Discovering Trends in an Online Microfinance Platform: A Statistical Analysis on Kiva.org

SM-4290: Research Project

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1. Abstract

Microfinance, microloans, microcredit, are all renowned buzzwords in discussions involving tools to fight poverty. Kiva.org, is currently one of the leading peer-to-peer lending online marketplace that advocates for poverty alleviation through microfinance. This study aims to extract meaningful insights on microloans made within Kiva by examining a number of variables related to Kiva borrowers and their respective loans such as their loan amount, gender, poverty index etc. All analyses were carried out using the R Statistical Software employing a number of non-parametric tests and two regression methods. Results of this study have found that the loan amount on Kiva is influenced by certain activity sectors, world region and the global MPI and that the subsequent loan status is influenced by the loan size.

2. Introduction

2.1 Background

Microfinance in History

Microfinance, as a type of financial service simultaneously revolves around the idea of microcredit or microloan and as their names suggests, it provides loans in small amounts to the underprivileged who are unable to access conventional banking and financial services. This fact was further recognized early in the 1980's by a recipient of the 2006 Nobel Peace Prize, Muhammad Yunus, where he founded the Grameen Bank in Bangladesh, renowned for its microfinance-oriented organisation. Muhammad Yunus believes that small amounts are able to inspire one to step out of poverty in addition to survive in life, once he said: "These millions of small people with their millions of small pursuits can add up to create the biggest development wonder" (Grameen Bank, 2021).

Ever since, microfinance has been a frequent topic argued when it comes to exploring tools for poverty alleviation. This subject had heads turned and not until 1997, the first ever *Microcredit Summit* was held in Washington, DC. In 2000, the *Millennium Development Goals (MDG)* was established, and Goal 1 was to eradicate extreme poverty and hunger by 2015. Fast forward to 2005, the United Nations made a proclamation that 2005 was the International Year of Microcredit in response to the MDG 1.

Then in 2015, when the United Nations first introduced the 2030 *Sust*ainable Development Goals (SDG); again, Goal 1 was designated for poverty reduction. With that, it is expected that by 2030, every individual will have equal access to basic and economic resources including microfinance (Goal 1: No Poverty, 2021).

Kiva.org: An Online Microfinance Platform

Kiva is a non-profit organization based in San Francisco which acts as a platform for peer-to-peer lending through a microfinance approach. Founded in 2005, Kiva have acknowledged that there are 1.7 billion people who do not have access to financial services and with that they aim to cater to these underserved communities by means of connecting borrowers and lenders from across the globe through selected field partners i.e., microfinance institutions (MFI). This online lending system of Kiva allows lenders to browse through a massive post of borrowers' profiles and loan descriptions which then may help them decide to invest in increments of $25. The MFIs are responsible to reach out to the poor communities within the locality in which they operate, to screen borrowers in order to be eligible to request loans through Kiva and post the borrower's profile on Kiva's website. Accordingly, loans funded on Kiva has enabled borrowers to either start businesses, invest in production or manufacturing equipment or some others can finally afford emergency healthcare (Kiva, 2021).

2.1 Study Objectives

Statement of Purpose

The purpose of this study was to gain meaningful insights of the underlying factors in relation to the microloans made within Kiva. Variables such as gender, world regions, loan use and the poverty indexes were mainly explored to answer the proposed research questions.

Hypotheses

(1) MPI (Multidimensional Poverty Index) of a country does not influence the size of loan.
(2) Loan usage sectors and world regions are independent.
(3) There is no difference in loan size between each loan usage sector in different world regions.
(4) Loans made by males and loans made by females are of the same size.
(5) The borrower's gender, loan use sector, country of origin, loan size and repayment interval are not significant contributing factors as to whether a particular loan was completely funded or otherwise.

3. Literature Review

There are definitely many reasons behind lender's decision on their investment through Kiva or generally microlending, so a number of studies on Kiva have investigated lending motivations and behaviors. A research conducted by Dorfleitner and Oswald (2016) approved the gender effect and that female individual borrowers have lower credit risk compared to male borrowers. In that sense, it is plausible to say that lenders should more likely invest on female borrowers. To engage with potential lenders, MFIs tend to post more female borrower's profiles and descriptions more than male borrowers. In addition to the lower credit risk criteria, the tendency of most MFIs to focus on women borrowers is due to the gender issues that women usually encounter at home or in any other circumstances (Balkenhol, 2007).

Loan requests posted through Kiva originates from different regions of the world especially from developing countries. Borrowers from countries that are of higher GDP per capita along with a favourable rate of agricultural production, have a lower probability of default. (Dorfleitner & Oswald, 2016). As aforementioned, loans with this attribute attracts potential lenders, which means that borrowers from poorer regions are unlikely to be chosen by lenders since the study found that these regions have a higher credit risk. This is further supported by the same study which observed the negative coefficient of the logarithm of GDP (per capita) upon fitting a probit model on individual loans and their entire data set.

Loan requests from borrowers who resides in the Sub-Saharan Africa approximately have shorter fundraising duration i.e., between the time loans were posted on Kiva's website until they were fully funded, compared to any other world regions (Heller & Badding, 2012). This may suggest that more lenders contribute to loans from the Sub-Saharan Africa, indicating that lenders are more captivated with loan requests from this region. Heller and Badding (2012) also believe that loan sectors are important predictors of lending decision and that they found that loans under education and healthcare have faster funding rates than for agricultural purposes.

4. Methodology

4.1 Data Collection

The data set, in the form of snapshots were obtained from Kiva's website where it was made available for researchers to conduct any relevant studies in accordance with Kiva's key mission to help fight poverty through microfinance. Kiva defined a term "Permitted Purpose" under their Term of Service for non-commercial occasions and that includes analyses of lending data to investigate trends (Kiva, 2013).

All files – in comma-separated values (csv) format, were downloaded directly from Kiva's website in July 2020. However, only one main file from Kiva was used throughout this study which contains all relevant information that sufficiently captures Kiva's microfinance activities. In addition to that, two other external data; on the Global Multidimensional Poverty Index (MPI) was employed and this was obtained in February 2021 directly from the United Nations Development Programme's website and the classification of developing countries into world developing regions as defined by the United Nations. Further details are discussed in the following sub-section.

4.2 Data and Variables Description

Initially, the cluttered Kiva data set is considerably large that is worth 3 gigabytes thus for efficient computation purposes, the Kiva data set was randomly sampled to a much smaller size, to only 1000 observations while retaining all variables such that it represents the original data set well. Observations were identified as loans made between the year 2006 and 2020. For the purpose of this study, only selected variables were used in the analyses as defined in *Table 1.*

Table 1: Description of variables from Kiva data set.

Variables	Description
Loan Amount (USD)	The amount disbursed by the field partners to the borrowers.
Status	A dummy variable for the loan status at the end of the funding period: funded, expired, fundraising or refunded
Sector Name	The sector in which the loans were used in: Agriculture, Arts, Clothing, Construction, Education, Food, Health, Housing, Manufacturing, Personal Use, Retail, Services, Transportation and Wholesale.
Borrower's Gender	A dummy variable for a female borrower, a male borrower, a group of male, a group of female or a mixed group of borrowers.
Repayment Interval	A dummy variable for monthly, irregular or bullet repayment.
Region	A new variable created to classify the countries according to their respective developing world regions.
MPI	The Global Multidimensional Poverty Index which measures the poverty level of a particular country.

Two new additional variables were created within the data set as mentioned – Region and the Multidimensional Poverty Index (MPI). To reduce complexity, the country names in which the loan was disbursed in i.e., the borrower's country of origin, were further classified into five developing world regions – Arab States, East Asia and the Pacific, Europe and Central Asia, Latin America and the Caribbean, South Asia and, Sub-Saharan Africa. However, this did not include the United States in any of the stated regions, hence it remained as it is.

The global Multidimensional Poverty Index (MPI) was launched by the Oxford Poverty and Human Development Initiative along with the Human Development Report Office of the United Nations Development Programme. The MPI measures complications of lives of the deprived according to 3 dimensions – health, education and standard of living. This index takes a minimum value of 0 and maximum of 1 where higher poverty is indicated by higher index. The way that these MPI's are calculated is by multiplying the proportion of poor people in a particular country and the average deprivation score – the sum of weights of 10 defined indicator of the deprived (The 2020 Global Multidimensional Poverty Index (MPI) | Human Development Reports, 2020)

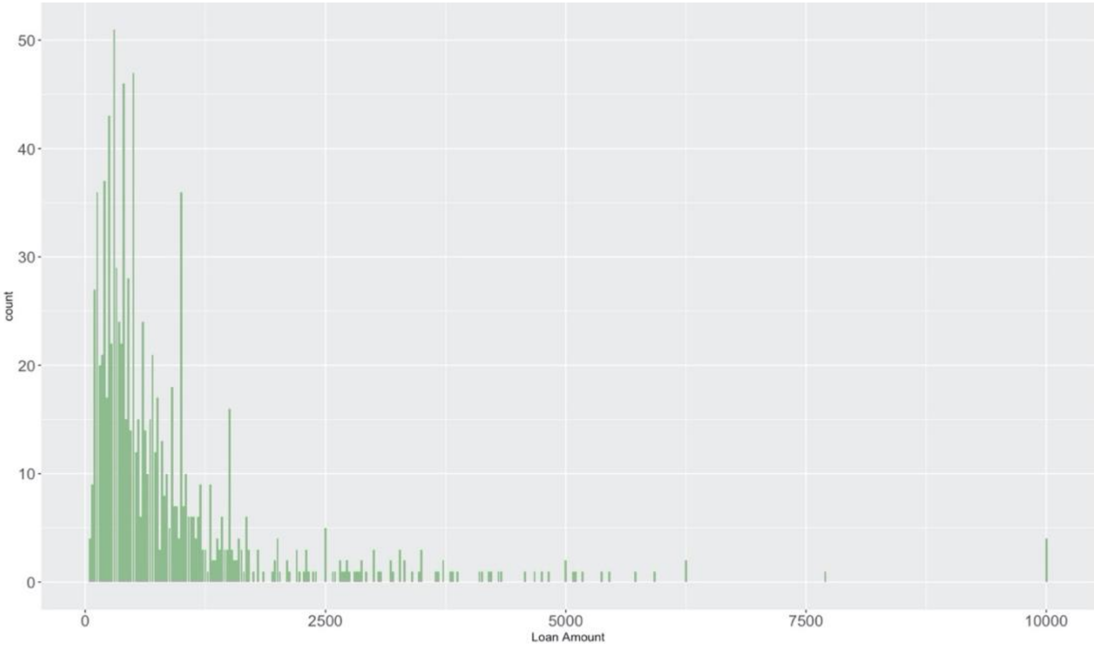
Another key covariate – borrower's gender was also classified such that the gender of borrowers was renamed as *Female* instead. This takes the value 1 (denoted as True) if the borrower is a female, a group of all females or a mixed group i.e., a group with at least 1 female, otherwise i.e., a male or a group of all males, 0 (denoted as False). For the purpose of analyses in this study, the MPI values were leveled into 2 groups with a cut-off point at the 3rd quartile which was found to be 0.18. Status of loans were also analysed on two levels – loans that were completely funded and expired loans only.

4.3 Statistical Procedures

Analyses were conducted using the R statistical software by applying appropriate statistical tests and techniques to answer the respective research questions. Non-parametric tests were mainly used in the analyses which includes the *Kruskal-Wallis Rank Sum Test, Wilcoxon Rank Sum Test* and the *Chi Square Test of Independence* whilst multivariate regression analyses were conducted using a logistic and an Ordinary Least Square method. For all analyses, the level of statistical significance was set at 5% with 95% Confidence intervals (C.I.) reported where appropriate.

4.4 Descriptive Statistics

Figure 1 Distribution of Loan Amount



The highlight of this study is the loan amount in which the minimum amount made was USD50 and a maximum of USD10,000 (mean = USD869.6; standard deviation = USD1109.14). On the other hand, the corresponding amount funded ranges from USD0 to USD10,000 (mean = 819.72; standard deviation = USD1007.73). As can be seen from *Figure 1*, the distribution of loan amount is highly skewed to the left.

The Multidimensional Poverty Index (MPI) of countries observed in Kiva ranges from as low as 0.001 to as high as 0.580 (mean = 0.11; standard deviation = 0.11). As other covariates are categorical, a summary of their respective proportions and their descriptive measures of the loan amount is shown in *Table 2*. The top 3 most common activity sectors for loans made through Kiva are agriculture, food and retail with more than half of Kiva borrowers are females. It can be seen from the same table, only one loan was made for wholesale activity, thus, this observation was incorporated into retail for simplicity. Majority of these borrowers resides in either East Asia and the Pacific, Sub-Saharan Africa or Latin America and the Caribbean.

Table 2: Proportions of loans out of 1000 and respective descriptive measures of Loan Amount (USD) grouped by MPI, Loan Status, Loan Sector, Country, Gender and World Region. SD: Standard Deviation.

Variables	Proportion, n (%)		Mean	Median	SD
MPI					
≤ 0.18	739	(79.8%)	751	475	872

> 0.18	187	(20.2%)	900	525	1071
Status					
Funded	949	(94.9%)	831	500	1024
Expired	39	(3.9%)	1697	1000	2191
Refunded	5	(0.5%)	860	550	733
Fundraising	7	(0.7%)	1446	700	1789
Sector Name					
Agriculture	254	(25.4%)	777	500	783
Arts	19	(1.9%)	826	450	929
Clothing	53	(5.3%)	1084	825	1017
Construction	12	(1.2%)	562	562	302
Education	35	(3.5%)	904	700	844
Food	210	(21%)	928	500	1282
Health	14	(1.4%)	986	550	990
Housing	44	(4.4%)	674	525	527
Manufacturing	12	(1.2%)	802	450	879
Personal Use	35	(3.5%)	451	200	540
Retail	208	(20.8%)	853	450	1277
Services	74	(7.4%)	1318	650	1706
Transportation	29	(2.9%)	728	600	617
Wholesale	1	(0.1%)	-	-	-
Borrower's Gender					
Male	201	(20.6%)	922	650	1147
Female	616	(63.1%)	580	400	742
All male group	3	(0.3%)	1742	1300	1901
All female group	95	(9.7%)	1739	1300	1368
Mixed group	62	(6.4%)	2041	1388	1793
Repayment Interval					
Monthly	857	(85.7%)	851	500	1144
Irregular	51	(5.1%)	1205	925	895
Bullet	92	(9.2%)	853	638	835
Region					
Arab States	49	(4.9%)	1226	1050	629
East Asia and the Pacific	320	(32.0%)	503	350	489
Europe and Central Asia	64	(6.4%)	1052	725	836
Latin America and the Carribbean	248	(24.8%)	1144	750	1193
Sub-Saharan Africa	266	(26.6%)	521	400	397
South Asia	41	(4.1%)	785	450	973
United States	12	(1.2%)	5612	5050	3491

5. Results

5.1 Non-Parametric Tests

Upon performing several exploratory data analyses, the loan amount was found to be skewed as described in the previous subsection such that the *Shapiro-Wilk Test of Normality* rejects the hypothesis which states that the loan amount is normally distributed. This leads to the use of non-parametric statistical tests to answer the above-stated hypotheses (2), (3) and (4).

Sectors and world regions association

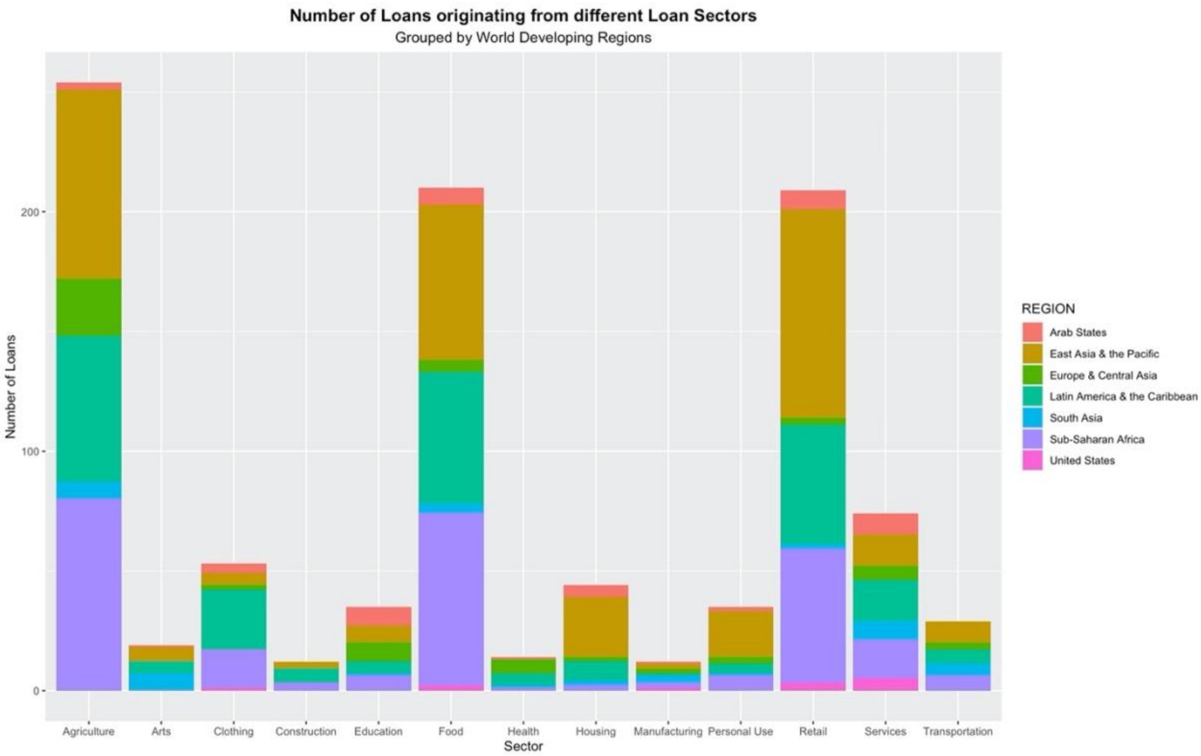


Figure 2 Number of loans from different sectors by regions

As above-mentioned, there are 13 unique activity sectors in which the loans on Kiva were being deployed, across 6 different developing regions and the United States. *Figure 2* visualizes the number of loans made within each activity sector across different world regions which immediately exhibit an obvious pattern of 3 most common sectors that originates mostly from three world regions. It was hypothesized (2) that there are no association between activity sectors and the world region where the loans were being used i.e., borrower's origin. The *Chi-Square Test of Independence* then revealed that the p-value is fairly low, so the null hypothesis is rejected such that there is evidence that sectors and regions are associated, and the strength of association was found to be only 0.23 (0.23-0.30).

Loan sizes in distinct activity sectors and in world regions

Figure 3 and *Figure 4* displays the distribution of loan amount in different activity sectors and different world regions respectively. Hence, to investigate as to whether there is any effect of activity sectors and world region on the size of loans made in Kiva (3), loan amounts in different activity sectors were first analyzed using *Kruskal-Wallis Rank Sum Test*. This test rejects the null hypothesis – the distribution or the median of loan amount is no different in every sector, as the p-value was found to be less than 0.05. This indicates that there is evidence that activity sectors do have a significant effect on the loan size. Likewise, loan amounts from different world regions were also analyzed which also rejects the hypothesis but with a much lower p-value, indicating that the distribution or the median of loan amount is not the same in different world regions.

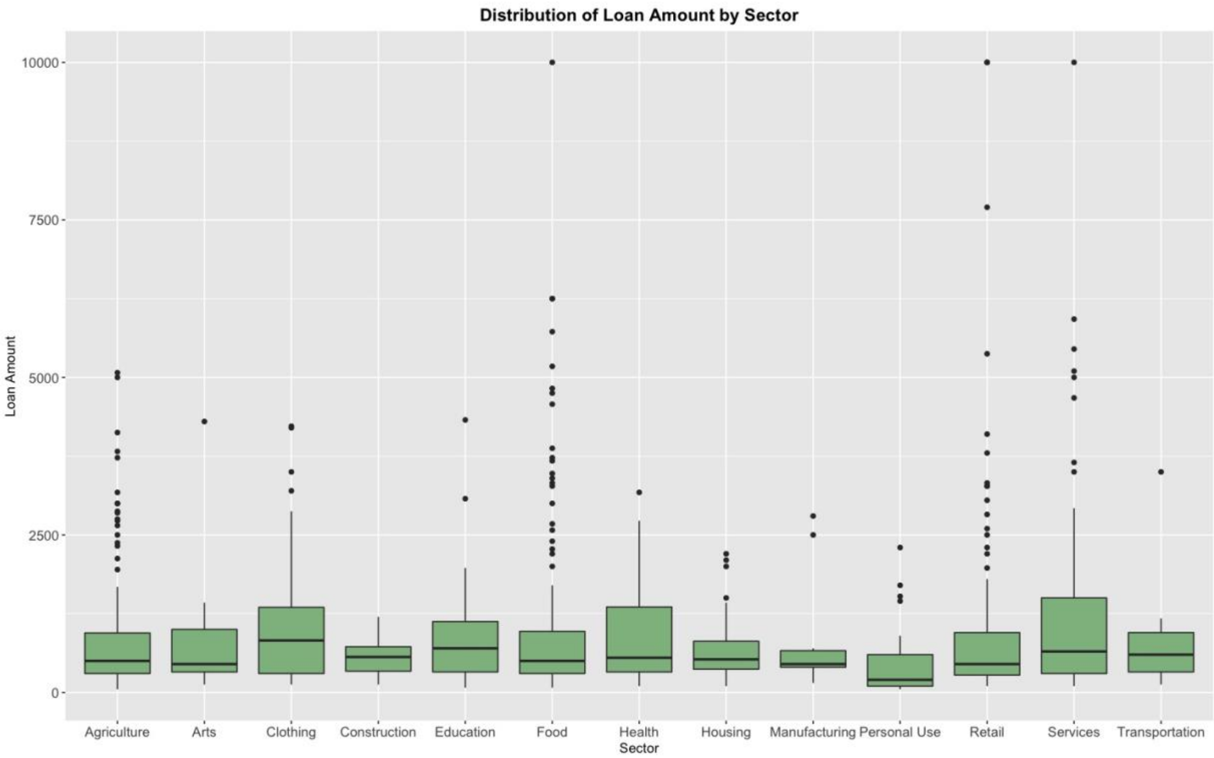


Figure 3 Distribution of Loan Amount in Different Sectors

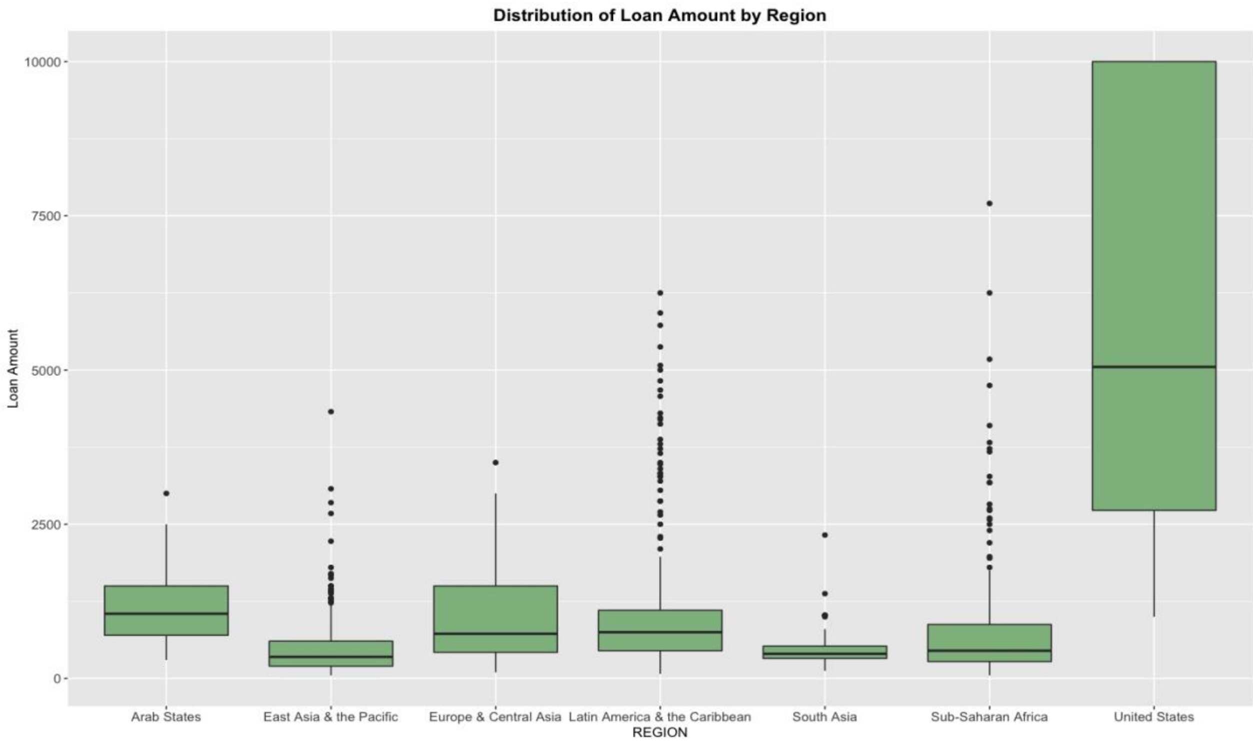


Figure 4 Distribution of Loan Amount in Different World Regions

Loan size comparison between borrower's gender

In the gender context, loan amounts between borrower's gender were also studied to inspect any significant difference in loan amount between female borrowers – that includes groups of at least one

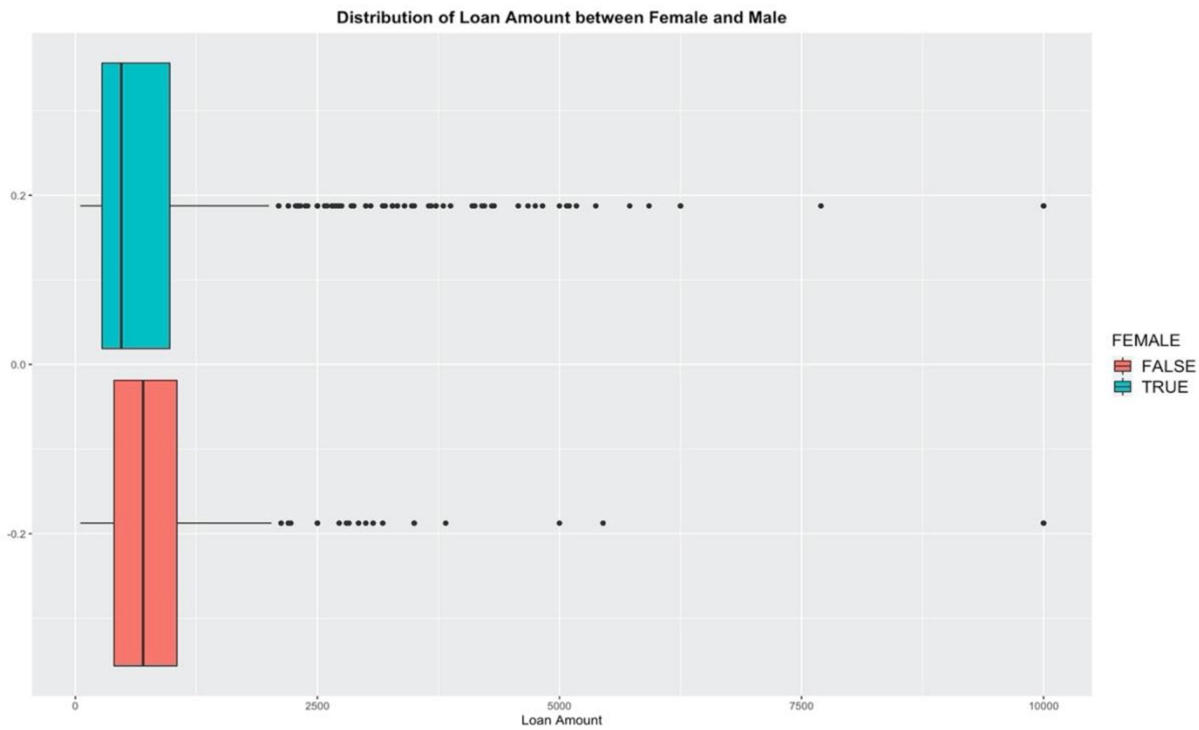


Figure 5 Distribution of Loan Amount by Gender

female, and male borrowers (4). *Figure 5* shows the distribution of loan amounts by gender. The *Wilcoxon Rank Sum Test* leads to the rejection of the hypothesis that the distribution or median of loan amount is no different between males and females as the p-value is relatively low. This suggests that there is evidence that females' loans are indeed different from loans made by males.

5.2 Multivariate Regressions

To evaluate how the explanatory variables i.e., the loan attributes affect the resulting loan status (5), a logistic regression was employed.

$$\text{logit}(P_i) = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \beta_5X_5 + \beta_6X_1X_2 + \beta_7X_1X_3 + \beta_8X_1X_4 + \beta_9X_1X_5 + \varepsilon;$$

where, X_i 's ($i = 1, 2, 3, 4, 5$) represents the explanatory variables i.e., gender of borrowers, loan sectors, world region, loan amount and the repayment interval respectively. ε is the residual. Interactions were allowed initially between borrower's gender (*Female*) and all the other variables as defined. The dependent variable is the loan status indicating either a loan is expired or funded. Consequently, the model was further simplified according to the model selection criteria – Aikaike Information Criterion (AIC) which results in the following logit model.

$$\text{logit}(P_i) = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_1X_2 + \beta_5X_1X_3 + \varepsilon;$$

Goodness of fit test have shown that this subsequent model is well specified. The resulting estimates are reported in *Table 3*. It is clear that the model simplification by AIC omitted 2 loan attributes – loan sector and the repayment interval. This suggests that loan sectors and the repayment interval do not have a significant effect on to whether a particular loan is funded or expired.

The analysis revealed that by keeping other variables constant, a USD1000 increase in loan amount, will decrease the log odds of getting completely funded by (-) 0.71 (-1.28, -0.21). For every USD1000 increase in loan amount, increases the log odds of any female being completely funded by 0.63

(0.027, 1.29) times higher. A female in East Asia & the Pacific has log odds of their loan being completely funded 3.67 (-0.16, 7.80) times higher compared to females in the Arab States.

Table 3 :Logistic regression estimates on Loan Status as the response; with Gender, Developing World Region and Loan Amount as the covariates. Reference level: Gender - male individuals/all male group, Region - Arab States

Variables	Estimate	SE	Z	p-value
(Intercept)	4.05	1.11	3.64	0.00027 ***
Gender				
Female	-0.70	1.52	-0.46	0.65
Region				
East Asia & the Pacific	-1.33	1.21	-1.09	0.27
Europe & Central Asia	0.04	1.46	0.03	0.98
Latin America & the Caribbean	-1.76	1.11	-1.59	0.11
South Asia	11.49	882.74	0.01	0.99
Sub-Saharan Africa	-0.59	1.16	-0.51	0.61
United States	1.55	2.25	0.69	0.49
(Loan Amount)/1000	-0.71	0.27	-2.61	0.009 **
Female x East Asia & the Pacific	3.67	1.88	1.96	0.05 •
Female x Europe & Central Asia	-0.80	1.88	-0.43	0.67
Female x Latin America & the Caribbean	2.27	1.59	1.43	0.15
Female x South Asia	-12.32	882.74	-0.01	0.99
Female x Sub-Saharan Africa	1.17	1.63	0.72	0.47
Female x United States	-4.04	2.76	-1.47	0.14
Female x Loan Amount	0.63	0.32	1.97	0.049 *
Null Deviance: 328.55 on 987 degrees of freedom				
Residual Deviance: 271.22 on 972 degrees of freedom				
AIC: 303.22				

•, *, **, *** indicates significance at the 90%, 95%, 99% and 99.9% level, respectively.
SE: standard error

Meanwhile, to examine how loan amount on Kiva is influenced by the borrower's gender, loan sectors, world region and the global MPI, an Ordinary Least Square method (OLS) was used for estimation. With natural logarithm of loan amount as the response variable, allowing interaction between gender and other defined explanatory variables, the OLS regression analysis – followed by observing the AIC for model selection, have omitted interaction between gender and loan sectors. Furthermore, the interaction between borrower's gender and MPI and world region also turned out to be insignificant in relation to the loan amount. Subsequently, a simplified OLS regression model only on the main effects i.e., without interaction between variables and excluding borrower's gender was performed. Performing model selection criteria using the AIC once again revealed that borrower's gender is not significant in affecting the loan amount such that only the following applies.

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon;$$

where, X_i 's (i = 1, 2, 3,) represents the explanatory variables i.e., loan sectors, world region and the global MPI respectively on the response variable i.e., natural logarithm of loan amount.

Subsequent estimates are reported in *Table 4* below. Loans made for personal use were found to be (-) 0.74 (-1.04, -0.43) times lower compared to agriculture in the log scale. Comparing loan size with the reference group while holding other variables constant, loans from Arab States, Europe & Central Asia and Latin America & the Caribbean is 0.78 (0.31, 1.25), 0.76 (0.39, 1.13) and 0.77 (0.46, 1.09) times higher than that of loans coming from South Asia respectively. Apparently, the size of loans from countries with MPI more than the 3rd quartile i.e., 0.18, are 0.36 (0.19, 0.54) higher compared to loans from developing countries with a much lower poverty index while holding other variables constant.

Table 4 : log(Loan Amount) as the response on loan sectors, world region and global MPI. Reference level: Sector – Agriculture, Region – South Asia, MPI – MPI ≤ 0.18

Variables	Estimate	SE	T	p-value
(Intercept)	5.90	0.16	37.63	$< 2\times10^{-16}$ ***
Sector				
Arts	-0.027	0.22	-0.12	0.902
Clothing	0.079	0.13	0.60	0.550
Construction	-0.18	0.25	-0.72	0.470
Education	0.016	0.16	0.099	0.921
Food	-0.028	0.081	-0.35	0.726
Health	-0.26	0.24	-1.09	0.275
Housing	-0.053	0.14	-0.37	0.713
Manufacturing	-0.26	0.29	-0.92	0.360
Personal Use	-0.74	0.16	-4.76	2.30×10^{-6} ***
Retail	-0.051	0.081	-0.62	0.533
Services	-0.045	0.12	-0.37	0.715
Transportation	0.068	0.17	0.39	0.697
Region				
Arab States	0.78	0.24	3.24	0.00123 ***
East Asia & the Pacific	0.023	0.16	0.15	0.884

Europe & Central Asia	0.76	0.19	4.02	6.25×10^{-5}***
Latin America & the Caribbean	0.77	0.16	4.86	1.35×10^{-6} ***
Sub-Saharan Africa	0.14	0.15	0.96	0.339
MPI				
> 0.18	0.36	0.089	4.08	4.82×10^{-5} ***

Residual Standard Error: 0.8321 on 907 degrees of freedom
Adjusted R-Squared: 0.1505
Multiple R-Squared: 0.167

•, *, **, *** indicates significance at the 90%, 95%, 99% and 99.9% level, respectively.

SE: Standard Error

6. Discussion

6.1 Gender-related

The outcome of analysis presented earlier shows that the distribution and/or the median of loan amounts is significantly different between genders such that one median is higher or lower in comparison with the other. Furthermore, when interaction is allowed between female and loan size, the logistic regression revealed that even though loan amount is higher, as long as the borrower is a female, a group of females or a group with at least one female, the log odds of their loans being completely funded is somewhat higher which opposes the result from the same analysis such that being a female in any general situation does not influence the status of their loans and that the main effect of increased loan amount alone decreases the log odds instead. One plausible reason behind this trend is that as studied by Dichter and Harper (2007), women save and repay more consistently than men, and work well in communities, since they are often the ones who seek to benefit the most from social reform. With respect to the renowned Grameen Bank's microfinance model that grants loans to support mainly women within the unfortunate communities in Bangladesh, many emerging microfinance initiatives have the Grameen model as reference. In a 2012 interview, Muhammad Yunus said that he and the Grameen Bank saw much more value that women borrowers gave back to their homes (Muhammad Yunus, 2014).

But unfortunately, according to the findings by Johnson and Rogaly (1997), women maintained substantial influence over the use of the loan in only 37% of cases, while the remaining 63% had minimal to no power over loan use. From *Figure 5* as well, one may observe vaguely that the median of loan amount for female borrowers in Kiva is lower in comparison to males. This might suggest that women are in general more reluctant to request for larger amounts due to several circumstances on control over loans post-disbursal. Johnson and Rogaly (1997) further added that when loan sizes are small and loan usage was focused on practices that did not contradict notions of equal employment for men and women, control was more likely to be retained.

Another noteworthy discovery is that loans by female borrowers are financed nearly 30% quicker than loans made by male borrowers. Nevertheless, in contrast to what have been studied by Dichter and Harper (2007), there is really little evidence that proves women outperform men in terms of good repayment behavior that supports the much-discussed gender effect. Funding female borrowers are just frequently considered as a form of social investment in addition to the fact that they demonstrate lower credit risk (Dorfleitner & Oswald, 2016).

6.2 Microloans in Activity Sectors

Previously, loan sizes on Kiva were found to differ significantly between different type or activities in which the loans were used in. A possible reason is that some activity sectors are seen to be requiring either a higher or lower fund compared to some other activities. In fact, the regression analysis also reported a lower loan size when a loan is made for personal use compared to agricultural purposes. As Dorfleitner and Oswald (2016) presented in their study, Larger loans prove to be more difficult to repay as it was found that the loan size has a significant positive effect on probability of defaulting. So intuitively, borrowers may opt to request for loans in somewhat smaller amounts.

However, the observed proportions of loans in Kiva for agricultural purposes is very much higher compared to for personal use as seen in *Table 2* in contrast to the Bangladesh Grameen Bank's 2004 list of activities, whereby only approximately 500,000 loans were made for agriculture and forestry purposes out of a total of 3.5 million, while over a million loans were made for trade and shopkeeping (Dichter & Harper, 2007). They subsequently argue that farming is and will likely continue to be the primary economic practice for many rural people, it is worth considering whether microfinance is not more widely used for farming.

Kiva borrowers tend to apply loans for agricultural purposes more than for personal use which may be an indicator that a large proportion of Kiva borrowers have acknowledged that venturing into agricultural industry has higher potential in generating profit despite the comparatively larger loan size when compared to personal use. In line with another claim made by Dichter and Harper (2007), borrowers will be less likely to obtain substantial gains if the loans are used in a less profitable manner which will in turn arise indebtedness instead. Nonetheless, not all microloans yield positive returns even if loans were invested in a manner such that it is worthwhile, especially for poor people employed in low-return activities in oversaturated, underdeveloped markets prone to environmental and economic shocks. A portion of poor borrowers face significant difficulty repaying loans due to conditions outside their control, a lack of expertise and experience, or making poor decisions (Dichter & Harper, 2007).

Although in this study loan sectors were found to be insignificant in determining the resulting status of loans of being completely funded or otherwise, apparently, loan sector was found to be a significant indicator of lending preferences by Heller and Badding (2012).

6.3 The Poor or The Poorest?

The earlier regression analysis result has shown that the loan size is directly proportional to the poverty index (MPI) of a developing country alone in which countries with MPI value above the 3rd quartile demonstrate a higher loan amount. Borrowers originating from countries in this group may be considered to be living in extreme or almost extreme poverty since higher index indicates higher poverty level as mentioned earlier. But credit risks of these poorer countries are relatively high which leads to lenders being unwilling to fund borrowers from these group of countries (Dorfleitner & Oswald, 2016). This might imply that loan sizes that are perceived to be of a high amount by lenders, may be less likely to be completely funded by the end of the crowdlending duration which indeed aligns with the outcome of this study's regression analysis on loan status – as the loan amount increase, the log odds of that particular loan being completely funded decreases.

While microloan is highly regarded as one of the tools that provides support for the underprivileged, they do not benefit the very poor and that there has been questions as to whether or not the incredibly vulnerable, who need development services the most, are still permitted to enroll in microcredit programs (Pretes, 2002). Again, referring to *Table 2*, the proportion of borrowers originating from countries with higher poverty index (MPI) i.e., more than 0.18, is only about one-fifth of the whole observation.

Pretes (2002) also stated that although Kiva has loan demands as low as $25, they also have individuals requesting loan amounts up to $2,000, implying that Kiva's microfinance activities have a strong bias towards the "middle disadvantaged" instead of the very vulnerable and extremely deprived communities, similar to other microfinance initiatives. However, this claim seems to be not in line with the outcome of this study which suggests that Kiva borrowers from poorer countries with higher MPI tend to have higher loan amount. But one shall not simply come to a conclusion that these loans from poorer countries will not be funded at most times. It has been argued in a study that the social effect of providing loans to low-GDP countries is recognized as more valuable. Results of the same report has shown that Kiva continues to draw investors who place a high priority on an MFI's social success and tend to invest in poorer countries (Dorfleitner et al., 2020).

7. Conclusion

The study has revealed several insights to the Kiva data set on their lending activities within the website. The loan size was found to differ much in certain world developing regions and a particular activity sector. There is also a weak association between activity sectors and world regions in which the borrower of Kiva resides. Furthermore, the consequent status of loans is influenced by several factors but mainly affected by the loan size. This research also discussed a few motives behind these trends and issues such as gender-relations in microloans, and the level of poverty of borrowers is considered to influence lending preferences. There are also certainly a number of limitations of this study. More meaningful insights may be discovered if the data set were to be utilized fully i.e., more variables analysed, and the original data set shall be used such that it may produce a more accurate outcome.

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