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Online Prosocial Microlending Decision Making: A Natural Experiment of Ebola Outbreak

Research-in-Progress

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Abstract

In 2014, a devastating Ebola virus epidemic burst in West Africa, which tremendously impaired the economies in the affected areas. During this crisis, in addition to traditional donations, some new forms of prosocial behaviors, such as online prosocial microlending, were adopted to help people in and near the affected areas. In this study, we extend the spotlight and gradient model to investigate people's online prosocial microlending decision making after natural disasters, which is both financial (rational) and prosocial (irrational) in nature. By leveraging the Ebola outbreak in 2014, we design a natural experiment to compare lender's online prosocial microlending behavior before and after the disaster. We find that the average amount of online prosocial microlending in unaffected areas increases after the natural disaster and the increase is negatively related to the distance between the borrower and the affected areas.

Keywords: Prosocial, microlending, disaster

Introduction

In 2014, a devastating Ebola virus epidemic burst in West Africa, which resulted in more than 28,600 suspected cases and more than 11,300 confirmed deaths (CDC 2016). More than 21 million populations mainly in the three countries of West Africa (i.e., Guinea, Liberia and Sierra Leone) extremely suffered from the danger of being infected. Moreover, this Ebola outbreak tremendously impaired the economies in the affected areas. According to reports from World Bank, for the three West African countries which were particularly hard-hit by the crisis, over 2.7 billion dollars had been lost due to the outbreak of Ebola virus, which was nearly 20 percent of their combined GDP (World Bank 2015; World Bank 2016). In order to fight against Ebola and help victims in West Africa, people across the world had made around 1.5 billion dollars donation to the governments and people in the affected areas (FTS 2016). Meanwhile, in addition to traditional donations, the emergence of crowdfunding platforms provided alternative approaches for individuals to help others who may need money. On these platforms, users can supply microloans to borrowers in need without any interest and collateral, and help them plan and expand business activities (Moss et al. 2015), which is called online prosocial microlending.

Compared to traditional donation which is purely charitable, online prosocial microlending is both financial (rational) and prosocial (irrational) in nature (Galak et al. 2011). On the one hand, it is financial-oriented because the principals of microloans are returned to the lenders, and investment-like metrics must be provided for lenders to evaluate. On the other hand, it also has some prosocial elements because microloans provided on these platforms are free of interest and collateral. Moreover, different from donations, which can be made to any people in any amount, online prosocial microlending can only be offered when borrowers initiate microloans on crowdfunding platforms. However, the occurrence of natural disaster may greatly impede the development of local business activities, and diminish the number of microloans from the affected areas on these crowdfunding platforms (Markham 2014). Under such circumstances, although individuals' empathy is generated by the massive media reports of natural disaster, they may not be able to find appropriate microloans in the affected areas to support. Therefore, our first research question is: *after the outbreak of natural disaster, do individuals offer online prosocial microlending to people in the unaffected areas if they cannot find appropriate microloans from the affected areas?* By looking into this research question, we are able to gain a better understanding of the semi-rational decision making process in the dilemma after natural disaster.

Moreover, if natural disaster does increase the amount of online prosocial microlending given to people in the unaffected areas, we are further interested in whether lender's preferences to offer online prosocial microlending are the same for all unaffected areas. Thus, our second research question is: *after the outbreak of natural disaster, how do individuals decide to offer online prosocial microlending among the microloans from the unaffected areas?* To answer this question, the spotlight and gradient model indicates that, in addition to the attention paid to the focus, people may also pay marginal attention to the areas surrounding the focus (Eriksen and Hoffman 1972), and the marginal attention gradually decreases with the distance away from the focus (LaBerge and Brown 1989). In the example of Ebola outbreak, people probably paid most attention to the affected West African countries, followed by unaffected West African countries, and the least attention to the rest unaffected African countries. As people's attention decreases with the increase of distance between the borrower and the affected areas, they may prefer to offer online prosocial microlending to people who are closer to the affected areas.

In this study, we utilize an occurring field dataset from Kiva.org. Kiva is the largest crowdfunding platform for online prosocial microlending in the world, where the majority of borrowers are from impoverished lands including Africa, Asia, etc. Using the microlending data from Kiva, we design a natural experiment to investigate individuals' online prosocial microlending decision making by leveraging the Ebola outbreak in West Africa in August 2014, which has been deemed as the largest Ebola outbreak since the virus was discovered. We compare lenders' online prosocial microlending behavior before and after the Ebola outbreak to reveal how natural disaster influences this new form of prosocial behavior.

Literature Review

Natural Disasters and Prosocial Behavior

Extant literature has demonstrated that natural disasters will motivate people's prosocial behavior (Bendapudi et al. 1996). Specifically, natural disasters, as external and uncontrollable causes, generate people's perception of need in the affected areas. This perception of need can promote people's altruistic motivation for helping. Altruistic motivation has the ultimate goal of increasing others' welfare, even at the expense of one's own welfare (Martin 1994). With massive media portrayals about victims in the affected areas, the perception of need is likely to be concretized and engender empathy (Bendapudi et al. 1996; Marjanovic et al. 2012). Defined as "being aware of another person's internal states and putting oneself in the place of another to experience his or her feeling", empathy is deemed as an important motivation of people's prosocial behavior (Hoffman 1984).

Prosocial behavior in the aftermath of natural disasters is not distributed equally or randomly (Kaniasty and Norris 1995; Khandker 1998). Priority is given to victims that are most exposed to the destructive power of disasters. For instance, after Hurricane Hugo in 1989, Kaniasty and Norris (1995) conducted a large scale interview with 1000 disaster victims and nonvictims. They found that victims of disaster received more tangible and emotional support than nonvictims. Among victims, disaster exposure (i.e., measured as loss of life and property) was highly associated with the amount of help received. Similarly, after Wenchuan earthquake in 2008, the most affected people had the priority to receive tangible resources as well as social support (Hu et al. 2010).

Different from these situations where natural disasters actually increase the need in the affected areas, existing literature has found that disasters have inevitable negative impacts on economic activities, which in turn limits people's prosocial microlending choices (Benson and Clay 2004; Bowles et al. 2015). Specifically, economic activities such as investment, consumption, production and employment will be largely reduced in the short term after natural disasters (Benson and Clay 2004). For epidemics like Ebola, the impact on economic activities can be even more severe. The fear of contagion prevents people from associating with others, resulting in employment and labor force reduction and trade disruption (Bowles et al. 2015; World Bank 2015). As a result, the number of microloans initiated by small business entrepreneurs from the disaster affected areas may drop significantly, although lenders are probably highly motivated to help. This leads to an imbalance between microloan supply and demand in the prosocial microlending context.

Microlending Decisions

Prosocial microlending is both financial and prosocial in nature, initiated in brick-and-mortar institutions and popularized on online crowdfunding platforms (Galak et al. 2011). These platforms enable people to provide small, uncollateralized loans to individuals in need and encouraging entrepreneurial growth (Allison et al. 2015). Extant literature related to prosocial lending behavior mainly focus on the determinants of loan recipient selection (Baron and Szymanska 2011; Burtch et al. 2014; Galak et al. 2011). Baron and Szymanska (2011) summarize a number of these factors, including the notions of parochialism, identifiability, prominence, etc.

Parochialism indicates that individuals prefer to benefit in-group members rather than outsiders (Schwartz-Shea and Simmons 1991). Some prosocial microlending literature has provided empirical evidences of this phenomenon. For example, researchers have shown that lenders prefer culturally similar and geographically proximate borrowers on prosocial microlending platforms (Burtch et al. 2014). Besides the cultural and geographical distances, Galak et al. (2011)'s work has demonstrated that lenders favor borrowers that are socially proximate to themselves. Specifically, people tend to lend to borrowers who have same gender, occupation or initial of first name. Agrawal et al. (2011) reach a similar conclusion that lenders prefer recipients who have personal connections with them (e.g., family and friends). Finally, Freeman et al. (2009) report an existing bias that donors prefer recipients within the same ethnic group.

Identifiability refers to the fact that lender prefer loan recipients who are identified. For example, Charness and Gneezy (2008) reveal that in a dictator game (i.e., one player owns an amount of money and decide how to divide it to others who have none), subjects tend to give more to the recipient who is identified by the family name. On prosocial microlending platforms, scholars have found that lenders prefer a single identifiable borrower, rather than a group of recipients, even though loans to groups have higher repayment rates historically (Galak et al. 2011). The authors argue that this may be due to the identifiable victim effect. That is, a single identifiable borrower tends to evoke a higher level of emotional response than unidentifiable borrower groups, thus attracting more lenders (Galak et al. 2011).

Prominence refers to the fact that lenders tend to pay attention to prominent attributes that they view as the most important. Previous literature underscores the important attributes embedded in loan narratives that affect people's lending decisions (Allison et al. 2015; Allison et al. 2013). For example, extant research has indicated that lenders respond more positively to narratives that highlight intrinsic cues (i.e., opportunities to help others), compared to those underscoring extrinsic cues (i.e., opportunities to earn money) (Allison et al. 2015). Similarly, lenders are revealed to react faster to narratives that indicate blame and concern than those highlighting tenacity, accomplishment and variety (Allison et al. 2013). Taken together, these studies have an assumption that lenders' preferential loans are always available. They neglect the potential imbalance of microloan supply and demand which can be caused by natural disasters.

Theoretical Background and Hypothesis Development

The Spotlight and Gradient Model

Attention is a cognitive selection process for allocating limited processing capacity (Anderson 1990). In attention research, individuals' attention is considered to operate in two stages. At the first stage, attention is distributed uniformly over a field. Second, when a cue appears in the field, it directs subjects' attention to that specific area selectively (Jonides 1980; Posner 1980). Many studies attempt to explain the distribution of attention in the second stage. Among them, one prominent model is the spotlight model. Inspired by James (1890)'s work, the spotlight model describes attention as having a focus, a fringe and a margin. The focus receives the most attentional resources, which is analogue to the center illuminated by a spotlight. Information processed here is with a high resolution. Surrounding the focus is the fringe receiving marginal attention. Information processed in this residual field is with a low resolution. The margin is the cut-off of a specific area the fringe extends out to (James 1890; Styles 2005).

Following the spotlight model, the gradient model mainly refines the attention distribution in the fringe area (LaBerge and Brown 1989). The gradient model proposes that attentional resources are allocated in a gradient fashion. Specifically, due to limited attention capacity, attentional resources are most concentrated in the center of the focus, and then decrease gradually with the distance away from the focus center (LaBerge and Brown 1989). Although both models are primarily used to explain people's attention in a visual field, they may be still applicable in the current setting as the Ebola outbreak serves as a cue to attract and distribute lenders' attention.

Prosocial Microlending Decisions after Natural Disasters

We investigate lenders' prosocial microlending decisions after natural disasters from both prosocial and financial aspects. From the prosocial perspective, natural disasters, as external and uncontrollable causes, can engender people's empathy and motivate their prosocial behavior (Bendapudi et al. 1996). Previous scholars have indicated that higher levels of empathy are strongly associated with more generous monetary offers to strangers (Barraza and Zak 2009). When a natural disaster occurs, it probably generates higher levels of empathy than usual for lenders, making them more generous in prosocial microlending. However, as aforementioned, lenders may confront the imbalance between microloan supply and demand after the natural disaster. It is interesting to find out the loan recipients of lenders' generous offers.

After a natural disaster occurs, tremendous media reports can raise public awareness and attention. The disaster serves as an external cue, directing people's attention to the affected region. As suggested in the spotlight model, people probably concentrate their attention in the affected region, and pay marginal attention to the surrounding areas (Styles 2005). When the preferential loans in the affected region are unavailable, this marginal attention is likely to make loans in the surrounding areas more identifiable, which can easily trigger lenders' availability heuristic to make decisions (Galak et al. 2011). Availability heuristic refers to a mental shortcut using immediate examples to make decisions (Tversky and Kahneman 1973). In our context, when there are few loans in the affected region, the loans in the surrounding areas will serve as immediate alternatives for lender to fund. Furthermore, according to the gradient model, people's attention around the disaster affected areas may distribute in a gradient fashion (LaBerge and Brown 1989). The model suggests that lenders probably pay more marginal attention to the nearer areas of the affected region than to the farther areas. As a result, microloans in the nearer areas tend to be more identifiable and are more likely to serve as immediate alternatives when lenders confront the imbalance.

From the financial aspect, lending to borrowers in the surrounding areas also has financial benefits. Compared to the loans in the disaster affected region, those in the surrounding areas are more financially secure. Without the negative impact of the natural disaster, borrowers in the surrounding areas can make good use of microloans to plan and develop their businesses. At the end of the loan term, they are more capable to return the principals compared to those in the disaster affected region. Taken these two aspects together, we hypothesize:

H1*: After natural disasters, the average amount of online prosocial microlending given to people near the affected areas increases.*

H2*: After natural disasters, the increase of the average amount of online prosocial microlending given to people surrounding the affected areas is negatively related to the distance between the borrower and the affected areas.*

Method

Research Context

Ebola outbreak: The Ebola outbreak in 2014 has been deemed as the most server and complex outbreak in the recorded history. It has caused more than 11,300 lives lost in the West African countries, including Guinea, Liberia and Sierra Leone (United Nations 2016). Since August 2014, the Ebola cases in these three countries increased exponentially. On August 8th, 2014, the International Health Regulations formally declared the Ebola outbreak in West Africa a Public Health Emergency of International Concern (PHEIC). Since then, the outbreak received much media coverage and public attention.

Kiva.org: We utilize a naturally occurring field dataset of Kiva.org to test our hypotheses. Kiva is the world's largest crowdfunding platform for online prosocial microlending. As of Apr 28th, 2016, Kiva has funded more than $842 million to nearly 2 million individuals in need (Kiva.org 2016). The loan recipients are mainly from impoverished lands including Africa, Asia and South America, while lenders are from all over the world.

As an intermediary for facilitating prosocial microlending, Kiva posts solicitations for microloans from individuals in need, which then are funded by lenders. Solicitations are in the form of loan recipient profile, which includes recipient personal information (e.g., name, location, photos, etc.) and loan information (e.g., loan amount, loan repayment term, loan purpose, etc.). Kiva also releases information about the field partner that initially sources the microloan and then manages it (e.g., field partner's name, default rate of all microloans managed by this partner). All loans on Kiva are listed randomly, which ensures our results are not driven by the website features.

As a lender, she primarily has two decisions to make. First, after browsing available loan requests, the lender decides which loan to fund. Notably, as Kiva lists borrower's location that includes country and region information, lenders can easily judge whether the microloan is from the Ebola unaffected countries. Second, the lender determines the lending amount in $25 increments. Neither Kiva nor lenders receive interests from borrowers. Instead, the field partners may charge some interests to cover the operation cost.

Data and Model Specification

The Kiva data set contains information of both lender side and recipient side at a loan level. The dataset covers all lending activities on Kiva from January 2014 to December 2014. We use August 8th, 2014 as the Ebola outbreak time point.

Among the three affected countries, Kiva only enters Liberia and Sierra Leone. Figure 1 depicts the number of microloans in these two affected countries. As we can see, the number of microloans drops dramatically after the Ebola outbreak as expected.

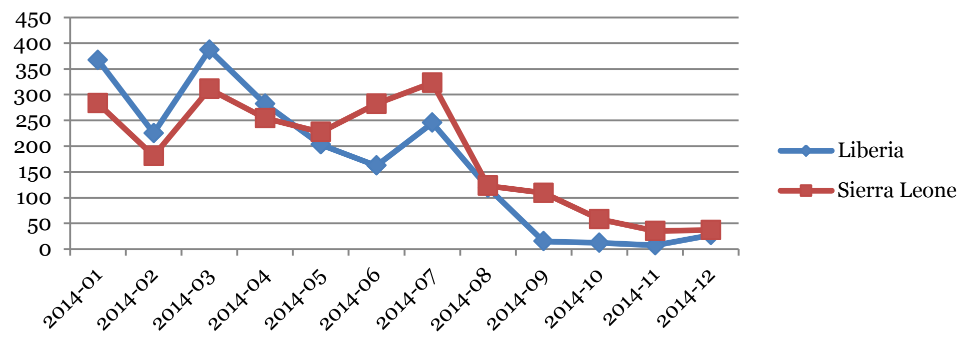

Figure 1. Number of Microloans in the Ebola Affected Countries

To test the two hypotheses, we construct two sets of treatment and control groups which have different distances between the borrower and the affected region. In the first set, we use microloans in the unaffected West African countries (i.e., Ghana, Nigeria, Togo, Mali and Senegal in the Kiva data) as the treatment group and those in the rest African countries (e.g., East Africa) as the control group. We select East African countries (i.e., Kenya, Uganda, Tanzania, Rwanda and Somalia in the Kiva data) because Kiva provides richer information of microloans in East Africa countries compared to those in the rest African countries. In the second set, we use microloans in East African countries as the treatment group and those in the other countries around the world (e.g., Asian countries) as the control group. With a similar reason, we choose microloans in the Asian countries (i.e., Cambodia, Tajikistan, Pakistan and Vietnam in the Kiva data) to construct the control group. We compare lenders' prosocial microlending behavior to these treatment and control groups before and after the Ebola outbreak. The difference-in-differences (DID) analysis adequately serves this purpose.

DID estimator (Φ) identifies the average treatment effect on the dependent variable. It compares the average change in the outcome before and after treatment for the treatment group ($\bar{y}_2^{tr} - \bar{y}_1^{tr}$), compared to the average change for the control group ($\bar{y}_2^{nt} - \bar{y}_1^{nt}$) (Cameron and Trivedi 2005). Hence, the estimator $\hat{\phi} = (\bar{y}_2^{tr} - \bar{y}_1^{tr}) - (\bar{y}_2^{nt} - \bar{y}_1^{nt})$. To implement DID analysis, we run a regression in the form

$$Lending\_amt_{i,t} = \beta 0 + \beta_1 * PostEbola_t + \beta_2 * Treatment_i + \beta_3 * PostEbola_t * Treatment_i + ControlVar_{i,t} + \varepsilon_{i,t}$$

where our interested outcome variable is the average lending amount to investigate whether people would lend more to borrowers near the Ebola affected region. It is operationalized as the average amount each lender funds a focal microloan. $PostEbola_t$ is a dummy variable which equals to 1 when t is after Ebola outbreak (i.e., Aug 2014), 0 otherwise. $Treatment_i$ is a dummy variable which equals to 1 when the loan i is in the treatment group, 0 otherwise. The coefficient β_3 is the difference-in-differences estimator which reveals the treatment effect (i.e., borrowers from countries surrounding the Ebola affected region) on lenders' average lending amount.

We also add control variables which may influence the outcome variable (Burtch et al. 2014; Galak et al. 2011). Specifically, we include whether the loan is raised by a group of borrowers[1], whether the loan is disbursed by field partners before it is posted on Kiva[2], the length of loan description and repayment

[1] Loans to groups have historically higher repayment rate (Galak et al. 2011).

[2] By doing this, the field partners assume the risk that if the loan is not funded by Kiva lenders, then they themselves have to fund the loan. It may give lenders a signal that the loan is at low risk of not repaying.

schedule (i.e., regularly or irregularly). In addition, we also introduce month dummies to control for the time effect. Table 1 presents the descriptive statistics.

Table 1. Descriptive Statistics

	Unaffected West Africa					East Africa				
	Obs	Mean	Std. Dev	Min	Max	Obs	Mean	Std. Dev	Min	Max
Loan amount	8559	821.96	1113.83	25	49250	23071	714.15	1022.50	25	50000
Lender count	8559	23.26	31.56	1	1297	23071	21.26	30.34	1	1581
Avg lending amt	8559	52.16	139.45	0	4200	23071	40.95	65.04	0	3675
	Asia									
Loan amount	18160	777.86	639.84	25	20000					
Lender count	18160	24.32	20.13	1	472					
Avg lending amt	18160	38.35	56.00	0	2050					

Preliminary Results

Unaffected West Africa vs. East Africa

In a DID analysis, the identification of causality hinges on a common trend assumption before the event. Figure 2 depicts the trend of average lending amount before and after the Ebola outbreak. As we can see from Figure 2, before the Ebola outbreak, lenders' average lending amount between treatment and control groups are almost common.

Before performing DID analysis, we use t-test to check whether there is a significant change in the loan amount in both groups. The results show that there is no such change after the Ebola outbreak (i.e., t(treatment)=0.198 and t(control)=0.634). The DID results are reported in Table 2.

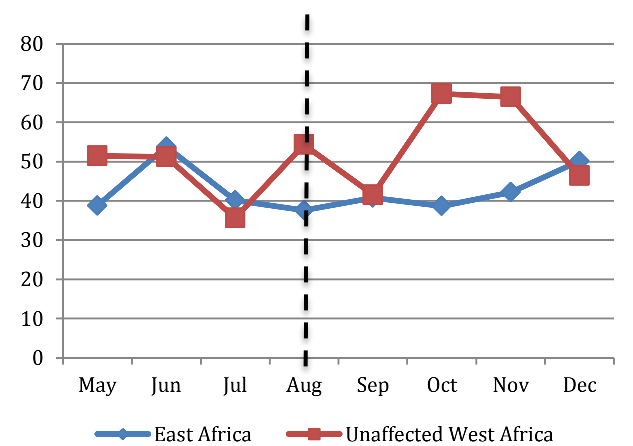

Figure 2. Trend of Average Lending Amount (Unaffected West Africa vs. East Africa)

Table 2. DID Results: WA vs. EA

Variable	Avg_lending_amt	Avg_lending_amt
Treatment	-3.023 (2.189)	-2.689 (2.315)
Post_Ebola	1.077 (0.861)	3.088** (1.478)
Treatment* Post_Ebola	**11.130*** (3.413)**	**10.470*** (3.521)**
Group Loan	25.229*** (2.283)	25.003*** (2.287)
Disbursed Before	8.991*** (1.138)	9.510*** (1.230)
Description Length	0.000337 (0.00110)	0.000168 (0.00111)
Irregular Repayment	-2.692*** (0.948)	-2.889*** (0.959)
Month Dummies		Yes
Constant	29.28*** (1.569)	26.90*** (1.726)
Obs	31630	31630
R-Squared	0.015	0.017
Robust standard errors in parentheses ***p<0.01, **p<0.05		

As can be seen in Table 2, the interaction term in the DID result is significant. It indicates that after the Ebola outbreak, lenders tend to lend $10.47 more to borrowers in the unaffected West African countries compared to those in the East African countries.

East Africa vs. Asia

Similarly, the trends of average lending amount between the treatment (i.e., loans in East Africa) and control (i.e., loans in Asia) groups are almost common as shown in Figure 3. The t-test shows there is no significant change in the loan amount (i.e., t(treatment)=0.634 and t(control)=0.144). The DID results are presented in Table 3.

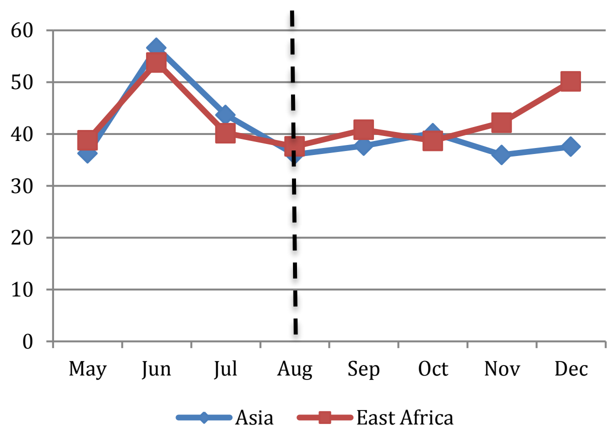

Figure 3. Trend of Average Lending Amount (East Africa vs. Asia)

Table 3. DID Results: EA vs. Asia

Variable	Avg_lending_amt	Avg_lending_amt
Treatment	1.636 (1.017)	1.387 (1.019)
Post_Ebola	-1.531* (0.805)	4.597*** (1.345)
Treatment* Post_Ebola	**3.403*** (1.184)**	**3.597*** (1.194)**
Group Loan	4.192*** (1.227)	3.572*** (1.202)
Disbursed Before	3.739*** (1.116)	3.157*** (1.115)
Description Length	-0.00107 (0.000933)	-0.00118 (0.000940)
Irregular Repayment	-3.169*** (0.580)	-3.415*** (0.595)
Month Dummies		Yes
Constant	35.80*** (1.537)	35.27*** (1.580)
Obs	41,231	41,231
R-Squared	0.002	0.009
Robust standard errors in parentheses ***p<0.01, **p<0.05		

As shown in Table 3, the estimation indicates that after the Ebola outbreak, lenders tend to lend $3.60 more to borrowers in the East African countries than those in the rest part around the world. Notably, the magnitude (i.e., $3.60) is smaller than that in the previous DID analysis (i.e., $10.47).

To check the robustness of our results, we incorporate the geographic distance between loan's location and the center of Ebola affected region into the regression. It allows us to gain a better understanding about the effect over distance. The model specification is as follows.

$$Lending\_amt_{i,t} = \beta 0 + \beta_1 * PostEbola_t + \beta_2 * Distance_i + \beta_3 * PostEbola_t * Distance_i + ControlVar_{i,t} + \varepsilon_{i,t}$$

We calculate $Distance_i$ (in 1000 miles) between two locations specified by latitude and longitude. Kiva provides each borrower's longitude and latitude information. We determine the coordinates of the Ebola outbreak center through averaging the longitudes and latitudes of the three countries (i.e., (11N, 10W) for Guinea; (8.5N, 11.5W) for Sierra Leone; (6.5N, 9.5W) for Liberia). Hence, (8.7N, 10.3W) is used to represent the center of Ebola outbreak region.

The results show that in general, after the Ebola outbreak, people tend to lend more (β_1 = 7.78***). However, this effect is mitigated with the increase of the distance between the borrower and the affected region (β_3 = -0.79***). It indicates that when a borrower is 1000 miles farther from the Ebola outbreak center, lenders lend $0.79 less in average after the outbreak. Hence, our two hypotheses are supported.

Conclusion and Future Plan

In this study, we investigate a new form of prosocial behavior, i.e., online prosocial microlending. Specifically, we look into online lenders' prosocial microlending decisions when they confront the imbalance of microloan supply and demand caused by the Ebola outbreak. By employing DID analyses, our preliminary results show that after the Ebola outbreak, lenders tend to lend more to borrowers from the countries surrounding the affected region. This effect is stronger in the nearer unaffected West African countries than in the rest African countries, following a gradient distribution.

This study has the potential to make both theoretical and practical implications. Theoretically, first, we enrich the literature of online prosocial microlending through investigating lenders' decisions when confronted with the imbalance. Second, we apply and extend attention theory to the online prosocial microlending context. Our results show lenders' attentional resources and lending resources after disasters are unequally distributed around the affected region as predicted in the spotlight and gradient models. Our research suggests the spotlight and gradient model is still applicable to spatial attention triggered by external events such as natural disasters. Practically, this study reveals the bright side of natural disasters for people near the affected region. Our findings suggest after disasters, people near the affected countries will receive more lending amount for expanding businesses. In addition, our research also provides insights for policy makers to allocate resources efficiently in the aftermath of disasters.

In the future complete paper, we will include more analyses to show the robustness of our findings. Currently, we only include 12-month data. In the full paper, we will extend the time span and investigate the effect over time. We may investigate another disaster and analyze lenders' prosocial microlending behavior to check whether the results are consistent with the current ones.

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