The Role of Online Peer-to-Peer Lending in Crisis Response: Evidence from Kiva

Abstract

Online peer-to-peer (P2P) lending, a new form of microfinance, has been touted as to its prominent potential for reducing world poverty. Although a growing body of IS research has been devoted to examining online P2P lending, how such platforms actually make a difference in curbing poverty has yet to be fully explored. The Ebola outbreak of 2014 provides us a unique empirical opportunity to explore such broader impacts of online P2P lending. Leveraging this event as a natural experiment, we investigate how the demand and supply sides of P2P lending platforms react to an unpredictable crisis. Employing a difference-in-difference identification strategy with data from Kiva.org, we conduct country- and loan-level estimations. Preliminary results show upward trends on both demand and supply sides of P2P lending; borrowers request more financial capital and lenders are more active in their lending behaviors in the post-crisis period. We extend online P2P lending literature by investigating the influences of “off-platform” shocks on within-platform behaviors.

Keywords: Online Peer-to-Peer Lending, Crisis Response, Prosocial Behavior, Online Microfinance, Difference-in-Difference
Introduction

Securing capital investments has become a challenging but crucial part of entrepreneurial processes (Allison et al. 2013; Cassar 2004; Yang and Hahn 2015). In developing countries, this challenge is even more pronounced given the lack of availability and accessibility of traditional sources of funding such as venture capital, business angels and banks (Pissarides 1999). Microfinance has emerged as a viable alternative for supplying critical financial capital to microenterprises, especially to those in impoverished districts (Dorado 2001). Recent statistics show that, in recent years, microfinance has issued more than $25 billion in loans to over 150 million individuals (Moss et al. 2015).

Recently, a novel type of online microfinance, in the form of online peer-to-peer (P2P) lending, has started to allow microlenders to break loans into multiple smaller loans and then to market them to individuals (Galak et al. 2011). Online P2P lending platforms, such as Kiva.org (henceforth, Kiva), which typically operate on the Internet, enable individual non-specialized lenders (i.e., the general public) to provide small loans for those entrepreneurs in need. This new business model helps needy entrepreneurs to directly tap the crowd as a source of funding. It is thus also be viewed as “crowd-empowered microfinance” (Marom 2013). Since its inception in 2005, up to mid 2016, Kiva has helped more than 1.9 million borrowers receive a total of $893 million for their small businesses. In fact, online P2P lending has played a leading role in reducing world poverty (Galak et al. 2011). As Kiva states, its mission is to connect people through lending to alleviate poverty (Waghorne 2013).

Given its salient socio-economic impacts, a nascent stream of research has begun to investigate this phenomenon. By and large, academic evaluation to date has largely focused on the impacts of within-platform factors, such as features of entrepreneurial narratives (Allison et al. 2015), on funding performance or on lenders’ decisions about which borrowers to support. However, little is known about the role of P2P lending platforms in addressing broader (off-platform) social problems. Specifically, it remains enigmatic how the emergence of this new business model influences extreme poverty, which is actually directly related to the purpose of microfinance. Indeed, scholars have recently articulated the importance of understanding the interplay between online microfinance platforms and social welfare (Agrawal et al. 2013).

The recent outbreak of the Ebola virus in Western Africa, although tragic in terms of mass casualties, provides us a unique context to explore such broader impacts of online P2P lending platforms. Disease crises and natural disasters, like the Ebola outbreak, have become one of the major obstacles for reducing extreme poverty, as they exert detrimental impacts on social welfare and economic growth (Hochrainer 2009; Von Peter et al. 2012). As reports show, the explosion of the Ebola disease has dramatically affected the operations of local businesses, employment rates, overall incomes as well as the demand for goods and services (Wood 2014). Entrepreneurs may resort to online platforms to acquire critical capital to help their small businesses survive the disaster. Investigating how online P2P lending reacts to crises such as the Ebola outbreak facilitates a better understanding of how online microfinance may help to address important social issues. Specifically, this study examines this impact from both demand and supply sides of the platform and explores how, and to what extent, the outbreak of a crisis influences borrowers’ and lenders’ behaviors in online peer-to-peer lending.

We empirically examine this question using data from Kiva, the world’s largest online P2P lending platform. By employing identification strategies using propensity score matching and difference-in-difference estimations, we conduct country- and loan-level analysis. Preliminary results suggest that there were upward trends on both demand and supply sides of P2P lending after the Ebola outbreak. On the demand side, the increase is driven by higher requested loan amount. On the supply side, the increase arises from the enhanced activeness of lenders, resulting in a significant increase in daily funding amount. Further falsification tests and robustness checks suggest that our results are robust to different estimation time windows and alternative explanations. The findings suggest that the Ebola virus outbreak has induced more prosocial lending activities on the P2P lending platform, and this lending behavior is primarily motivated by altruism (Simon 1993) — the willingness to help those in need. Our study extends the extant literature in online P2P lending by documenting robust empirical evidence of how this new business model reacts to poverty and increases financial inclusion.

---

1 See: http://www.kiva.org/about/stats (visited in September 2016)
Related Literature

Crisis Response

During the past decade, crisis related studies have garnered substantial academic attention (e.g., Berg and Schrader 2012; Dayton 2004; Phan and Airoldi 2015; Tim et al. 2013). A series of crises or disasters have exerted prolonged and devastating impacts on a variety of socio-economic conditions (Hosono et al. 2012; Laframboise and Loko 2012). At the macro level, existing studies suggest that disasters have a significantly detrimental impact on real GDP and economic growth (Hochrainer 2009; Von Peter et al. 2012). At the micro level, it has been shown that stakeholders suffer from business interruptions, lowered personal incomes or even extreme poverty. In general, the detrimental impacts on developing countries are more devastating compared to those on developed nations (Laframboise and Loko 2012).

Apart from their socio-economic impacts, crises are widely believed to exert severe financial impacts on society, particularly on firms’ and individuals’ financing behaviors (Benson and Clay 2004). Some relevant studies investigated the changes of loan demand after natural disasters such as volcanic eruptions (Berg and Schrader 2012) and floods (Del Ninno et al. 2003). They find that while credit demand increases after such crises, access to lending remains restricted. Even though the financing market has been shown to react to unpredicted shocks (e.g., crises/disaster), there is still a lack of comprehensive understanding about the changes in financial behaviors and the reactions of financial markets in response to such unpredicted exogenous shocks. Our study therefore aims to examine how the demand and supply sides of the lending market change as a result of unpredictable disasters.

Microfinance and Online Peer-to-Peer Lending

Our study is also related to the literature on microfinance. Microfinance, the “open access to capital for individuals previously shut out of financial services” (Khavul 2010, p.58), has been increasingly viewed as a powerful means to alleviate poverty and reduce social exclusion (Moss et al. 2015). Traditionally, entrepreneurs gain access to financial capital primarily through financial institutions. But financial institutions, especially those in the developing world, find it risky and expensive to serve the poor, as the poor are often illiterate, do not have officially available credit scores and are often dispersed across rural geographic regions (Khavul 2010). Furthermore, they usually operate as small-scale businesses (Webb et al. 2009), which often entail agency and transaction cost problems that are not easy for traditional banks to overcome. Fortunately, microfinance offers an innovative solution for entrepreneurs by resolving problems of adverse selection, moral hazard and transaction costs to a great extent (Khavul 2010).

The recent emergence of online peer-to-peer lending (Galak et al. 2011) enables microlenders to break loans into multiple smaller loans and then to market them to the general public (Allison et al. 2013; Galak et al. 2011). Facilitated by the Internet, online microfinance taps “the crowd” as a source of funding (Duncan 2014; Marom 2013) by mobilizing a large community (i.e., the crowd) to give small amounts of money to ventures and initiatives they find attractive. The sum of small contributions may add up to a sum that is substantial enough for business start-ups.

Recently, a growing body of IS research has begun to examine this phenomenon. In general, there have been two streams of studies – 1) studies investigating potential drivers of funding success and loan performance, and 2) those that investigate motivations and determinants of lenders’ contribution behaviors. In the first stream, several studies have focused on the influences of entrepreneurial narratives on fundraising outcome. Entrepreneurs’ behavioral intentions (Moss et al. 2015), valence (Allison et al. 2013) and language framing (Allison et al. 2015) of entrepreneurial narratives have been found to be associated with loan performance. For instance, Moss et al. (2015) found that those narratives that signal competitive aggressiveness and risk-taking are inclined to receive more funding and also at higher funding speeds. Allison et al. (2013) showed that entrepreneurial narratives indicating blame and concern result in more rapid funding speeds than those indicating accomplishment. In the second stream, studies primarily examined the impacts of prior contributions and characteristics of borrowers on lenders’ decisions about which borrowers to support. Geography and culture have been considered to be two major relevant characteristics, and these two characteristics have also been prevalently discussed in the literature (e.g., Agrawal et al. 2012; Agrawal et al. 2011; Burch et al. 2014). Galak et al. (2011) suggest that the social distance between borrowers and lenders also plays a role in lenders’ decisions. In addition, Zhang and Liu (2012) found that higher prior contributions are likely to attract more subsequent lenders as a result of herding behaviors.
As can be seen, the existing online P2P lending literature mainly concentrates on the impacts of within-platform factors on funding performance and lenders’ decision-making. Amongst these works, little consideration has been given to the broader off-platform effects, such as the explosion of unpredictable crises and social problems, on within-platform behaviors which are more relevant since the primary aim of online microfinance is to alleviate poverty and increase social welfare especially in developing countries by connecting geographically separated individuals through online lending (Waghorn 2013). But no prior work has considered the role of online P2P lending platforms in overall poverty reduction. In particular, it still remains unclear how borrowers and lenders alter their behaviors in response to unpredictable crises that exacerbate extreme poverty. Our study offers a step forward in this regard by assessing how the outbreak of an unpredictable disaster (i.e., the Ebola outbreak) affects online P2P lending. Specifically, we investigate this effect from both the demand and supply sides of the platform. Investigating this question enriches our understanding of the role of online P2P lending platforms in affecting socio-economic conditions.

**Methods**

**Study Context & Data**

Kiva is the largest online P2P lending platform that provides loans to small businesses, which to a large extent, are located in developing countries. Kiva has the mission to alleviate poverty, increase social welfare, and minimize social exclusion by ensuring access to credit. Kiva collaborates with local micro-financial institutions (MFI) within each country to fulfill their mission. Borrowers on Kiva can be entrepreneurs, small businesses or microenterprises. Local MFI act as the mediation between potential borrowers and Kiva. MFI work directly with local ventures. They are responsible for working directly with borrowers to service the loans (Moss et al. 2015). Local MFI assist borrowers in creating their own profiles, which are then submitted to Kiva. The profile generally includes both soft and hard information about the borrowers, such as their biography, purpose of loan, requested loan amount, repayment schedule and information about the corresponding local MFI (Burtech et al. 2014). Funding amount provided by each lender typically start from $25 onwards. Each loan has a predetermined funding duration to reach the required funding amount. Lenders do not earn any interest on the funds they supply on Kiva.

Our data is retrieved using the public API provided by Kiva. Our data consists of three parts: information on the loans, the borrowers and the lenders. Loan information includes loan location (i.e., country), image, sector, usage, delinquency indicator, geographic location, loan amount, lender count, posted date, expiration date, paid date and loan description (the narrative). Borrower information includes name, gender and profile picture. Lender information includes the name, picture, occupation, loan reason and the number of loans to which they have previously contributed.

In 2014, the outbreak of the Ebola virus in Western Africa was the largest and most complex in the history of the disease (Alexander et al. 2014). This outbreak resulted in a great number of casualties primarily in three countries: Sierra Leone, Liberia and Guinea. On August 8, 2014, the World Health Organization (WHO) designated the Western African outbreak as a Public Health Emergence of International Concern (PHEIC). After that, the number of Ebola cases in the three affected countries increased dramatically. By the end of July 2015, there were no vaccines licensed for the use in humans to protect against the Ebola Virus Disease (Callaway 2015). The Ebola outbreak has exerted severe socio-economic impacts on affected areas, especially Liberia and Sierra Leone, in part because the disease took hold in densely populated areas. Various sectors, ranging from agriculture to services, have also been hit hard by this crisis. The disease affected operations of local businesses, employment rates, incomes and demand for goods and services (Wood 2014). In light of the unique scope and scale of impact, we employ this event as a natural experiment to explore variations in borrowers’ and lenders’ financial behaviors and in turn to understand the broader impacts of online P2P lending.

**Crisis Explosion & Peer-to-Peer Lending**

In the emergence of an unpredictable crisis, we expect two plausible effects on the demand (borrower)
side of online P2P lending. On the one hand, our review of the literature and basic intuition would suggest that a crisis outbreak would dramatically worsen economic conditions and disrupt normal operations of local small businesses in sectors, such as agriculture, food, health and services. Entrepreneurs in crisis-hit areas would be exposed to economic disruptions and increased operational risks. Faced with this adverse shock, borrowers may be in need of liquidity and therefore increase their demand for loans. A greater amount of financial capital would be needed to assist their businesses in surviving through such a crisis. Given this risk effect, we expect an increase in loan demand after the outbreak of an unpredictable crisis. On the other hand, crises also pose a health threat on entrepreneurs. Severely affected districts are exposed to market closures and entrepreneurs in these areas may find it difficult to continue their operations and may choose to temporarily suspend them. This would lead to a decline in their economic activities and in turn reduces their demand for loans. Thus, loan demand may also decrease after a crisis.

The economics literature has typically attributed contribution behavior to altruistic or egoistic motives (Allison et al. 2013; Simon 1993). Altruistically-motivated giving is primary driven by the willingness to help, whereas egoistically-motivated giving is mainly driven by external returns (e.g., financial interest). On Kiva, lenders do not receive any interest on the funds they lend to borrowers (Galak et al. 2011). In other words, their lending behaviors cannot be motivated by financial returns (Allison et al. 2013). The contribution behaviors can be seen as a form of prosocial lending (Allison et al. 2015). This motive also naturally fits the explanations of warm-glow-motivated giving (Andreoni 1990).

A crisis outbreak threatens social welfare and the economic conditions of affected areas. Business operations in affected areas are likely to be undermined by the deteriorating macroeconomic condition. The worsened situation may influence individual lenders’ decisions by increasing the warm glow felt as a result of lending. Prosocial lending, a form of altruistic behavior, is mainly motivated by lenders’ desire to help others. Taking actions to help those in need provides them with a positive affective state. In this regard, a crisis outbreak is expected to increase prosocial lending behaviors (Andreoni 1990; Cialdini et al. 1973). Besides, the decision making literature suggests the “identified victim effect” (Kogut and Ritov 2005a; Kogut and Ritov 2005b), which means people are more inclined to support a victim if she is identified compared to if she is unidentified. A crisis outbreak may arouse empathic emotions towards borrowers from affected areas, since people are likely to imagine how people are struggling to overcome the current crisis (Davis 1994). This is likely to evoke empathy, which induces them to help those “identified victims” (Batson et al. 1991; Batson et al. 1995). Based on the above, we expect an increase in the supply side of online P2P lending whereby lenders are more inclined to offer loans to borrowers in crisis-affected areas. However, the crisis response literature suggests that disasters are likely to induce a higher default rate for loans (Berg and Schrader 2012). Crises dramatically threaten the businesses of local entrepreneurs, which may in turn lead to an increase in delinquency rate. Even though the lending behavior on Kiva is a form of prosocial lending (i.e., no interest rate), borrowers need to pay back the loans following a certain repayment schedule. Therefore, in the post-crisis period, lenders are also exposed to increased risks arising from potential higher delinquency and default rates. This risk effect may reduce lenders’ propensity to help. Given this argument, we also expect a decrease in the supply side of online P2P lending. Due to the dual potential effects based upon the existing literature, we examine the overall impacts empirically.

**Identification: Difference-in-Difference Approach**

The outbreak of the Ebola virus disease in Western Africa provides us a unique context to explore such broader impacts of online P2P lending platforms. We employ a difference-in-difference (DID) approach to estimate the changes in P2P lending after Ebola outbreak. Since the Ebola outbreak was formally designated by the WHO on 8 August 2014 as a PHEIC, we take August 2014 as the event month. We investigate its impact within a 9-month window, with April to July as the pre-Ebola period and September to December as the post-Ebola period. We also include the sample in the event month (i.e., August).

The Ebola outbreak occurred in three Western African countries including Liberia, Sierra Leone and Guinea, but only two of them are available on Kiva. Therefore, our treatment group includes the two Ebola-affected countries: Liberia and Sierra Leone. To evaluate a before-after effect, we select countries that were not affected by Ebola outbreak in our dataset as the control group. However, countries (as well as loans in these countries) that were not affected by Ebola may have different characteristics with the countries (and loans) in the treatment group. These country level factors may affect lenders’ behaviors regarding the loans in specific countries, which can undermine the assumptions of DID. In order to alleviate such potential endogeneity issues, we use Propensity Score Matching (PSM) to find other countries to form the control group. In the first stage, we estimate a Probit model to calculate the
propensity score. The dependent variable in the Probit model is a dummy variable that equals to 1 if the country is affected by Ebola, and 0 otherwise. The independent variables are socio-economic factors that are likely to affect the Ebola outbreak in a certain country, including Sanitation (i.e., the percentage of the population with access to improved sanitation facilities), Water (i.e., the percentage of the population with access to improved water sources), Livestock (i.e., the livestock production index), and Population (i.e., the annual increase in the urban population). We derive these data for each county and each month from the World Bank’s World Development Index 2014. These independent variables are considered as the potential factors that are associated with the outbreak of Ebola (Alexander et al. 2014). Such a procedure allows us to select similar countries that had a high chance of being affected by Ebola but were not affected into the control group.

The matching method we use is nearest neighbor matching. The result shows that the matching procedure resulted in two groups that were comparable on most observable accounts, indicating satisfactory matching. The control group we find through PSM includes one country: Togo. Both countries in the treatment group are matched with this country using nearest neighbor matching. This selected country is also located in Western Africa. We therefore use loans in Togo as the control group to estimate the changes in loans in the affected countries after the Ebola outbreak.

Before our regression analyses, to generate an intuition about the changes of loan count after Ebola outbreak, we plotted the number of initiated loans in each month for the three countries (see Figure 1). As shown in Figure 1, before the Ebola outbreak, changes in number of loans for the three countries roughly follow a common trend (Angrist and Pischke 2008). We also notice that the number of loans in Sierra Leone and Liberia decrease dramatically after the event, whereas in Togo, the count increases slightly. The graph shows that there is a decrease in the demand side of P2P lending in terms of loan count after the event, whereas in Togo, the count increases slightly. Implied is a series of potential impacts on platform response from the Ebola outbreak.

![Figure 1. Number of Loans Before and After Ebola Outbreak](image)

Next, utilizing the difference-in-difference approach, we conduct two sets of regression analyses at country and loan levels, respectively. First, following the evidence shown in Figure 1, we examine the macro impact of Ebola at the country level where country-month is the unit of analysis. Second, we perform regression analysis with loans as the unit of analysis to generate a nuanced insight for its impact. We estimate the effects on the demand and supply sides of P2P lending. Within our analysis window, Sierra Leone, Liberia and Togo have 27 country-month pairs as well as 1451, 1074 and 774 loans respectively. The basic econometric model specification is:

\[ LoanIndicators = \beta_0 + \beta_1 \times PostEbola + \beta_2 \times Treatment + \beta_3 \times Interaction + CONTROL + \alpha + \mu \]

where the LoanIndicators represents demand side or supply side loan indicators. PostEbola equals to 1 if the month is August or after, and 0 otherwise. Treatment is equal to 1 if the country or the borrower’s country is an Ebola-affected country (i.e., Liberia or Sierra Leone), and 0 otherwise (i.e., Togo). Interaction is the multiplication between PostEbola and Treatment. The coefficient of interest is \( \beta_3 \), which captures the difference between treatment and control group that is induced by Ebola in the post-Ebola period – i.e., the effect we intend to estimate.
Preliminary Results

Our estimations are conducted by utilizing dependent variables representing the demand and supply sides of P2P lending. At country level, the number of loans posted (LoanCount) and average loan amounts for all launched loans (AveLoanAmount) in a certain month and certain country are used for the demand side, while average funded amount (AveFundedAmount), average number of lenders (AveLenderCount), average funded amount per lender (AvePerLender) and average funded amount per day (AvePerDay) across all loans in a certain month and certain country are examined for the supply side. Month and country fixed effects are also included given our 9 months’ window. For the loan-level analysis, on the demand side, the requested loan amount by borrowers (LoanAmount) is used. On the supply side, the funded amount (FundedAmount), the number of lenders (LenderCount), the average funded amount per lender (AvePerLender), and the average daily funded amount (AvePerDay) are used. Besides, a series of loan level characteristics are included in the loan-level estimations to control for loan-specific factors.

Table 1 presents our country level estimations. For the demand side, in Model 1, the coefficient of the interaction term is negative and significant ($\beta=-2.539$, $p<0.01$), suggesting that the number of loans posted decreases significantly in the Ebola-affected countries after the outbreak, consistent with the evidence in Figure 1. But the amount of needed funds set by borrowers in the treatment group increases after the crisis, as shown by the positive interaction term in Model 2 ($\beta=1.004$, $p<0.01$). Model 3-6 show the results of the supply side, where lenders tend to be more active in supporting the loans. The average amount funded (Model 3), average number of lenders (Model 4) and average speed of funding (Model 6) in the treatment group countries increase, while average funded amount of each lender (Model 5) is not affected by the event. These macro level results suggest that borrowers tend to seek more funds, while lenders actively and timely react to the crisis by providing their support.

We then conduct a more nuanced analysis at the loan level to examine the impacts on individual loans. The results of our loan-level estimations are presented in Table 2 and do not deviate from our country level analysis. Model 7 shows the result for the demand side, and Model 8 to 11 show the results for the supply side. For the demand side, the results suggest that the outbreak of Ebola is associated with an increase in borrowers’ requested loan amounts, suggesting that borrowers need more financial capital for their small businesses after the disease outbreak (Model 7: Interaction: $\beta=1.442$, $p<0.01$). It seems because the crisis dramatically threatens the performance of local businesses and they are in desperate need of extra financial resources to survive, consistent with our arguments about the risk effect on borrowers.

In the supply side, the outbreak of Ebola triggers an increase in the supply side of P2P lending, which exhibits as higher funded amounts (Model 8: Interaction: $\beta=1.386$, $p<0.01$), greater number of lenders (Model 9: Interaction: $\beta=1.221$, $p<0.01$), and higher daily funded amounts (Model 11: Interaction: $\beta=0.299$, $p<0.01$). But average lending amount by individuals does not show a significant increase (Model 10: Interaction: $\beta=0.0510$, ns). The results suggest that even though the Ebola crisis may increase delinquency and default rates, this risk effect was not dominant. A possible reason is that in microlending

| Table 1. Regression Results for Country Level Analysis |
|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| VARIABLES       | Model1          | Model2          | Model3          | Model4          | Model5          | Model6          |
| LoanCount       | LoanCount       | AveLoanAmount   | AveFundedAmount | AveLenderCount  | AvePerLender    | AvePerDay       |
| Post Ebola      | 0.503           | -0.469”         | -0.461”         | -0.407”         | -0.0764         | -0.119          |
| Treated countries | (0.470)          | (0.182)         | (0.183)         | (0.198)         | (0.123)         | (0.313)         |
| Interaction term | 1.858”           | -0.0929         | -0.102          | -0.0687         | -0.101          | -0.0832         |
| Constant        | (0.271)         | (0.124)         | (0.123)         | (0.132)         | (0.0631)        | (0.234)         |
| AveLoanAmount   | (0.506)         | (0.204)         | (0.202)         | (0.202)         | (0.0901)        | (0.325)         |
| AveFundedAmount | 3.923”          | 6.250”          | 6.241”          | 2.734”          | 3.676”          | 5.120”          |
| AveLenderCount  | (0.340)         | (0.110)         | (0.107)         | (0.118)         | (0.0553)        | (0.252)         |
| AvePerLender    | 1.004”          | 0.996”          | 0.929”          | 0.0786          | 0.617”          |
| AvePerDay       | 0.780           | 0.882           | 0.881           | 0.866           | 0.442           | 0.549           |
| Observations    | 27              | 27              | 27              | 27              | 27              | 27              |

Notes: 1) The log form of all dependent variables are used in the estimations to account for their skewed distributions; 2) Robust standard errors are reported in parentheses.

Significance Levels: ”p<0.01, “p<0.05, “p<0.1
platforms, especially at Kiva which mainly targets entrepreneurs and small businesses, lending behavior is predominantly driven by altruistic motives (Allison et al. 2013). In other words, the primary motivation for lending is that lenders want to take actions to help those in need. The Ebola outbreak undermines the economic situation in the affected districts, which induces a growth in prosocial lending. Furthermore, the increased daily amount confirms that the outbreak of crisis prompts lenders to be more active. This is also consistent with the finding in the finance literature that people prefer to approach desirable outcomes early (Benzion et al. 1989). The crisis outbreak may have aroused empathic emotions and lenders may have been more inclined respond to affected borrowers faster with an expectation of helping them recover early.

### Table 2. Regression Results for Loan Level Analysis

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Model 7 LoanAmount</th>
<th>Model 8 FundedAmount</th>
<th>Model 9 LenderCount</th>
<th>Model 10 AvePerLender</th>
<th>Model 11 AvePerDay</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post Ebola</td>
<td>-1.542***</td>
<td>-1.484***</td>
<td>-1.401***</td>
<td>0.115</td>
<td>-0.148</td>
</tr>
<tr>
<td></td>
<td>(0.140)</td>
<td>(0.140)</td>
<td>(0.129)</td>
<td>(0.0615)</td>
<td>(0.135)</td>
</tr>
<tr>
<td>Treated countries</td>
<td>-0.772***</td>
<td>-0.808***</td>
<td>-0.730***</td>
<td>-0.0371</td>
<td>-0.141</td>
</tr>
<tr>
<td></td>
<td>(0.0564)</td>
<td>(0.0563)</td>
<td>(0.0582)</td>
<td>(0.0345)</td>
<td>(0.0753)</td>
</tr>
<tr>
<td>Interaction term</td>
<td>1.442***</td>
<td>1.386***</td>
<td>1.221***</td>
<td>0.0510</td>
<td>0.299***</td>
</tr>
<tr>
<td></td>
<td>(0.0678)</td>
<td>(0.0757)</td>
<td>(0.0694)</td>
<td>(0.0407)</td>
<td>(0.0862)</td>
</tr>
<tr>
<td>Constant</td>
<td>5.709***</td>
<td>5.790***</td>
<td>2.425***</td>
<td>3.820***</td>
<td>2.973***</td>
</tr>
<tr>
<td></td>
<td>(0.255)</td>
<td>(0.255)</td>
<td>(0.270)</td>
<td>(0.162)</td>
<td>(0.245)</td>
</tr>
<tr>
<td>R²</td>
<td>0.455</td>
<td>0.409</td>
<td>0.382</td>
<td>0.021</td>
<td>0.187</td>
</tr>
</tbody>
</table>

**Notes:** 1) Loan characteristics, sector dummies, month dummies and country dummies are included in our estimations. The results remain consistent when we hierarchically include the control variables; 2) the log form of all dependent variables are used in the estimations to account for their skewed distributions; 3) Robust standard errors are reported in parentheses.

**Significance Levels:** ***p<0.01, **p<0.05, *p<0.1

To further verify the responses to Ebola outbreak, we also conducted PSM at loan level where we matched loans that were not posted in Ebola-affected countries but with similar loan characteristics (i.e., loan level control variables). The matching was performed separately on the loans before and after the Ebola outbreak. Similar loans in Western Africa countries except Sierra Leone and Liberia were selected into control group using the nearest neighbor matching. The estimations of the new sample (2,525 loans in each group) are presented at Table 3. From Model 12 to Model 16, the results (Interaction term) are consistent with the estimates in Table 3. These results validate our loan level analysis and provide stronger evidence for our findings.

### Table 3. Regression Results for Loan Level Analysis with Loan-level PSM

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Model 12 LoanAmount</th>
<th>Model 13 FundedAmount</th>
<th>Model 14 LenderCount</th>
<th>Model 15 AvePerLender</th>
<th>Model 16 AvePerDay</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post Ebola</td>
<td>-0.738***</td>
<td>-0.755***</td>
<td>-0.668***</td>
<td>0.00208</td>
<td>-0.204</td>
</tr>
<tr>
<td></td>
<td>(0.157)</td>
<td>(0.164)</td>
<td>(0.148)</td>
<td>(0.0698)</td>
<td>(0.164)</td>
</tr>
<tr>
<td>Treated countries</td>
<td>0.970***</td>
<td>1.037***</td>
<td>0.672***</td>
<td>0.170***</td>
<td>0.872***</td>
</tr>
<tr>
<td></td>
<td>(0.0706)</td>
<td>(0.0809)</td>
<td>(0.0672)</td>
<td>(0.0300)</td>
<td>(0.111)</td>
</tr>
<tr>
<td>Interaction term</td>
<td>1.076***</td>
<td>1.104***</td>
<td>0.949***</td>
<td>0.0526</td>
<td>0.317***</td>
</tr>
<tr>
<td></td>
<td>(0.0550)</td>
<td>(0.0720)</td>
<td>(0.0548)</td>
<td>(0.0420)</td>
<td>(0.0778)</td>
</tr>
<tr>
<td>Constant</td>
<td>4.825***</td>
<td>4.773***</td>
<td>1.732***</td>
<td>3.412***</td>
<td>2.767***</td>
</tr>
<tr>
<td></td>
<td>(0.313)</td>
<td>(0.319)</td>
<td>(0.296)</td>
<td>(0.146)</td>
<td>(0.327)</td>
</tr>
<tr>
<td>R²</td>
<td>0.600</td>
<td>0.583</td>
<td>0.511</td>
<td>0.032</td>
<td>0.278</td>
</tr>
<tr>
<td>Observations</td>
<td>5,050</td>
<td>5,050</td>
<td>5,050</td>
<td>5,050</td>
<td>5,050</td>
</tr>
</tbody>
</table>

**Notes:** 1) Loan characteristics, sector dummies, month dummies and country dummies are included in our estimations. The results remain consistent when we hierarchically include the control variables; 2) the log form of all dependent variables are used in the estimations to account for their skewed distributions; 3) Robust standard errors are reported in parentheses.

**Significance Levels:** ***p<0.01, **p<0.05, *p<0.1

We also conducted additional falsification tests and robustness checks. A potential concern one might raise is that the country chosen for the control group is not a good match. That is, there may be error in the matching process and perhaps the results are only showing spurious correlations. Therefore, we conducted a falsification test by replacing the two Ebola-affected countries with other randomly selected countries but keeping Togo as the control group. The insignificant results in the falsification test show that our results are valid and robust. This gives us confidence that our identification strategy for the changes in borrowers’ and lenders’ behaviors is appropriate and that our findings are not the result of
spurious associations. In addition, we conducted three sets of analyses to rule out alternative explanations by possible shocks across time. First, we exclude all loans whose funding periods are coincided with the Ebola outbreak. Second, we exclude all the loans that are posted within the month when the Ebola emerged. Third, we use different time windows in our estimations. Instead of using 9 months’ time window, we run the analysis with 7 months’ time window (3 months before + 3 months after + event month). All tests resulted in similar significance levels and identical directions of all relevant coefficients.

Conclusions and Expected Contributions

In this study, employing the Ebola outbreak as a natural experiment and with data from Kiva, we investigate the changes in borrowers’ and lenders’ behaviors on P2P lending platforms before and after a crisis. We find empirical evidence of increases in both demand and supply sides of P2P lending after the crisis outbreak. Specifically, on the demand side, the increase is due to higher loan amount. Even though there is a significant decline in the loan count, for those borrowers who still initiate their loans in the post-Ebola period, they need more financial capital for their businesses. On the supply side, the Ebola outbreak induced lenders to respond more actively, resulting in higher daily funding amounts for loans that were posted after the event.

Our study extends IS literature on online P2P lending by investigating the influences of “off-platform” shocks (e.g., the Ebola disease outbreak) on within-platform behaviors. This is particularly important because the primary purpose of online microfinance platforms is to alleviate poverty and increase social welfare. Disease crises and natural disasters have become one of the major causes of intensified poverty. Investigating how external crises alter borrowers’ and lenders’ behaviors facilitates a better understanding of the role and potential of P2P lending in reducing world poverty and addressing social problems. In addition, the prior online P2P lending literature has primarily focused on the impacts from within-platform factors, such as borrowers’ characteristics, on lending decisions. Our study suggests that offline factors play an important role in lenders’ decision making about which borrowers to support. Since microlending is mainly altruistically motivated, the “willingness to help” acts as a primary driver for lending behavior. Our results show that offline conditions (e.g., unexpected crisis, economic conditions) play a prominent role in influencing lending behaviors.

Practically, we offer implications for online P2P lending platform design. These platforms are encouraged to increase the exposure of certain loans whose borrowers are in urgent need (e.g., loans from the disaster-hit countries). Since prosocial lending is dominant on this platform, the high exposure of certain loans induces lenders to contribute more actively to those borrowers in need. This also facilitates them to better address the broader socio-economic problems and in turn to fulfill their mission more effectively.

Our on-going research extends the current work by pursuing several directions. First, our current focus is on the reactions of borrowers and lenders on the platform. The initial evidence prompts us to seek more evidence from multiple channels to understand the role of P2P lending platforms in crisis response from a broader perspective. Second, we find out that altruistic lending is prevalent on Kiva. That is, lenders’ contributions are mainly driven by their willingness to help those in need. Still, lenders’ motivations are mixed and they would react differently in the disease outbreak. In our future work, we intend to delve into the behaviors of different lenders to examine who played the key roles in crisis response. This will help us to understand the mechanism behind the role of P2P lending platforms. Third, we currently estimate the effects on the demand and supply sides separately. Given the simultaneity and interplay between the two sides of P2P lending platform, our future research will enrich our estimation approach by adopting systems of simultaneous equations and structural analysis (Porter 1983) to evaluate the effects together.

Acknowledgements

The authors would like to thank the two anonymous reviewers and the associate editor who provided helpful suggestions for improvement. In addition, they thank Sumit Agarwal and doctoral students in the departments of Information Systems, Finance, Marketing, Accounting, Strategy and Real Estate at the National University of Singapore for their valuable feedback on earlier version of this paper. They also thank Xinjiao Guan for research assistance at early stages of this work.
References


