns. More specifically, our results show the particular launch days and months where lenders' engagement with new prosocial campaigns tends to be higher looking, and, consequently, when crowdfunding campaigns are more likely to be successfully fully funded, get higher amounts funded, a larger number of lenders and are funded at a higher speed. Our results also allow us to identify the launch days and months when the opposite happens, and crowdfunding campaigns present an overall poor performance.

To what concerns the TOTM effect, our findings provide an alternative view from the literature on stock returns, as we detected a reverse TOTM effect. The TOTM effect is significantly negative across all measures of crowdfunding success we study, drawing us to conclude that, in fact, campaigns launched during the 4-day period of the turn of the month have a poorer crowdfunding performance, being less likely to be successfully funded, in the context of prosocial P2P lending crowdfunding. As such, to entrepreneurs determined to launch a crowdfunding campaign, requesting loans from the crowd, it is recommended to avoid launching their campaigns in the turn of the month period.

Due to liquidity reasons and the assumed higher availability of investor's cash flows at month-end, resulting from the payment of salaries and other forms of remuneration, it was expected that, as it happens in the stock market, a larger amount of funds going into the prosocial crowdfunding market during the turn of the month. However, we recognize that differences in the nature between financial markets and prosocial crowdfunding market might drive these results that are, to some extent, contrary to our expectations. In the prosocial P2P lending crowdfunding, monetary gains are not what motivates lenders to direct their personal savings to projects, since they do not get interest from their loans. On financial markets, investors' main motivation is precisely the potential financial returns on their investments. We assume that lending money on an interest rate-free crowdfunding platform is not individuals' priority in terms of income allocation. To such extent, investors (i.e., prosocial lenders) may only decide to lend their money to support a prosocial project after they fulfilled their more urgent financial needs and potential investment objectives. Therefore, there may be less attention paid by the lenders to new campaigns launched during the turn of the month, which may lead to lower inflows in this time horizon.

Some of our findings regarding the MOTY effect are partially in line to what has already been found in financial markets' literature, in particular in the stock market. We identify a January effect in the prosocial P2P lending crowdfunding, with this month being positive and significantly linked to campaigns' success. This result may be explained by two main reasons. First, liquidity reasons, one of the main justifications in the stock market literature for this effect. In January, working individuals supposedly have more spare money due to the year-end bonuses and subsidies they receive. Second, the turn of the year gives people a sense of 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. Further, due to the proximity of the month of January and the Christmas season, we consider that during this time frame, lenders are more motivated to support and contribute to social causes, which is in line with the scope of prosocial P2P lending crowdfunding. Indeed, in the U.S., December is the most popular month for charitable giving[6], with a considerable percentage of all giving happening in the last three days of the year[7]. Surprisingly, the January effect appear to be amplified to a larger time frame from December to March. Therefore, from the end of the previous year to the beginning of the year (i.e., the first quarter), lenders' engagement with new prosocial campaigns tends to be higher looking, thus increasing the success of P2P lending campaigns, hence helping the underprivileged that are trying, through crowdfunding, to improve their quality of life. In an opposite direction, mainly in the second and third quarters our findings show a negative association with crowdfunding performance outcomes.

The most interesting and puzzling finding of the present study is that there is a clear distinction between quarters and seasons of the year and its effects on crowdfunding performance. Most Kiva lenders are from North America, with the U.S. being the country with most lenders, and from Europe[8]. In these two continents, the summer season runs from June to August, and the winter season starts in December and goes until February. Our

[6] https://www.definefinancial.com/blog/charitable-giving-statistics/(Accessed September 02, 2022).
[7] https://www.qgiv.com/blog/fundraising-statistics/ (Accessed September 02, 2022).
[8] https://www.tableaudor.com/kiva-lenders (Accessed August 02, 2022).

results point towards a significantly negatively influence of the end of spring and all summer period, on the changes of funding success of a prosocial crowdfunding campaign. Conversely, during winter and surrounding cold months, prosocial crowdfunding campaigns present a better funding performance and a higher likelihood of achieving success. The lender's behaviour may be weather-induced and/or dependent on time-availability. Although, one limitation of our study is that we lack access on weather data, thus we leave this as a future research avenue. Normally, working individuals take their long vacations during summer, a period during which they may be more engaged in outdoors activities. As, typically, this is a period of rest and relaxation for people, they naturally are more disconnected, spending less time on their phones and on the Internet, therefore not having much time nor availability to explore the different prosocial projects in order to find the ones they most identify with. Furthermore, it can be the time of the year when they are spending more money on holidays, travelling, and on everything involving activities of leisure. For this reason, it can be the time where their priority is personal spending, and as such, they may be more financially constraint, not having a lot of spare money to lend. Therefore, our MOTY findings suggest a positive winter prosocial effect and negative summer prosocial effect.

Regarding the DOTW effect, we show that the likelihood of funding success for prosocial crowdfunding consistently increases (decreases) when campaigns are launched on Tuesdays (Thursdays). Furthermore, we got statistically significant estimations for all days of the week (except Saturday) when measuring for the funding *Speed* of fully funded campaigns. Results show that prosocial crowdfunding campaigns launched at the end of the weekend and beginning of the weekdays are fully funded faster (i.e., Sundays, Mondays and Tuesdays); while campaigns launched at the last weekdays (i.e., Wednesdays, Thursdays and Fridays) take a longer time to get to the funding goal. We can associate theses finding to 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 is approaching, people start to make plans and estimating the spendings that they are going to have during the weekend. So, during this period prior to the weekend, people are more interested in saving money for the planned and unplanned weekends' spendings. Therefore, crowdfunding campaigns launched in the last weekdays and before the weekends take more time to be fully funded. After the weekends, individuals already had their big spendings, and know how much of their spare money they can direct to lending on prosocial crowdfunding platforms, increasing lender's engagement with new campaigns. Accordingly, campaigns launched in the beginning of the week are fully funded faster, and present higher success levels if launched particularly on Tuesdays. Our DOTW findings suggest a positive Tuesday effect and negative Thursday effect affecting *Funded* likelihood, *Amount* funded, and number of *Lenders*. Regarding funding *Speed* we found evidence of a beginning-week-days effect, and a negative last-weekdays effect.

8. Conclusions

Crowdfunding is a rather recent phenomenon that has been experiencing 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 associated with an increased crowdfunding campaign success are of entrepreneurs' interest. Despite the high funding success rates of prosocial crowdfunding, such as Kiva platform, this might not be always the case in other types of crowdfunding. Based on previous research of calendar anomalies in financial markets that defy the Efficient Market Hypothesis, we verify if there are similar or alternative time patterns in lender' behaviour and funding decisions in prosocial P2P crowdfunded microfinance. Secondly, we analyse if they are strong enough to impact campaigns' performance, and, therefore, be considered determinants of crowdfunding success.

Using data collected from Kiva, a leading prosocial P2P lending crowdfunding operating on "All-or-Nothing" model, on 177,093 crowdfunding projects launched from 2006 to 2021, we examined the effect of turn of the month period, all the 12 months of the year, and the 7 days of the week on prosocial crowdfunding success outcomes, relying on univariate and a multivariate analysis.

Based on four performance measures of crowdfunding success (i.e., *Funded* likelihood, *Amount* funded, number of *Lenders*, and funding *Speed*) we offer consistent evidence on calendar effects on P2P lending campaigns impacting crowdfunding performance in prosocial crowdfunding. Overall, we conclude that campaigns have worst performances and are less likely to succeed if launched during the 4-days window of the turn of the month – reverse TOTM effect – as well as in summer and neighbouring months – negative summer prosocial effect –, from the perspective of the north hemisphere (where there is a greater concentration of lenders), and on Thursdays – negative Thursday effect. On the contrary, campaigns are more successful and present an overall good performance if launched during the winter and colder months – positive winter prosocial effect –, and on Tuesdays – positive Tuesday effect. Surprisingly, these results suggest that the timing of campaign launch can be critical to the success of a debt campaigns in prosocial P2P lending crowdfunding. This determinant of crowdfunding performance appears to receive little attention in crowdfunding literature so far. Our study brings awareness to time effects that might be confounding factors if not properly addressed by crowdfunding performance studies and crowdfunding scholars. Thus, we recommend scholars to account for potential time patterns and seasonality, or following best practices in crowdfunding performance at least account for time fixed effects, such as day-of-the-week, month and year (e.g., Kuppuswamy & Bayus, 2017).

This study offers several contributions to both crowdfunding and entrepreneurship literature, and to practitioners. First, we add to the growing literature on crowdfunding suggesting that time-patterns determinants play a role in crowdfunding success. Second, we take a step forward by investigating the funding behaviour of lenders in crowdfunding, extending the literature on behavioural finance to the context of prosocial crowdfunding microfinance by studying calendar effects on crowdfunding performance. Third, by identifying time patterns in lenders' behaviour that induce different success outcomes of campaigns in the prosocial P2P lending crowdfunding, we offer time-patterns insights towards best practices in market timing to launch prosocial campaigns. This might be valuable to entrepreneurs and borrowers seeking for financial capital so they can maximize the success of their campaigns by incorporating time patterns in their decision making. Those insights might also be relevant to field partner, in order to obtain refunding faster to facilitate funding to new borrowers, as well as to crowdfunding platforms run more efficient business models or even choose timing to introduce new platform design and changes in their website. Finally, even indirectly, based on new evidence on campaigns funding success, this study aims to contribute to promote the success of prosocial P2P lending crowdfunding platforms that provide a relevant service in achieving various societal challenges in poor settings, namely by mitigating poverty, financial exclusion, and social inequalities.

This present study suffers from one major limitation, related to the fact that on the Kiva platform lenders can choose anonymity. Kiva has a global crowd, from many different countries, and because lenders might decide to not provide information regarding their country, our time patterns may be somewhat affected. Despite the consistence, we recommend caution before generalizing our findings to other crowdfunding contexts. Kiva platform represents a segment of the crowdfunding universe that might be unique: the prosocial P2P lending crowdfunding. One natural avenue to extend the time pattern and calendar effects literatures in crowdfunding is to explore whether and how these time effects affect crowdfunding performance on other types of crowdfunding, including in crowdfunding platforms operating in a "Keep it all" based model and in crowdfunding schemes offering returns for investors/lenders, a context more closely related to traditional financial markets. We also suggest that alternative time effects, such as time-of-the-day (e.g., Li & Wang, 2019) might be a further research avenues for crowdfunding scholars. Additionally, further research can explore time patterns, such as TOTM effect, across sectors in crowdfunding markets, extending evidence of stock market literature (e.g., Sharma & Narayan, 2014).

References

Aghion, B. A. de, Armendáriz, B., & Morduch, J. (2007). *The Economics of Microfinance*. MIT Press.

Agrawal, A., Catalini, C., & Goldfarb, A. (2014). Some Simple Economics of Crowdfunding. *Innovation Policy and the Economy*, *14*, 63–97. https://doi.org/10.1086/674021

Agrawal, A. K., Catalini, C., & Goldfarb, A. (2011). *The Geography of Crowdfunding* (Working Paper N. 16820; Working Paper Series). National Bureau of Economic Research. https://doi.org/10.3386/w16820

Agrawal, A., & Tandon, K. (1994). Anomalies or illusions? Evidence from stock markets in eighteen countries. *Journal of International Money and Finance*, *13*(1), 83–106. https://doi.org/10.1016/0261-5606(94)90026-4

Aharon, D. Y., & Qadan, M. (2019). Bitcoin and the day-of-the-week effect. *Finance Research Letters*, *31*. https://doi.org/10.1016/j.frl.2018.12.004

Ahlers, G. K. C., Cumming, D., Günther, C., & Schweizer, D. (2015). Signaling in Equity Crowdfunding. *Entrepreneurship Theory and Practice*, *39*(4), 955–980. https://doi.org/10.1111/etap.12157

Al-Khazali, O., & Mirzaei, A. (2017). Stock market anomalies, market efficiency and the adaptive market hypothesis: Evidence from Islamic stock indices. *Journal of International Financial Markets, Institutions and Money*, *51*, 190–208. https://doi.org/10.1016/j.intfin.2017.10.001

Ariel, R. A. (1987). A monthly effect in stock returns. *Journal of Financial Economics*, *18*(1), 161–174. https://doi.org/10.1016/0304-405X(87)90066-3

Barone, E. (1990). The italian stock market: Efficiency and calendar anomalies. *Journal of Banking & Finance*, *14*(2), 483–510. https://doi.org/10.1016/0378-4266(90)90061-6

Basher, S. A., & Sadorsky, P. (2006). Day-of-the-week effects in emerging stock markets. *Applied Economics Letters*, *13*(10), 621–628. https://doi.org/10.1080/13504850600825238

Belleflamme, P., Lambert, T., & Schwienbacher, A. (sem data). *2010): "Crowdfunding: An Industrial Organization Perspective," Working Paper, Universite Catholique de Louvain*.

Belleflamme, P., Lambert, T., & Schwienbacher, A. (2014). Crowdfunding: Tapping the right crowd. *Journal of Business Venturing*, *29*(5), 585–609. https://doi.org/10.1016/j.jbusvent.2013.07.003

Berger, S. C., & Gleisner, F. (2009). Emergence of Financial Intermediaries in Electronic Markets: The Case of Online P2P Lending. *Business Research*, *2*(1), 39–65. https://doi.org/10.1007/BF03343528

Berns, J. P., Figueroa-Armijos, M., da Motta Veiga, S. P., & Dunne, T. C. (2020). Dynamics of Lending-Based Prosocial Crowdfunding: Using a Social Responsibility Lens. *Journal of Business Ethics*, *161*(1), 169–185. https://doi.org/10.1007/s10551-018-3932-0

Block, J. H., Colombo, M. G., Cumming, D. J., & Vismara, S. (2018). New players in entrepreneurial finance and why they are there. *Small Business Economics*, *50*(2), 239–250. https://doi.org/10.1007/s11187-016-9826-6

Borrero-Domínguez, C., Cordón-Lagares, E., & Hernández-Garrido, R. (2020). Analysis of success factors in crowdfunding projects based on rewards: A way to obtain financing for socially committed projects. *Heliyon*, *6*(4), e03744. https://doi.org/10.1016/j.heliyon.2020.e03744

Brabham, D. C. (2013). *Crowdsourcing*. MIT Press.

Bradford, C. S. (2012). Crowdfunding and the Federal Securities Laws. *Columbia Business Law Review*, *2012*(1), 1–150.

Brown, T. E., Boon, E., & Pitt, L. F. (2017). Seeking funding in order to sell: Crowdfunding as a marketing tool. *Business Horizons*, *60*(2), 189–195. https://doi.org/10.1016/j.bushor.2016.11.004

Bruton, G., Khavul, S., Siegel, D., & Wright, M. (2015). New Financial Alternatives in Seeding Entrepreneurship: Microfinance, Crowdfunding, and Peer–to–Peer Innovations. *Entrepreneurship Theory and Practice*, *39*(1), 9–26. https://doi.org/10.1111/etap.12143

Buysere, K. D., Gajda, O., Kleverlaan, R., & Marom, D. (2012). *A Framework for European Crowdfunding*. 40.

Caporale, G. M., & Plastun, A. (2019). The day of the week effect in the cryptocurrency market. *Finance Research Letters*, *31*. https://doi.org/10.1016/j.frl.2018.11.012

Chaudhary, A. K. (2013). Impact of behavioral finance in investment decisions and strategies – a fresh approach. *International Journal of Management Research and Business Strategy*.

Chen, H., & Singal, V. (2004). All Things Considered, Taxes Drive the January Effect. *Journal of Financial Research*, *27*(3), 351–372. https://doi.org/10.1111/j.1475-6803.2004.00095.x

Ciccone, S. J. (2011). Investor Optimism, False Hopes and the January Effect. *Journal of Behavioral Finance*, *12*(3), 158–168. https://doi.org/10.1080/15427560.2011.602197

Cordova, A., Dolci, J., & Gianfrate, G. (2015). The Determinants of Crowdfunding Success: Evidence from Technology Projects. *Procedia - Social and Behavioral Sciences*, *181*, 115–124. https://doi.org/10.1016/j.sbspro.2015.04.872

Cross, Frank. (1973). The Behavior of Stock Prices on Fridays and Mondays. *Financial Analysts Journal*, *29*(6), 67–69. https://doi.org/10.2469/faj.v29.n6.67

Cumming, D., Leboeuf, G., & Schwienbacher, A. (2014). Crowdfunding Models: Keep-it-All vs. All-or-Nothing. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2447567

Defazio, D., Franzoni, C., & Rossi-Lamastra, C. (2021). How Pro-social Framing Affects the Success of Crowdfunding Projects: The Role of Emphasis and Information Crowdedness. *Journal of Business Ethics*, *171*(2), 357–378. https://doi.org/10.1007/s10551-020-04428-1

Devaraj, S., & Patel, P. C. (2016). Influence of number of backers, goal amount, and project duration on meeting funding goals of crowdfunding projects. *Economics Bulletin, 36(2)*, 1242-1249.

Dorfleitner, G., Oswald, E.-M., & Zhang, R. (2021). From Credit Risk to Social Impact: On the Funding Determinants in Interest-Free Peer-to-Peer Lending. *Journal of Business Ethics*, *170*(2), 375–400. https://doi.org/10.1007/s10551-019-04311-8

Duan, Y., Hsieh, T.-S., Wang, R. R., & Wang, Z. (2020). Entrepreneurs' facial trustworthiness, gender, and crowdfunding success. *Journal of Corporate Finance*, *64*, 101693. https://doi.org/10.1016/j.jcorpfin.2020.101693

Emanuel-Correia, R., Duarte, F., Gama, A. P. M., & Augusto, M. (2021). Does peer-to-peer crowdfunding boost refugee entrepreneurs? *Finance Research Letters*, 102264. https://doi.org/10.1016/j.frl.2021.102264

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, *25*(2), 383–417. https://doi.org/10.2307/2325486

Fang, L., Lin, C., & Shao, Y. (2018). School Holidays and Stock Market Seasonality. *Financial Management*, *47*(1), 131–157. https://doi.org/10.1111/fima.12182

Forbes, H., & Schaefer, D. (2017). Guidelines for Successful Crowdfunding. *Procedia CIRP*, *60*, 398–403. https://doi.org/10.1016/j.procir.2017.02.021

French, K. R. (1980). Stock returns and the weekend effect. *Journal of Financial Economics*, *8*(1), 55–69. https://doi.org/10.1016/0304-405X(80)90021-5

Galak, J., Small, D., & Stephen, A. T. (2011). Microfinance Decision Making: A Field Study of Prosocial Lending. *Journal of Marketing Research*, *48*(SPL), S130–S137. https://doi.org/10.1509/jmkr.48.SPL.S130

Gama, A. P. M., Emanuel-Correia, R., Augusto, M., & Duarte, F. (2021). Bringing modernity to prosocial crowdfunding's campaigns: An empirical examination of the transition to modern sectors. *Applied Economics*, *53*(49), 5677–5694. https://doi.org/10.1080/00036846.2021.1927968

Gao, Z., Guo, Z., & Tang, Q. (2021). How do monetary incentives influence giving? An empirical investigation of matching subsidies on kiva. *Information Systems and E-Business Management*. https://doi.org/10.1007/s10257-021-00515-6

Gerber, E. M., & Hui, J. (2013). Crowdfunding: Motivations and deterrents for participation. *ACM Transactions on Computer-Human Interaction*, *20*(6), 1–32. https://doi.org/10.1145/2530540

Greenberg, J., & Mollick, E. (2017). Activist Choice Homophily and the Crowdfunding of Female Founders. *Administrative Science Quarterly*, *62*(2), 341–374. https://doi.org/10.1177/0001839216678847

Haferkorn, M., & Quintana Diaz, J. M. (2015). Seasonality and Interconnectivity Within Cryptocurrencies—An Analysis on the Basis of Bitcoin, Litecoin and Namecoin. Em A. Lugmayr (Ed.), *Enterprise Applications and Services in the Finance Industry* (pp. 106–120). Springer International Publishing. https://doi.org/10.1007/978-3-319-28151-3_8

Hakenes, H., & Schlegel, F. (2014). Exploiting the Financial Wisdom of the Crowd—Crowdfunding as a Tool to Aggregate Vague Information. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2475025

Hartley, S. E. (2010). *Kiva.org: Crowd-Sourced Microfinance and Cooperation in Group Lending* (SSRN Scholarly Paper ID 1572182). Social Science Research Network. https://doi.org/10.2139/ssrn.1572182

Haug, M., & Hirschey, M. (2006). The January Effect. *Financial Analysts Journal*, *62*(5), 78–88. https://doi.org/10.2469/faj.v62.n5.4284

Hervé, F., & Schwienbacher, A. (2018). Crowdfunding and Innovation. *Journal of Economic Surveys*, *32*(5), 1514–1530. https://doi.org/10.1111/joes.12274

Hooghiemstra, S., & Buysere, K. (2016). *The Perfect Regulation of Crowdfunding: What Should the European Regulator Do?* (pp. 135–165). https://doi.org/10.1007/978-3-319-18017-5_10

Jenik, I., Lyman, T., & Nava, A. (2017). Crowdfunding and financial inclusion. *CGAP* (Consultative Group to Assist the Poor) working paper, 41.

Kaiser, L. (2019). Seasonality in cryptocurrencies. *Finance Research Letters*, *31*. https://doi.org/10.1016/j.frl.2018.11.007

Keim, D. B. (1983). Size-related anomalies and stock return seasonality: Further empirical evidence. *Journal of Financial Economics*, *12*(1), 13–32. https://doi.org/10.1016/0304-405X(83)90025-9

Kinateder, H., & Papavassiliou, V. G. (2021). Calendar effects in Bitcoin returns and volatility. *Finance Research Letters*, *38*, 101420. https://doi.org/10.1016/j.frl.2019.101420

Kromidha, E., & Robson, P. (2016). Social identity and signalling success factors in online crowdfunding. *Entrepreneurship & Regional Development*, *28*(9–10), 605–629. https://doi.org/10.1080/08985626.2016.1198425

Kunkel, R. A., Compton, W. S., & Beyer, S. (2003). The turn-of-the-month effect still lives: The international evidence. *International Review of Financial Analysis*, *12*(2), 207–221. https://doi.org/10.1016/S1057-5219(03)00007-3

Kuppuswamy, V., & Bayus, B. L. (2017). Does my contribution to your crowdfunding project matter? *Journal of Business Venturing*, *32*(1), 72–89. https://doi.org/10.1016/j.jbusvent.2016.10.004

Kuppuswamy, V., & Bayus, B. L. (2018). Crowdfunding Creative Ideas: The Dynamics of Project Backers. Em D. Cumming & L. Hornuf (Eds.), *The Economics of Crowdfunding: Startups, Portals and Investor Behavior* (pp. 151–182). Springer International Publishing. https://doi.org/10.1007/978-3-319-66119-3_8

Kuti, M., & Madarász, G. (2014). Crowdfunding. *Public Finance Quarterly*, *59*(3), 355–366.

Kutner, M. H., Nachtsheim, C. J., Neter, J., & Li, W. (2005). Applied Linear Statistical Models, 2005. McGraw Hill Irwin, New York. NY, 409.

Lakonishok, J., Shleifer, A., Thaler, R., & Vishny, R. (1991). *Window Dressing by Pension Fund Managers* (Working Paper N. 3617). National Bureau of Economic Research. https://doi.org/10.3386/w3617

Lakonishok, J., & Smidt, S. (1988). Are Seasonal Anomalies Real? A Ninety-Year Perspective. *The Review of Financial Studies*, *1*(4), 403–425. https://doi.org/10.1093/rfs/1.4.403

Latif, M., Arshad, S., Fatima, M., & Farooq, S. (2011). Market Efficiency, Market Anomalies, Causes, Evidences, and Some Behavioral Aspects of Market Anomalies. *Research Journal of Finance and Accounting*, *2*(9), 15.

Leboeuf, G., & Schwienbacher, A. (2018). Crowdfunding as a New Financing Tool. Em *The Economics of Crowdfunding: Startups, Portals and Investor Behavior* (pp. 11–28). https://doi.org/10.1007/978-3-319-66119-3_2

Lehner, O. M., Grabmann, E., & Ennsgraber, C. (2015). Entrepreneurial implications of crowdfunding as alternative funding source for innovations. *Venture Capital*, *17*(1–2), 171–189. https://doi.org/10.1080/13691066.2015.1037132

Li, G., & Wang, J. (2019). Threshold Effects on Backer Motivations in Reward-Based Crowdfunding. *Journal of Management Information Systems*, *36*(2), 546–573. https://doi.org/10.1080/07421222.2019.1599499

Ligon, J. A. (1997). A Simultaneous Test of Competing Theories Regarding the January Effect. *Journal of Financial Research*, *20*(1), 13–32. https://doi.org/10.1111/j.1475-6803.1997.tb00234.x

Long, H., Zaremba, A., Demir, E., Szczygielski, J. J., & Vasenin, M. (2020). Seasonality in the Cross-Section of Cryptocurrency Returns. *Finance Research Letters*, *35*, 101566. https://doi.org/10.1016/j.frl.2020.101566

Lukkarinen, A., Teich, J. E., Wallenius, H., & Wallenius, J. (2016). Success drivers of online equity crowdfunding campaigns. *Decision Support Systems*, *87*, 26–38. https://doi.org/10.1016/j.dss.2016.04.006

Ly, P., & Mason, G. (2012). Competition Between Microfinance NGOs: Evidence from Kiva. *World Development*, *40*(3), 643–655. https://doi.org/10.1016/j.worlddev.2011.09.009

Macht, S. A., & Weatherston, J. (2014). The Benefits of Online Crowdfunding for Fund-Seeking Business Ventures. *Strategic Change*, *23*(1–2), 1–14. https://doi.org/10.1002/jsc.1955

Marakkath, N., & Attuel-mendes, L. (2015). Can microfinance crowdfunding reduce financial exclusion? Regulatory issues. *International Journal of Bank Marketing*, *33*(5), 624–636. https://doi.org/10.1108/IJBM-06-2014-0080

McConnell, J. J., & Xu, W. (2008). Equity Returns at the Turn of the Month. *Financial Analysts Journal*, *64*(2), 49–64. https://doi.org/10.2469/faj.v64.n2.11

Moleskis, M., & Canela, M. A. (2016). *Crowdfunding Success: The Case of Kiva.Org* (SSRN Scholarly Paper N. 2769841). https://doi.org/10.2139/ssrn.2769841

Moller, N., & Zilca, S. (2008). The evolution of the January effect. *Journal of Banking & Finance*, *32*(3), 447–457. https://doi.org/10.1016/j.jbankfin.2007.06.009

Mollick, E. (2014). The dynamics of crowdfunding: An exploratory study. *Journal of Business Venturing*, *29*(1), 1–16. https://doi.org/10.1016/j.jbusvent.2013.06.005

Moss, T. W., Neubaum, D. O., & Meyskens, M. (2015). The Effect of Virtuous and Entrepreneurial Orientations on Microfinance Lending and Repayment: A Signaling Theory Perspective. *Entrepreneurship Theory and Practice*, *39*(1), 27–52. https://doi.org/10.1111/etap.12110

Moutinho, N., & Leite, E. P. (2013). *Critical Success Factors in Crowdfunding: The Case of Kickstarter*. 25.

N. Berger, A., & F. Udell, G. (1998). The economics of small business finance: The roles of private equity and debt markets in the financial growth cycle. *Journal of Banking & Finance*, *22*(6), 613–673. https://doi.org/10.1016/S0378-4266(98)00038-7

Nasir, muhammad ali, Rossi, M., & Khan, K. (2017). The calendar anomalies on performance and volatility of stock market: The effects of Ramadan on Karachi Stock Exchange. *Global Business and Economics Review*, *19*, 54. https://doi.org/10.1504/GBER.2017.10000917

Navarro, J. M., Sanchís-Pedregosa, C., & Alfonso, M. D. (2018). Relationship between crowdfunding and microfinance: A theoretical approach. *Finance, Markets and Valuation*, *4*, 63–72. https://doi.org/10.46503/POYR6349

Nikkinen, J., Sahlström, P., & Äijö, J. (2007). Turn-of-the-month and intramonth effects: Explanation from the important macroeconomic news announcements. *Journal of Futures Markets*, *27*(2), 105–126. https://doi.org/10.1002/fut.20244

Ogden, J. P. (1990). Turn-of-Month Evaluations of Liquid Profits and Stock Returns: A Common Explanation for the Monthly and January Effects. *The Journal of Finance*, *45*(4), 1259–1272. https://doi.org/10.2307/2328723

Onyuma, S. O. (2008). Assumptions about Microenterprise Lending as a Precondition for Development: A Critical Review. *Eastern Africa Social Science Research Review*, *24*(1), 109–134. https://doi.org/10.1353/eas.2008.0004

Osborne, M. F. M. (1962). Periodic Structure in the Brownian Motion of Stock Prices. *Operations Research*, *10*(3), 345–379.

Patel, J. B. (2008). Calendar Effects In The Indian Stock Market. *International Business & Economics Research Journal (IBER)*, *7*(3), Article 3. https://doi.org/10.19030/iber.v7i3.3234

Penman, S. H. (1987). The distribution of earnings news over time and seasonalities in aggregate stock returns. *Journal of Financial Economics*, *18*(2), 199–228. https://doi.org/10.1016/0304-405X(87)90039-0

Reinganum, M. R. (1983). The anomalous stock market behavior of small firms in January: Empirical tests for tax-loss selling effects. *Journal of Financial Economics*, *12*(1), 89–104. https://doi.org/10.1016/0304-405X(83)90029-6

Ricciardi, V., & Simon, H. K. (2001). *What is Behavioral Finance?* (SSRN Scholarly Paper N. 256754). https://papers.ssrn.com/abstract=256754

Rossi, M. (2014). The New Ways to Raise Capital: An Exploratory Study of Crowdfunding. *International Journal of Financial Research*, *5*(2), p8. https://doi.org/10.5430/ijfr.v5n2p8

Rossi, M. (2015). The efficient market hypothesis and calendar anomalies: A literature review. *International Journal of Managerial and Financial Accounting*, *7*, 285. https://doi.org/10.1504/IJMFA.2015.074905

Rozeff, M. S., & Kinney, W. R. (1976). Capital market seasonality: The case of stock returns. *Journal of Financial Economics*, *3*(4), 379–402. https://doi.org/10.1016/0304-405X(76)90028-3

Rystrom, D. S., & Benson, E. D. (1989). Investor Psychology and the Day-of-the-Week Effect. *Financial Analysts Journal*, *45*(5), 75–78.

Shafi, K., & Mohammadi, A. (2020). Too gloomy to invest: Weather-induced mood and crowdfunding. *Journal of Corporate Finance*, *65*, 101761. https://doi.org/10.1016/j.jcorpfin.2020.101761

Sharma, S. S., & Narayan, P. K. (2014). New evidence on turn-of-the-month effects. *Journal of International Financial Markets, Institutions and Money*, *29*, 92–108. https://doi.org/10.1016/j.intfin.2013.12.002

Shneor, R., & Vik, A. A. (2020). Crowdfunding success: A systematic literature review 2010–2017. *Baltic Journal of Management*, *15*(2), 149–182. https://doi.org/10.1108/BJM-04-2019-0148

Siegel, J. J. (2014). *Stocks for the long run: The definitive guide to financial market returns & long-term investment strategies* (Fifth edition). McGraw-Hill Education.

Singh, G., Bhattacharjee, K., & Kumar, S. (2020). Turn-of-the-month effect in three major emerging countries. *Managerial Finance*, *47*(4), 555–569. https://doi.org/10.1108/MF-01-2020-0013

Taeuscher, K., Bouncken, R., & Pesch, R. (2021). Gaining Legitimacy by Being Different: Optimal Distinctiveness in Crowdfunding Platforms. *Academy of Management Journal*, *64*(1), 149–179. https://doi.org/10.5465/amj.2018.0620

Thaler, R. (1987). Anomalies: Seasonal Movements in Security Prices II: Weekend, Holiday, Turn of the Month, and Intraday Effects. *Journal of Economic Perspectives*, *1*(2), 169–177. https://doi.org/10.1257/jep.1.2.169

Urquhart, A., & McGroarty, F. (2014). Calendar effects, market conditions and the Adaptive Market Hypothesis: Evidence from long-run U.S. data. *International Review of Financial Analysis*, *35*, 154–166. https://doi.org/10.1016/j.irfa.2014.08.003

Valanciene, L., & Jegeleviciute, S. (2013). VALUATION OF CROWDFUNDING: BENEFITS AND DRAWBACKS. *Economics and Management*, *18*(1), 39–48. https://doi.org/10.5755/j01.em.18.1.3713

Vidal, M., & Vidal-García, J. (2022). Turn of the Month Effect. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4106003

Vismara, S. (2016). Equity retention and social network theory in equity crowdfunding. *Small Business Economics*, *46*(4), 579–590. https://doi.org/10.1007/s11187-016-9710-4

Wang, Y.-J., & Walker, M. M. (2000). An empirical test of individual and institutional trading patterns in Japan, Hong Kong, and Taiwan. *Journal of Economics and Finance*, *24*(2), 178–194. https://doi.org/10.1007/BF02752711

Yalçın, K. C. (2010). Market rationality: Efficient market hypothesis versus market anomalies. *European Journal of Economic and Political Stud*ies, 3(2), 23-38.

Zhao, H., Ge, Y., Liu, Q., Wang, G., Chen, E., & Zhang, H. (2017). P2P Lending Survey: Platforms, Recent Advances and Prospects. *ACM Transactions on Intelligent Systems and Technology*, *8*(6), 1–28. https://doi.org/10.1145/3078848

Zheng, H., Li, D., Wu, J., & Xu, Y. (2014). The role of multidimensional social capital in crowdfunding: A comparative study in China and US. *Information & Management*, *51*(4), 488–496. https://doi.org/10.1016/j.im.2014.03.003

Zoricak, M., & Stofa, T. (2016). *Selected Success Factors of Crowdfunding Projects*.

Appendices

Appendix I – Table A1. Sample test composition

	Number of projects	Percentage of total projets	Funded Number	Funded Rate
Panel A: by Sector of Activity				
Agriculture	45,130	25.48%	42,555	94.29%
Food	39,538	22.33%	37,806	95.62%
Retail	32,826	18.54%	30,806	93.85%
Services	11,391	6.43%	10,625	93.28%
Clothing	9,173	5.18%	8,576	93.49%
Housing	8,735	4.93%	8,035	91.99%
Personal Use	7,691	4.34%	7,466	97.07%
Education	7,514	4.24%	7,419	98.74%
Arts	3,957	2.23%	3,926	99.22%
Transportation	3,900	2.20%	3,477	89.15%
Health	2,700	1.52%	2,483	91.96%
Construction	2,172	1.23%	2,087	96.09%
Manufacturing	1,913	1.08%	1,909	99.79%
Entertainment	228	0.13%	205	89.91%
Wholesale	225	0.13%	221	98.22%
Panel B: by Country of the borrower				
Philippines	41,143	23.23%	40,661	98.83%
Kenya	18,982	10.72%	17,721	93.36%
Cambodia	9,187	5.19%	9,000	97.96%
Peru	8,937	5.05%	8,745	97.85%
Uganda	6,425	3.63%	5,818	90.55%
El Salvador	6,350	3.59%	5,376	84.66%
Tajikistan	5,314	3.00%	4,831	90.91%
Ecuador	5,156	2.91%	4,963	96.26%
Pakistan	4,399	2.48%	4,189	95.23%
Nicaragua	4,250	2.40%	4,001	94.14%
Colombia	4,164	2.35%	3,263	78.36%
Vietnam	2,940	1.66%	2,823	96.02%
Paraguay	2,887	1.63%	2,840	98.37%
India	2,424	1.37%	2,388	98.51%
Lebanon	2,405	1.36%	2,177	90.52%
Ghana	2,386	1.35%	2,361	98.95%
Nigeria	2,340	1.32%	2,228	95.21%
Togo	2,298	1.30%	2,283	99.35%
Liberia	2,253	1.27%	2,253	100.00%
Madagascar	2,025	1.14%	2,022	99.85%
Mexico	1,979	1.12%	1,884	95.20%
Tanzania	1,918	1.08%	1,813	94.53%

Appendix I – Table A1. Sample test composition (continued)

Indonesia	1,917	1.08%	1,840	95.98%
Bolivia	1,914	1.08%	1,711	89.39%
Samoa	1,884	1.06%	1,700	90.23%
Rwanda	1,860	1.05%	1,707	91.77%
Honduras	1,791	1.01%	1,681	93.86%
Sierra Leone	1,758	0.99%	1,702	96.81%
Palestine	1,647	0.93%	1,471	89.31%
Guatemala	1,479	0.84%	1,394	94.25%
Kyrgyzstan	1,302	0.74%	1,152	88.48%
Senegal	1,268	0.72%	1,220	96.21%
Jordan	1,235	0.70%	1,059	85.75%
Armenia	1,175	0.66%	825	70.21%
Mali	1,164	0.66%	1,086	93.30%
Zimbabwe	927	0.52%	913	98.49%
Timor-Leste	839	0.47%	780	92.97%
Burkina Faso	798	0.45%	787	98.62%
Mongolia	791	0.45%	753	95.20%
Mozambique	777	0.44%	720	92.66%
Haiti	749	0.42%	740	98.80%
Georgia	748	0.42%	681	91.04%
Azerbaijan	685	0.39%	605	88.32%
United States	668	0.38%	255	38.17%
The Democratic Republic of the Congo	656	0.37%	633	96.49%
Costa Rica	596	0.34%	572	95.97%
Cameroon	551	0.31%	536	97.28%
South Sudan	527	0.30%	527	100.00%
Benin	524	0.30%	518	98.85%
Ukraine	482	0.27%	475	98.55%
Albania	459	0.26%	392	85.40%
Egypt	422	0.24%	414	98.10%
Dominican Republic	419	0.24%	404	96.42%
Turkey	345	0.19%	345	100.00%
Malawi	320	0.18%	320	100.00%
Lesotho	316	0.18%	316	100.00%
Fiji	298	0.17%	291	97.65%
Nepal	289	0.16%	289	100.00%
Solomon Islands	289	0.16%	275	95.16%
Yemen	286	0.16%	268	93.71%
Myanmar (Burma)	282	0.16%	225	79.79%
Iraq	275	0.16%	233	84.73%
Tonga	263	0.15%	262	99.62%
Zambia	251	0.14%	245	97.61%
Kosovo	242	0.14%	200	82.64%
Moldova	208	0.12%	197	94.71%

Appendix I – Table A1. Sample test composition (continued)

Brazil	169	0.10%	164	97.04%
Afghanistan	155	0.09%	155	100.00%
Lao People's Democratic Republic	150	0.08%	150	100.00%
Burundi	120	0.07%	114	95.00%
Thailand	94	0.05%	93	98.94%
Chile	79	0.04%	79	100.00%
Congo	67	0.04%	66	98.51%
South Africa	57	0.03%	57	100.00%
Vanuatu	52	0.03%	52	100.00%
Bosnia and Herzegovina	46	0.03%	46	100.00%
Israel	46	0.03%	45	97.83%
Panama	46	0.03%	46	100.00%
Papua New Guinea	31	0.02%	31	100.00%
Cote D'Ivoire	28	0.02%	28	100.00%
Bulgaria	25	0.01%	25	100.00%
Suriname	22	0.01%	21	95.45%
Sri Lanka	19	0.01%	19	100.00%
Belize	17	0.01%	17	100.00%
Somalia	12	0.01%	12	100.00%
China	11	0.01%	11	100.00%
Puerto Rico	5	0.00%	2	40.00%
Namibia	3	0.00%	3	100.00%
Saint Vincent and the Grenadines	1	0.00%	1	100.00%
Panel C: by Year				
2006	283	0.16%	283	100.00%
2007	2,223	1.26%	2,223	100.00%
2008	4,190	2.37%	4,190	100.00%
2009	7,475	4.22%	7,472	99.96%
2010	8,424	4.76%	8,413	99.87%
2011	9,992	5.64%	9,980	99.88%
2012	10,762	6.08%	10,075	93.62%
2013	11,670	6.59%	11,255	96.44%
2014	13,258	7.49%	12,280	92.62%
2015	13,637	7.70%	12,402	90.94%
2016	15,874	8.96%	14,373	90.54%
2017	19,266	10.88%	18,313	95.05%
2018	19,235	10.86%	17,507	91.02%
2019	18,069	10.20%	16,503	91.33%
2020	11,953	6.75%	11,721	98.06%
2021	10,782	6.09%	10,606	98.37%

Appendix II – Table A2. Correlation Matrix (for continuous covariates)

Dependent variables		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Funded	**1**	1								
Amount	**2**	0.853*	1							
Lenders	**3**	0.560*	0.832*	1						
Speed	**4**	0.723*	0.542*	0.278*	1					
Covariates										
Female	**5**	0.187*	0.130*	0.035*	0.185*	1				
Ln(project size)	**6**	-0.232*	0.301*	0.517*	-0.305*	-0.098*	1			
Ln(project duration)	**7**	-0.219*	-0.082*	0.111*	-0.247*	-0.152*	0.252*	1		
Repayment Schedule	**8**	0.039*	0.008*	-0.051*	0.038*	0.184*	-0.055*	-0.132*	1	
Direct Loan	**9**	-0.104*	-0.096*	-0.058*	-0.097*	-0.010*	0.046*	-0.028*	0.021*	1

*** p<0.01, ** p<0.05, * p<0.1

Appendix III – Table A3. Univariate tests: *Funded*

	Subsamples descriptive statistics				T-test (parametric test)		Wilcoxon rank-sum test (non-parametric test)
	=1		=0		Mean Diff.	Pr(|T|>|t|)	Prob > |z|
	Obs.	Mean	Obs.	Mean			
Variables							
TOTM	19,546	0.932	157,547	0.948	-0.017	0.000	0.000
Month							
January	13,644	0.952	163,449	0.946	0.006	0.002	0.002
February	15,126	0.977	161,967	0.944	0.033	0.000	0.000
March	16,216	0.968	160,877	0.944	0.024	0.000	0.000
April	13,837	0.942	163,256	0.947	-0.005	0.013	0.013
May	14,380	0.924	162,713	0.948	-0.024	0.000	0.000
June	14,202	0.931	162,891	0.948	-0.017	0.000	0.000
July	14,377	0.923	162,716	0.948	-0.025	0.000	0.000
August	14,375	0.942	162,718	0.947	-0.004	0.022	0.022
September	15,445	0.947	161,648	0.946	0.001	0.701	0.701
October	15,848	0.935	161,245	0.948	-0.013	0.000	0.000
November	15,075	0.955	162,018	0.946	0.009	0.000	0.000
December	14,568	0.957	162,525	0.945	0.012	0.000	0.000
Week Day							
Sunday	4,807	0.949	172,286	0.946	0.003	0.407	0.407
Monday	31,568	0.950	145,525	0.946	0.004	0.003	0.003
Tuesday	33,795	0.951	143,298	0.945	0.006	0.000	0.000
Wednesday	33,777	0.944	143,316	0.947	-0.003	0.065	0.065
Thursday	34,119	0.942	142,974	0.947	-0.006	0.000	0.000
Friday	31,735	0.945	145,358	0.947	-0.002	0.110	0.110
Saturday	7,292	0.947	169,801	0.946	0.001	0.669	0.669

T-test null hypothesis: The difference in group means is zero; Wilcoxon rank-sum test null hypothesis: The two groups have the same distribution; *** p<0.01, ** p<0.05, * p<0.1

Appendix IV – Table A4. Univariate tests: *Amount*

	Subsamples descriptive statistics				**T-test (parametric test)**		**Wilcoxon rank-sum test (non-parametric test)**
	=1		=0		Mean Diff.	Pr(|T|>|t|)	Prob > |z|
	Obs.	Mean	Obs.	Mean			
Variables							
TOTM	19,546	5.657	157,547	5.784	-0.127	0.000	0.000
Month							
January	13,644	5.877	163,449	5.761	0.116	0.000	0.000
February	15,126	5.997	161,967	5.749	0.248	0.000	0.000
March	16,216	5.920	160,877	5.755	0.165	0.000	0.000
April	13,837	5.779	163,256	5.769	0.010	0.466	0.000
May	14,380	5.670	162,713	5.779	-0.108	0.000	0.988
June	14,202	5.678	162,891	5.778	-0.100	0.000	0.004
July	14,377	5.580	162,716	5.787	-0.207	0.000	0.000
August	14,375	5.706	162,718	5.776	-0.070	0.000	0.000
September	15,445	5.722	161,648	5.774	-0.052	0.000	0.000
October	15,848	5.643	161,245	5.782	-0.139	0.000	0.000
November	15,075	5.757	162,018	5.771	-0.014	0.317	0.000
December	14,568	5.898	162,525	5.758	0.140	0.000	0.000
Week Day							
Sunday	4,807	5.936	172,286	5.765	0.171	0.000	0.000
Monday	31,568	5.799	145,525	5.764	0.035	0.001	0.001
Tuesday	33,795	5.794	143,298	5.764	0.030	0.002	0.569
Wednesday	33,777	5.755	143,316	5.773	-0.018	0.067	0.353
Thursday	34,119	5.724	142,974	5.781	-0.057	0.000	0.000
Friday	31,735	5.744	145,358	5.776	-0.032	0.001	0.001
Saturday	7,292	5.816	169,801	5.768	0.049	0.012	0.000

T-test null hypothesis: The difference in group means is zero; Wilcoxon rank-sum test null hypothesis: The two groups have the same distribution; *** p<0.01, ** p<0.05, * p<0.1

Appendix V – Table A5. Univariate tests: *Lenders*

	Subsamples descriptive statistics				**T-test (parametric test)**		**Wilcoxon rank-sum test (non-parametric test)**
	=1		=0		Mean Diff.	Pr(|T|>|t|)	Prob > |z|
	Obs.	Mean	Obs.	Mean			
Variables							
TOTM	19,546	2.366	157,547	2.446	-0.080	0.000	0.000
Month							
January	13,644	2.540	163,449	2.429	0.111	0.000	0.000
February	15,126	2.562	161,967	2.425	0.137	0.000	0.000
March	16,216	2.488	160,877	2.432	0.056	0.000	0.000
April	13,837	2.453	163,256	2.436	0.018	0.056	0.005
May	14,380	2.405	162,713	2.440	-0.035	0.000	0.252
June	14,202	2.391	162,891	2.441	-0.050	0.000	0.001
July	14,377	2.309	162,716	2.448	-0.139	0.000	0.000
August	14,375	2.402	162,718	2.440	-0.039	0.000	0.000
September	15,445	2.393	161,648	2.441	-0.048	0.000	0.000
October	15,848	2.359	161,245	2.445	-0.085	0.000	0.000
November	15,075	2.408	162,018	2.440	-0.032	0.000	0.000
December	14,568	2.538	162,525	2.428	0.110	0.000	0.000
Week Day							
Sunday	4,897	2.539	172,286	2.434	0.105	0.000	0.000
Monday	31,568	2.453	145,525	2.434	0.019	0.003	0.002
Tuesday	33,795	2.448	143,298	2.435	0.014	0.029	0.201
Wednesday	33,777	2.435	143,316	2.438	-0.003	0.631	0.868
Thursday	34,119	2.412	142,974	2.443	-0.031	0.000	0.000
Friday	31,735	2.422	145,358	2.441	-0.019	0.003	0.001
Saturday	7,292	2.447	169,801	2.437	0.010	0.399	0.187

T-test null hypothesis: The difference in group means is zero; Wilcoxon rank-sum test null hypothesis: The two groups have the same distribution; *** p<0.01, ** p<0.05, * p<0.1

Appendix VI – Table A6. Univariate tests: *Speed*

	Subsamples descriptive statistics				T-test (parametric test)		Wilcoxon rank-sum test (non-parametric test)
	=1		=0				
	Obs.	Mean	Obs.	Mean	Mean Diff.	Pr(|T|>|t|)	Prob > |z|
Variables							
TOTM	19,546	4.717	157,547	4.900	-0.183	0.000	0.000
Month							
January	13,644	5.482	163,449	4.830	0.652	0.000	0.000
February	15,126	5.084	161,967	4.861	0.222	0.000	0.000
March	16,216	5.071	160,877	4.861	0.210	0.000	0.000
April	13,837	4.757	163,256	4.891	-0.134	0.000	0.000
May	14,380	4.725	162,713	4.894	-0.169	0.000	0.000
June	14,202	4.677	162,891	4.898	-0.221	0.000	0.000
July	14,377	4.612	162,716	4.904	-0.291	0.000	0.000
August	14,375	4.720	162,718	4.894	-0.174	0.000	0.000
September	15,445	4.784	161,648	4.889	-0.106	0.000	0.000
October	15,848	4.736	161,245	4.894	-0.158	0.000	0.000
November	15,075	4.860	162,018	4.882	-0.022	0.110	0.030
December	14,568	5.063	162,525	4.864	0.200	0.000	0.000
Week Day							
Sunday	4,807	4.950	172,286	4.878	0.072	0.002	0.838
Monday	31,568	5.038	145,525	4.846	0.192	0.000	0.000
Tuesday	33,795	4.977	143,298	4.857	0.119	0.000	0.000
Wednesday	33,777	4.834	143,316	4.891	-0.057	0.000	0.000
Thursday	34,119	4.785	142,974	4.903	-0.118	0.000	0.000
Friday	31,735	4.764	145,358	4.906	-0.141	0.000	0.000
Saturday	7,292	4.872	169,801	4.881	-0.009	0.658	0.012

T-test null hypothesis: The difference in group means is zero; Wilcoxon rank-sum test null hypothesis: The two groups have the same distribution; *** p<0.01, ** p<0.05, * p<0.1