Do Microfinance Institutions Prioritise Need? Evidence from Loan Allocation and Repeat Borrowing Patterns

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ABSTRACT

This study investigates whether microfinance institutions (MFIs) allocate loan capital in proportion to borrower financial need and whether repeated borrowing promotes financial inclusion or reinforces credit dependency. Using a global dataset of over 950,000 loans from Kiva.org, we employ a large language model (LLM) to classify expressed financial need in borrower narratives, then train a machine learning classifier to scale this categorisation across the entire sample. Regression analysis reveals that high-need borrowers receive loans that are, on average, 8.7% smaller, even after controlling for regional poverty (MPI), gender, and loan-specific characteristics. Panel regressions with borrower fixed effects indicate that within-borrower loan growth over time is modest and economically insignificant, and does not vary systematically with need classification. These results suggest that MFIs do not dynamically adjust capital allocation based on borrower vulnerability, potentially undermining their stated pro-poor objectives. While this study introduces a scalable, text-based proxy for financial distress, future research could examine lender selection effects, institutional lending constraints, or the long-run welfare impacts of repeated borrowing.

Replication Link: https://github.com/Jakub-Riha/ECO225-Replication.git

I. Introduction

Microfinance is widely promoted as a mechanism to promote financial inclusion by extending small-scale credit to individuals excluded from traditional banking systems. Hermes and Lensink (2011) argue that microfinance institutions play an important role in expanding access to financial services for those excluded from formal financial markets. These loans are intended to support entrepreneurship, reduce poverty, and foster economic mobility in underserved communities. However, two central questions remain unresolved: To what extent are microfinance loans allocated based on borrower financial need, and do these loans promote economic growth or reinforce financial dependency over time?

This paper investigates both aspects by analysing how microfinance loan amounts relate to indicators of borrower vulnerability, and how loan sizes evolve as borrowers return for subsequent financing. The first part of the analysis explores whether more financially vulnerable borrowers, those facing higher poverty levels or expressing greater financial need through their loan descriptions, receive larger loans. A study by Domanban, P. B. (2023) suggests that more vulnerable borrowers, characterised by larger households and potentially lower incomes, may receive smaller loans. The second part examines whether repeated borrowing is associated with loan growth, suggesting upward mobility, or whether loan sizes remain stagnant or decline, potentially indicating borrower dependence or cautious institutional lending. Field et al. (2013) show that rigid microfinance structures can sometimes discourage entrepreneurial expansion, raising questions about whether repeated borrowing fosters growth or maintains dependence.

To address these questions, we use a pooled cross-sectional dataset from Kiva.org, a global microfinance platform facilitating peer-to-peer lending. The dataset includes loan-level observations from 2006 to 2017 across dozens of countries, with information on borrower demographics, loan characteristics, geographic coordinates, and loan narratives. Using this data, we estimate a series of regression models to evaluate the effect of textually expressed need, and loan sequence, on loan size. We estimate determinants of loan size, incorporating borrower level controls (gender, sentiment, borrower count, etc), loan level controls (term, number of lenders, funding speed, etc), and fixed effects for country, sector, and year.

Financial need is measured using two main indicators. The first is a Need Score derived from the loan narrative: a large language model (LLM) is used to classify a sample of loan descriptions based on expressed financial hardship, and this labelled subset is used to train a logistic regression model that classifies the remaining loans. Recent studies have demonstrated the efficacy of LLMs, such as BERT, in analysing textual data to assess financial risk. For instance, Sanz-Guerrero and Arroyo (2024) utilised LLMs to process loan descriptions and assign risk scores, highlighting the potential of these models in evaluating borrower information. The second is the Multidimensional Poverty Index (MPI) of the borrower's region, which captures area-level deprivation. The MPI is a widely recognised measure that captures multiple deprivations experienced by individuals in health, education, and standard of living. Developed by Alkire and Santos (2010), it provides a comprehensive assessment of regional poverty. While both indicators are used separately in the analysis, they provide complementary perspectives, one reflecting localised poverty, the other individualised need as expressed by the borrower.

Finally, to understand whether borrowers are growing or becoming reliant over time, we analyse sequential borrowing patterns. By following individual borrowers across multiple loans, we assess whether loan sizes increase, suggesting business expansion and financial progress, or whether they plateau or shrink, potentially signalling borrower dependence or more cautious institutional lending. This second component transforms the dataset from pooled cross-sectional loan-level data into panel borrower-level data, allowing us to control for borrower-specific fixed effects and isolate within borrower dynamics. This approach expands on prior work by Banerjee et al. (2015), who find that repeat microfinance borrowers tend to increase their loan amounts over time, with some evidence of business growth, but limited improvements in household income and consumption. While their study focuses on a randomised intervention in one city, our analysis broadens this investigation to a global sample and incorporates measures of expressed financial need and comparing loan trajectories across need classifications.

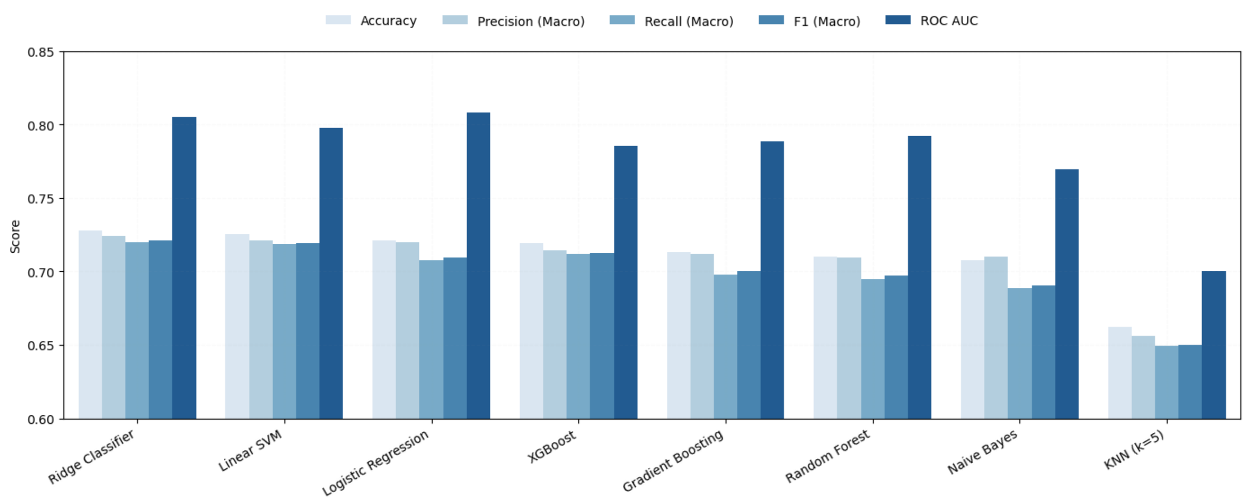
II. Context and Data

II.I Machine Learning Classification of Financial Need

To operationalise the text-based measure of financial need, we construct a binary classification model that scales the labelling process across the full dataset. While the initial Need Scores are derived from a manually labelled random sample of 2000 loan descriptions using a large language model (LLM), these labels serve as training data for a supervised machine learning classifier.[1] The goal is to predict financial hardship using only the textual content of loan narratives, enabling scalable and consistent need assessment at the borrower level. In this section, we describe the training process, evaluate multiple classification models using cross-validation, and present the final logistic regression model selected for its robustness, interpretability, and strong predictive performance.

FIGURE I

CROSS-VALIDATION METRICS BY MODEL



A variety of models were evaluated using 5-fold cross-validation, including logistic regression, ridge classifier, support vector machine (SVM), random forest, gradient boosting, and XGBoost. As shown in Figure I, logistic regression performed competitively across all metrics, with a

[1] The full prompt and LLM model used to classify the training sample is included in the appendix I

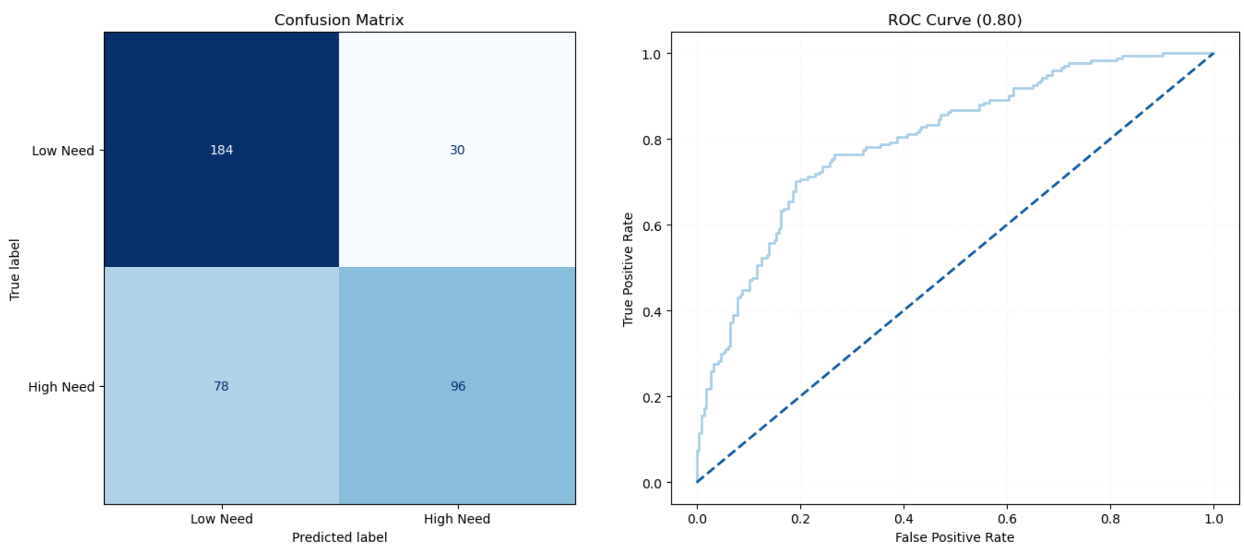
strong ROC AUC (0.81), F1 score, and balanced precision-recall tradeoffs. While tree-based models such as XGBoost also showed strong performance, the added complexity and lower interpretability made them less suitable for binary classification in this context. Logistic regression was chosen for its simplicity, strong generalisability, and highest ROC AUC. The model estimates the probability that a loan is high-need based on its TF-IDF features, following the form:

$$\hat{y}_i = \frac{1}{1 + e^{-(\beta_0 + \mathbf{x}_i^\top \boldsymbol{\beta})}}$$

where $\hat{y}_i$ = predicted probability that observation i is classified as high-need,
$\mathbf{x}_i$ = vector of features extracted from the loan description (TF-IDF scores),
$\boldsymbol{\beta}$ = vector of feature weights learned by the model,
β_0 = intercept term .

To evaluate the logistic model's performance on the labelled sample, we present the confusion matrix alongside the ROC curve:

FIGURE II
LOGISTIC REGRESSION PERFORMANCE ON LABELED LOAN SAMPLE



As shown in Figure II, the logistic regression model, when applied to the full labelled sample, demonstrates strong discriminative power, achieving an ROC AUC of 0.80. The confusion matrix further reveals reasonably balanced performance across both classes, correctly identifying 96 out of 174 high-need loans and 184 out of 214 low-need loans. While the model tends to be more precise in identifying low-need loans, it misclassifies a notable share of high-need observations as low-need. This asymmetry reflects a common challenge in text classification tasks, particularly when dealing with conceptually fuzzy categories like financial hardship.

The implication for the broader analysis is that while the model provides a strong signal of need, it is not perfect; some high-need borrowers may be underrepresented due to false negatives, and any misclassification of need may bias the coefficients toward zero (attenuation bias). This introduces a conservative bias into the subsequent regressions: any association between need and loan size is likely understated, not overstated. Despite this limitation, the model performs well on key evaluation metrics, including macro-averaged precision and recall, justifying its use for labelling the full dataset. The resulting binary variable serves as the primary proxy for borrower financial need in the analysis and enables a scalable, text-driven approach to measuring subjective hardship at the individual level.

II.II Descriptive Statistics and Dataset Composition

With a binary need classification in place, we now turn to exploring the broader composition of the dataset. This section presents summary statistics and visualisations that contextualise the loan allocation landscape across borrower demographics, loan characteristics, and sectoral distributions. By linking descriptive tables with relevant figures, we highlight patterns in loan sizes, funding dynamics, and borrowing behaviour, both across and within groups defined by gender and expressed need. These descriptive insights serve to ground the empirical strategy that follows by revealing key patterns and disparities in how microfinance capital is distributed.

Table I presents summary statistics for key continuous and discrete variables in the dataset, which contains nearly one million microloans issued across 46 countries. The average loan amount is 621 USD, though the high standard deviation (780 USD) and maximum value (100,000 USD) indicate a skewed distribution. Most loans fall within a more modest range—250 to 750 USD—consistent with microfinance's focus on small-scale lending. The average GDP per capita of borrower countries is 2,639 USD, reinforcing the dataset's wide geographic and economic diversity.

TABLE I

SUMMARY STATISTICS OF KEY VARIABLES

	Observations	Mean	Standard Deviation	Min	Q1	Q2	Q3	Max
Loan Amount (USD)	956,593	621.2	780.4	25.0	250.0	425.0	750.0	100,000.0
GDP per Capita (USD)	956,593	2,638.7	1,729.3	231.5	1,418.3	2,176.0	3,153.3	12,406.6
Funding Time (Days)	956,593	11.7	11.6	0.0	3.4	7.3	16.7	176.6
Regional MPI (Std.)	956,593	0	1	-1.0	-0.6	-0.4	0.5	4.5
Loan Sequence	956,168	4.0	11.0	1.0	1.0	1.0	3.0	347.0
Total Loans (Per Borrower)	956,168	7.1	18.6	1.0	1.0	2.0	5.0	347.0
Borrower Count	956,593	1.6	2.3	1.0	1.0	1.0	1.0	50.0
Loan Term (Months)	956,576	11.9	6.5	2.0	8.0	11.0	14.0	158.0
Lenders per Loan	956,593	17.9	22.6	1.0	7.0	13.0	22.0	3,045.0

Notes:
Loan Amount is the disbursed value per loan in USD. GDP per Capita is sourced from IMF data and reflects borrower country income levels. Time to Funding measures the number of days from loan posting to full funding. Regional MPI is a standardised multidimensional poverty index capturing area-level deprivation. Loan Sequence is the chronological number of a borrower's loan. Total Loans (Per Borrower) counts all loans received by a borrower. Borrower Count indicates the number of individuals per loan. Loan Term is the intended repayment period in months. Lenders per Loan is the number of contributors per loan.

Funding time, which may proxy lender risk perception or borrower appeal, averages 11.7 days but ranges from instantaneous disbursement to nearly half a year (177 days). Research by Huang et al. (2019) suggests that loans funded more quickly are viewed as less risky, with longer funding times reflecting higher perceived risk. The standardised Multidimensional Poverty Index (MPI) ranges from –1 to 4.5, capturing substantial variation in regional deprivation. Borrowers have, on average, taken four loans, with the total number per borrower averaging 7.1 but ranging up to 347, indicating substantial heterogeneity in borrowing patterns. Most loans are issued to individuals (mean borrower count of 1.6), with typical loan terms of around 12 months. On average, 18 lenders contribute to each loan, though some loans attract over 3,000 backers.[2]

FIGURE III

DISTRIBUTION OF LOAN CHARACTERISTICS

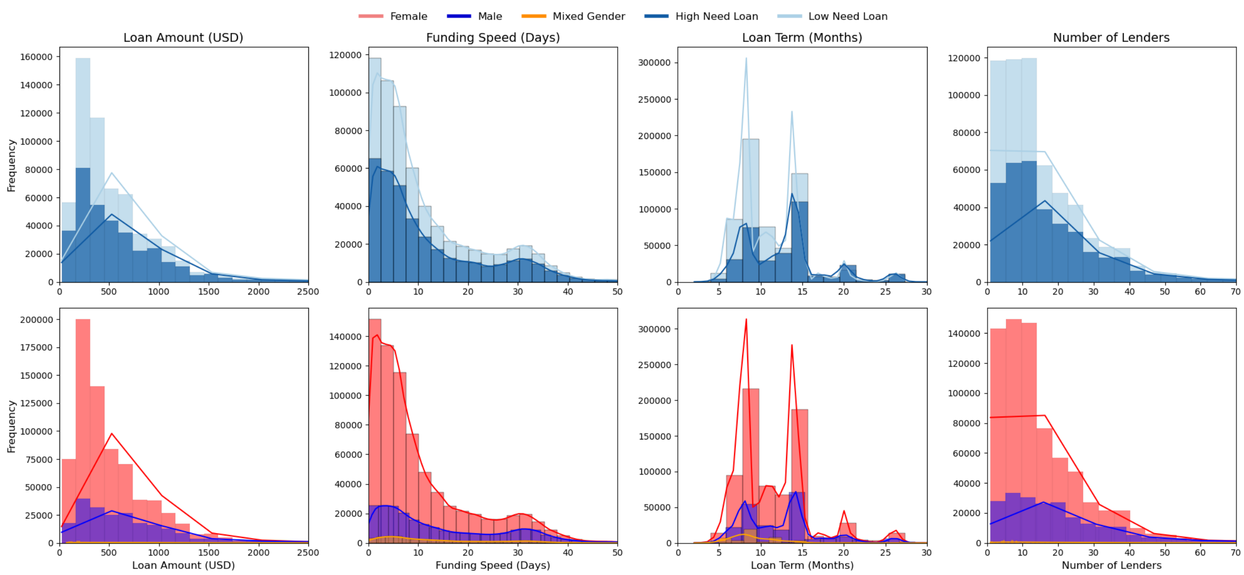


Figure III visualises the distribution of key loan attributes across borrower gender and need classifications. High-need loans tend to cluster around lower amounts, shorter terms, and fewer lenders, suggesting constrained borrowing capacity or more conservative asks. These loans also take slightly longer to fund, reinforcing the earlier finding that funding delays may reflect higher perceived risk (Huang et al., 2019). The lower panels highlight gender-based disparities: male borrowers receive larger and longer-term loans but are funded more slowly than female borrowers. Female borrowers dominate the distribution of smaller, short-term loans, while mixed-gender groups remain rare. These descriptive patterns align with regression findings that show persistent gaps in loan conditions by gender and expressed financial need.

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[2] See Appendix II and III for full distributions of borrower count and loan per borrower

Table II presents the distribution of loans across key borrower and loan characteristics. The dataset is heavily skewed toward female borrowers, who account for 76.2% of all loans, compared to 19.3% for male borrowers and only 4.5% for mixed-gender borrowing groups. This pattern reflects the gendered orientation of many microfinance initiatives, which often prioritise women due to their perceived creditworthiness and social impact. Studies show that women are more likely to repay their loans than men, making them attractive clients for microfinance institutions (D'Espallier et al., 2011). Visual borrower representation is also prevalent: 87.8% of loans include a borrower photo, suggesting that visual storytelling plays a significant role in attracting lenders on platforms like Kiva.

TABLE II

LOAN BREAKDOWN BY GENDER, LOAN TYPE & NEED

Female Borrowers	729,248.0	76.2
Male Borrowers	184,385.0	19.3
Mixed-Gender Borrowers	42,960.0	4.5
Loan Includes Borrower Photo	839,554.0	87.8
Group Loan	117,042.0	12.2
Repeat Borrower	418,128.0	43.7
High-Need Loan	348,556.0	36.4
Low-Need Loan	608,037.0	63.6

Notes:
Gender categories reflect the composition of borrowers associated with each loan. Mixed-gender loans involve more than one borrower of different genders. Group Loans refer to loans with multiple borrowers, regardless of gender composition. Repeat Borrowers are those with more than one loan record in the dataset. High-Need Loans are identified through a machine learning classifier trained on LLM-labeled narratives. "Loan Includes Borrower Photo" indicates whether the loan listing contained an image of the borrower.

Figure IV plots average loan amounts by borrower loan sequence, disaggregated by high- and low-need classifications. A declining trend is observed for both groups in the early stages, with loan amounts falling steadily during the first 30 borrowing instances. This pattern may reflect declining marginal institutional support, potentially due to lender caution or efforts to spread capital more broadly, or borrower dependency, whereby repeat users rely on recurring small loans without progressing toward financial independence. Beyond the 80th loan, however, the data becomes erratic. This volatility is likely due to the limited number of observations in this range: only around 4,000 loans in the dataset correspond to borrowers on their 80th loan or beyond. At that point, estimates are driven by a small group of outlier borrowers, making them highly sensitive to noise and less reliable for inference. Thus, trends at the far right tail should be interpreted cautiously.

FIGURE IV

AVERAGE LOAN AMOUNT BY BORROWER LOAN NUMBER

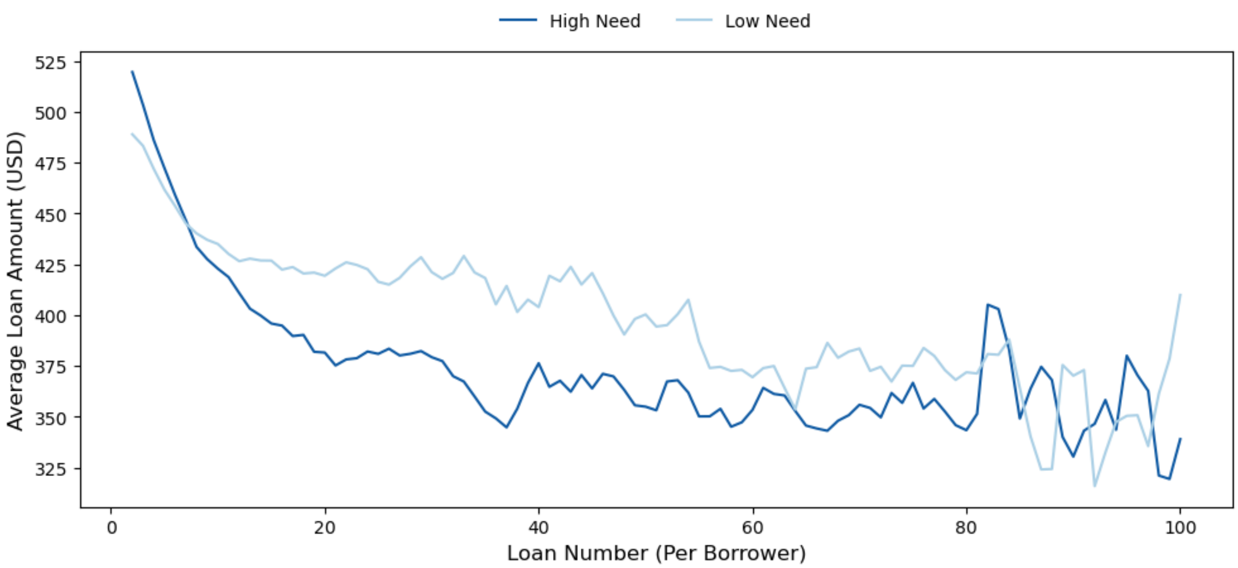


Table III provides an overview of microfinance loan distributions across sectors, highlighting borrower characteristics and loan purposes. The dataset is heavily concentrated in agriculture (24.1%), food (23.4%), and retail (21.8%), which together account for nearly 70% of all loans. This reflects the rural and subsistence-oriented focus of microfinance in developing countries, where agriculture and food-related activities are core to household income (FAO, 2024).

TABLE III

LOAN BREAKDOWN BY SECTOR, NEED, GENDER & LOAN TYPE

	Total Loans	High	Group	Female	Mixed-	Male	Total Loans
Agriculture	230,406.0	48.6	14.4	65.7	6.4	27.9	24.1
Food	223,480.0	28.9	10.9	86.3	3.4	10.4	23.4
Retail	208,981.0	15.3	8.0	85.7	2.7	11.6	21.8
Services	62,718.0	32.8	7.2	75.8	2.1	22.1	6.6
Clothing	50,703.0	28.3	16.0	86.9	4.0	9.1	5.3
Personal Use	40,174.0	77.0	52.8	59.5	22.1	18.5	4.2
Housing	34,514.0	65.1	4.4	72.4	1.1	26.5	3.6
Transportation	27,688.0	42.8	3.9	52.7	1.3	46.0	2.9
Education	25,169.0	73.7	2.6	57.7	1.6	40.7	2.6
Arts	18,613.0	41.5	12.9	86.4	2.3	11.3	1.9
Construction	11,726.0	42.6	8.9	52.0	3.6	44.4	1.2
Manufacturing	10,858.0	29.9	6.9	60.2	1.9	37.9	1.1
Health	8,914.0	52.9	12.6	65.9	7.6	26.5	0.9
Wholesale	1,492.0	29.6	9.7	66.8	2.9	30.4	0.2
Entertainment	1,157.0	23.7	4.9	55.8	1.9	42.3	0.1

Notes:
The table reports loan counts and the percentage of loans in each sector falling into specified categories. "High Need" refers to loans classified as such using the machine learning model described in Section II.I. Gender categories indicate the share of loans made to female, male, or mixed-gender borrower groups. "Group Loan" reflects whether the loan involved multiple borrowers. Sector categories follow Kiva's internal classification. Percentages may not sum to 100 due to rounding and overlapping classifications.

The prevalence of high-need loans varies substantially across sectors. Sectors associated with urgent consumption or basic services, such as personal use (77.0%), education (73.7%), housing (65.1%), and health (52.9%), exhibit disproportionately high shares of high-need loans. In contrast, sectors like retail (15.3%) and clothing (28.3%) show much lower need intensity, aligning with their business-oriented nature. This pattern is consistent with findings from the Abdul Latif Jameel Poverty Action Lab, which suggest that microfinance is often used for consumption smoothing and risk management rather than business expansion (Banerjee et al., 2015).

Figure V visualises average loan amounts across sectors, with bars disaggregated by need category to show the proportion of high and low-need loans within each sector. The figure highlights how much of each sector's total lending volume is allocated to high versus low-need borrowers.

Notably, sectors such as education, housing, and manufacturing not only receive higher average loan amounts overall but also show a sizable portion of these funds going to high-need borrowers. In contrast, sectors like retail, personal use, and entertainment allocate a much larger share of their loan volume to low-need borrowers, despite often serving high-need populations. This suggests that while high-need loans are present across all sectors, the largest loans within each sector may still be directed toward lower-need cases, raising questions about the extent to which financial vulnerability drives loan allocation decisions.

FIGURE V

AVERAGE LOAN AMOUNT BY SECTOR

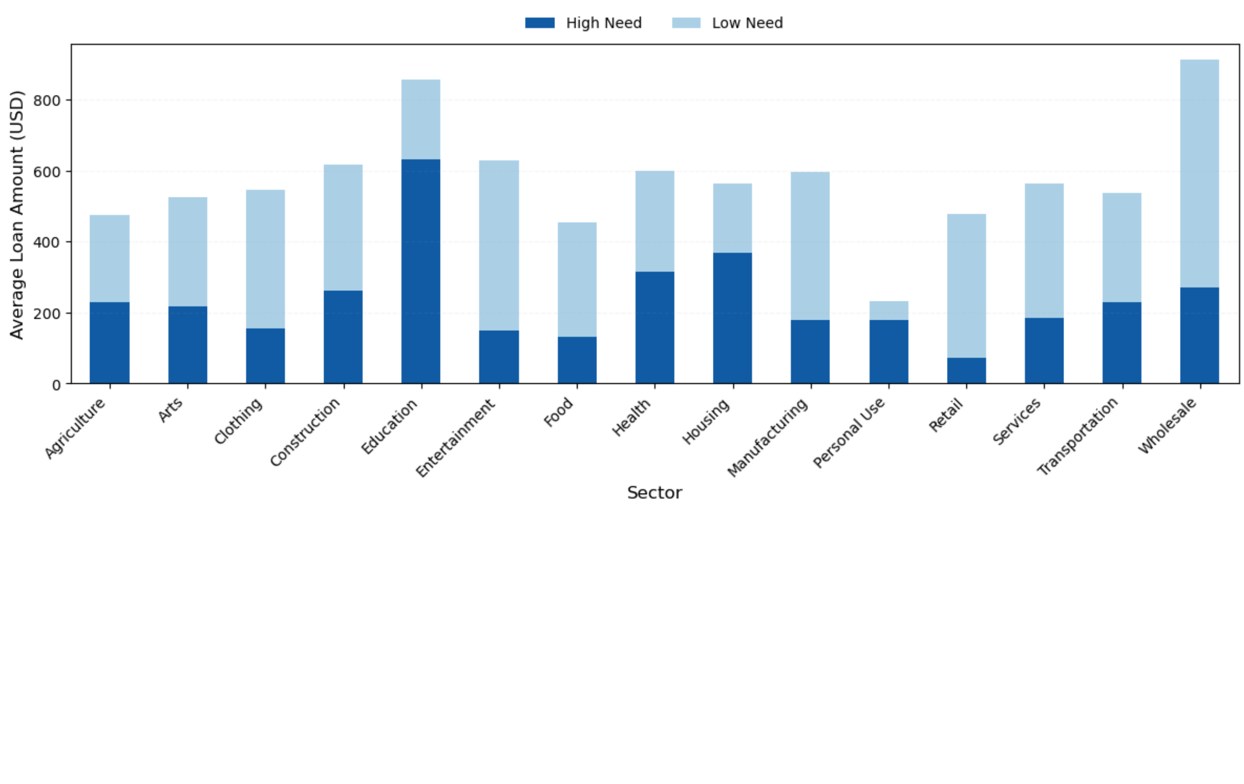
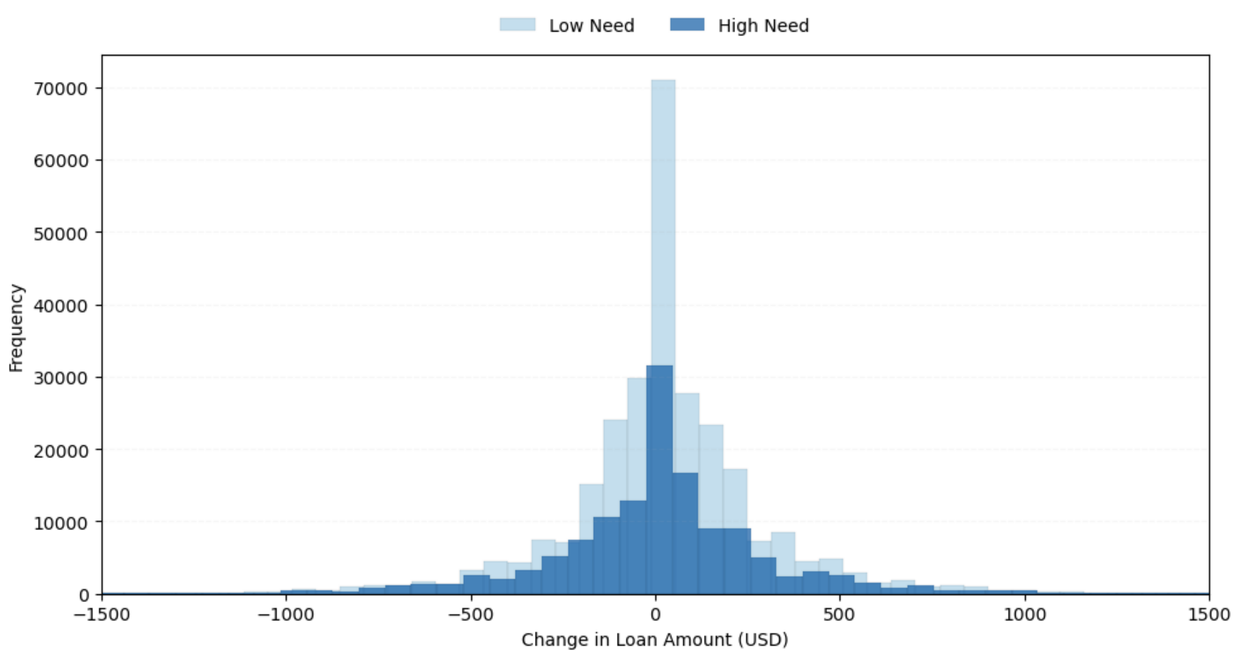


Figure VI displays the distribution of changes in loan amounts between sequential loans of the same borrowers, separated by high and low-need classifications. While the distributions for both groups are centred around zero and seem to follow a normal distribution, indicating that most borrowers receive similar loan amounts over time, high-need borrowers exhibit a slightly wider spread. This suggests greater variability in loan growth for financially vulnerable clients, but the overall similarity in shapes implies that loan progression is not heavily influenced by borrower need classification. However, this pattern masks considerable regional heterogeneity: in some areas, high-need borrowers appear to receive consistently smaller or less frequent increases in loan size across borrowing cycles, while in others, growth rates are more comparable across groups. These differences may reflect local lending practices, institutional constraints, or the strength of borrower-lender relationships in different regions.[3]

FIGURE VI

DISTRIBUTION OF CHANGE IN LOAN AMOUNT BETWEEN SEQUENTIAL LOANS



[3] See Appendix Figures IV and V for regional breakdowns of borrower need, average loan size, and loan growth in the Philippines and Kenya, respectively.

III. Regression Analysis

To examine how loan allocation is associated with borrower characteristics, loan traits, and regional indicators of need, this section begins by modelling the determinants of loan size using a series of Ordinary Least Squares (OLS) regressions. The dependent variable is the natural logarithm of the loan amount, and the primary explanatory variable of interest is the binary indicator for whether the borrower is classified as "high need." The analysis incrementally adds borrower demographics, loan level features, and fixed effects for sector, year, and country. This allows for a progressively more robust comparison of loan sizes across different borrower profiles while controlling for potential sources of omitted variable bias. The full model in the first regression table is specified as:

$$\log(\text{LoanAmount}_i) = \beta_0 + \beta_1 \cdot \text{HighNeed}_i + \mathbf{X}_i\boldsymbol{\gamma} + \alpha_s + \delta_t + \lambda_c + \epsilon_i$$

$$\begin{aligned} \text{where} \quad \text{HighNeed}_i &= \text{dummy equal to 1 if the loan is classified as high-need,} \\ \mathbf{X}_i &= \text{vector of borrower and loan-level controls (gender, group loan, loan term),} \\ \alpha_s &= \text{sector fixed effects,} \\ \delta_t &= \text{year fixed effects,} \\ \lambda_c &= \text{country fixed effects,} \\ \epsilon_i &= \text{error term} \,. \end{aligned}$$

Regression I explores how need level relates to loan amounts using OLS models with progressively more controls and interactions. A consistent finding is that mixed-gender borrowing groups receive significantly smaller loans, 13.4 percentage points less than female-only groups, even after adjusting for sector, year, and country, suggesting either institutional bias or lower demand from such groups. Another robust result is the negative relationship between MPI and loan size: a one standard deviation increase in MPI corresponds to a 3–7% reduction in loan amount, likely due to lower purchasing power in poorer regions.

REGRESSION I

REGRESSIONS OF LOG LOAN AMOUNT ON NEED-LEVEL

	Baseline Model	Add Basic Controls	Need × MPI Interaction	Need × Gender Interaction	Both Interactions	Full Controls	Full + Need × MPI	Full + Need × Gender	Full + Both Interactions
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High Need Loan Dummy	0.037^{***} (0.002)	0.017^{***} (0.002)	0.018^{***} (0.002)	-0.088^{***} (0.003)	-0.083^{***} (0.003)	-0.072^{***} (0.001)	-0.073^{***} (0.001)	-0.083^{***} (0.002)	-0.087^{***} (0.002)
MPI Value (Standardised)	-	-0.078^{***} (0.001)	-0.064^{***} (0.001)	-0.079^{***} (0.001)	-0.067^{***} (0.001)	-0.031^{***} (0.001)	-0.043^{***} (0.001)	-0.031^{***} (0.001)	-0.043^{***} (0.001)
Female Borrower Dummy	-	-0.258^{***} (0.002)	-0.255^{***} (0.002)	-0.310^{***} (0.002)	-0.304^{***} (0.002)	-0.041^{***} (0.001)	-0.042^{***} (0.001)	-0.047^{***} (0.002)	-0.050^{***} (0.002)
Mixed-Gender Loan Dummy	-	-0.392^{***} (0.005)	-0.387^{***} (0.005)	-0.371^{***} (0.005)	-0.368^{***} (0.005)	-0.030^{***} (0.004)	-0.031^{***} (0.004)	-0.028^{***} (0.004)	-0.028^{***} (0.004)
Number of Borrowers	-	0.143^{***} (0.000)	0.144^{***} (0.000)	0.142^{***} (0.000)	0.143^{***} (0.000)	0.052^{***} (0.000)	0.052^{***} (0.000)	0.052^{***} (0.000)	0.052^{***} (0.000)
High Need × MPI	-	-	-0.039^{***} (0.002)	-	-0.034^{***} (0.002)	-	0.026^{***} (0.001)	-	0.026^{***} (0.001)
High Need × Female	-	-	-	0.140^{***} (0.004)	0.133^{***} (0.004)	-	-	0.014^{***} (0.002)	0.019^{***} (0.002)
Borrower Pictured in Loan Ad	-	-	-	-	-	0.243^{*} (0.136)	0.248^{*} (0.136)	0.243^{*} (0.136)	0.248^{*} (0.136)
Group Loan Dummy	-	-	-	-	-	0.447^{***} (0.136)	0.451^{***} (0.136)	0.447^{***} (0.136)	0.451^{***} (0.136)
Repeat Borrower Dummy	-	-	-	-	-	0.082^{***} (0.001)	0.082^{***} (0.001)	0.082^{***} (0.001)	0.082^{***} (0.001)
Funding Speed (Days)	-	-	-	-	-	0.010^{***} (0.000)	0.010^{***} (0.000)	0.010^{***} (0.000)	0.010^{***} (0.000)
Loan Term (Months)	-	-	-	-	-	0.014^{***} (0.000)	0.014^{***} (0.000)	0.014^{***} (0.000)	0.014^{***} (0.000)
Number of Lenders	-	-	-	-	-	0.015^{***} (0.000)	0.015^{***} (0.000)	0.015^{***} (0.000)	0.015^{***} (0.000)
Sector Fixed Effects	-	-	-	-	-	✓	✓	✓	✓
Year Fixed Effects	-	-	-	-	-	✓	✓	✓	✓
Country Fixed Effects	-	-	-	-	-	✓	✓	✓	✓
Observations	956593	956593	956593	956593	956593	956576	956576	956576	956576
R^2	0.001	0.162	0.163	0.163	0.164	0.616	0.616	0.616	0.616
Root MSE	0.791	0.724	0.724	0.724	0.724	0.490	0.490	0.490	0.490

Notes:
*The dependent variable is the natural logarithm of loan amount (USD). High Need Loan Dummy equals 1 for loans classified as high-need based on the machine learning model. Robust standard errors are shown in parentheses. Statistical significance is denoted as follows: ***p < 0.01, **p < 0.05, *p < 0.10.*

The high-need dummy initially shows a positive effect but becomes significantly negative (–8.7%) in the fully controlled model, implying that loans perceived as high-need are penalized once borrower and contextual factors are considered. Interestingly, its interaction with MPI becomes positive in the final model, suggesting this penalty weakens in poorer regions.

Gender interactions further reveal that while female borrowers receive smaller loans on average (–5%), those expressing high-need get relatively larger loans than low-need women, partially offsetting the gender gap. Repeat borrowers receive 8.2% larger loans, consistent with relationship lending. Other controls behave as expected: longer loan terms, faster funding speeds, and more lenders are associated with larger disbursements.

Regression II shifts focus to loan evolution over time, analysing how loan size changes across borrowing sequences. By introducing loan sequence and borrower-level fixed effects, the model tracks whether institutions increase, maintain, or reduce support over time. This approach effectively transforms the data into a borrower-level panel, allowing a closer study of lending dynamics:

$$\log(\mathrm{LoanAmount}_{it}) = \alpha + \beta_1 \mathrm{LoanSeq}_{it} + \mathbf{X}_{it}'\boldsymbol{\gamma} + \mathbf{Z}_{it}'\boldsymbol{\delta} + \boldsymbol{\lambda}_{\mathrm{sector}} + \boldsymbol{\theta}_{\mathrm{country}} + \varepsilon_{it}$$

where

$$\begin{aligned} \mathrm{LoanSeq}_{it} &= \text{loan sequence number (1st, 2nd, 3rd loan)},\\ \mathbf{X}_{it} &= \text{time-varying borrower characteristics (gender, expressed financial need)},\\ \mathbf{Z}_{it} &= \text{loan-level characteristics (loan term, funding speed, number of lenders)},\\ \boldsymbol{\lambda}_{\mathrm{sector}} &= \text{sector fixed effects},\\ \boldsymbol{\theta}_{\mathrm{country}} &= \text{country fixed effects},\\ \varepsilon_{it} &= \text{error term}. \end{aligned}$$

This setup allows us to estimate how loan size evolves across borrowing rounds while controlling for observed heterogeneity.

REGRESSION II

REGRESSIONS OF LOG LOAN AMOUNT ON LOAN SEQUENCE

	Baseline Sequence Trend	Interaction w/ Gender	Interaction w/ Need	Interaction w/ Gender & Need	Full Model w/ Controls
	(1)	(2)	(3)	(4)	(5)
Loan Sequence	-0.004^{***} (0.000)	-0.009^{***} (0.000)	-0.004^{***} (0.000)	-0.009^{***} (0.000)	-0.004^{***} (0.000)
Female Borrower Dummy	-	-0.334^{***} (0.002)	-	-0.337^{***} (0.002)	-0.066^{*} (0.001)
Mixed-Gender Borrower Dummy	-	-1.253^{***} (0.004)	-	-1.249^{***} (0.004)	-0.369^{***} (0.003)
High Need Loan Dummy	-	-	-0.041^{**} (0.002)	-0.017^{***} (0.002)	-0.056^{***} (0.001)
Loan Sequence × Female	-	0.007^{***} (0.000)	-	0.008^{***} (0.000)	0.004^{***} (0.000)
Loan Sequence × High Need	-	-	0.000 (0.000)	-0.001^{***} (0.000)	-0.001*** (0.000)
Borrower Pictured in Loan Ad	-	-	-	-	0.994*** (0.002)
Loan Term (Months)	-	-	-	-	0.015*** (0.000)
Funding Speed (Days)	-	-	-	-	0.009*** (0.000)
Number of Lenders	-	-	-	-	0.014*** (0.000)
Repeat Borrower Dummy	-	-	-	-	0.081*** (0.001)
Sector Fixed Effects	-	-	-	-	✓
Country Fixed Effects	-	-	-	-	✓
Observations	956168	956168	956168	956168	956151
R^2	0.003	0.099	0.003	0.099	0.601
Root MSE	0.783	0.744	0.783	0.744	0.495

Notes:
*The dependent variable is the natural logarithm of loan amount (USD). Loan Sequence refers to the chronological number of each loan issued to a borrower (e.g., 1st, 2nd, 3rd loan). Robust standard errors are shown in parentheses. Statistical significance is denoted as follows: ***p < 0.01, **p < 0.05, *p < 0.10.*

Regression II explores the relationship between loan size and sequential borrowing behaviour across all borrowers in the dataset. Model (1) shows that loan amounts slightly decrease with each subsequent borrowing: the coefficient of -0.004 suggests a 0.4% reduction in loan size with each additional loan on average, across all borrowers. However, this pooled result might conflate two effects: individual borrower trajectories and differences between borrowers at different borrowing stages.

Model (2) adds gender controls and interactions. The positive interaction between loan sequence and female (0.007) suggests that, over time, female borrowers see a modest increase in loan size relative to male borrowers, though the baseline trend remains negative.

The full model (Model 5), which includes sector and country fixed effects and controls for loan characteristics, confirms these findings. The loan sequence coefficient remains negative, albeit small (−0.004), and the high-need dummy remains strongly negative (−0.056), even after accounting for other factors. This again suggests that institutions are not rewarding perceived financial need with larger loans, and may be doing the opposite.

However, because this model does not control for unobserved borrower-level heterogeneity, observed patterns may be driven by differences between borrowers rather than changes within them. For example, borrowers who take out many loans may be systematically different (more financially constrained or less creditworthy) than those who take out fewer, and those differences may drive the observed decline in loan size over time.

To more accurately isolate how loan sizes evolve within individual borrowers, Regression III applies borrower-fixed effects. By controlling for borrower-specific, time-invariant characteristics, the fixed effects model removes this confounding and captures true within borrower dynamics. However, including fixed effects for nearly a million borrowers is computationally infeasible using dummy variables. Instead, the model employs a within transformation, where both the dependent and independent variables are mean-centred at the borrower level. Mathematically, each variable X_{it} is transformed as:

$$\tilde{X}_{it} = X_{it} - \bar{X}_i$$

Where $\bar{X}_i$ is the average of the variable X across all loans for borrower i. The regression is then run on these transformed variables:

$$\tilde{Y}_{it} = \beta \tilde{X}_{it} + \epsilon_{it}$$

This is algebraically equivalent to including individual dummy variables for each borrower, like in a fixed effects model, but is far more efficient computationally. It also means that only time-varying variables (like loan sequence or need) can be interpreted, while any time-invariant characteristics (gender, initial risk profile) are absorbed by the fixed effect. Regression III uses this transformation to evaluate whether borrowers experience consistent growth (or decline) in loan size across sequential borrowings, relative to their historical averages. The model being estimated is:

$$\tilde{Y}_{it} = \beta_1 \widetilde{\text{loan\_sequence}}_{it} + \beta_2 \widetilde{\text{need\_label}}_{it} + \beta_3 (\widetilde{\text{loan\_sequence}}_{it} \cdot \widetilde{\text{need\_label}}_{it}) + \tilde{\mathbf{X}}_{it}' \boldsymbol{\gamma} + \tilde{\varepsilon}_{it}$$

$$\begin{aligned} \text{where} \quad \tilde{Y}_{it} &= \text{demeaned log loan amount for borrower } i \text{ at time } t, \\ \widetilde{\text{loan\_sequence}}_{it} &= \text{demeaned loan sequence number}, \\ \widetilde{\text{need\_label}}_{it} &= \text{demeaned indicator for high-need classification}, \\ \tilde{\mathbf{X}}_{it} &= \text{vector of demeaned time-varying controls (loan term, number of lenders, funding speed)}, \\ \boldsymbol{\gamma} &= \text{vector of coefficients on control variables}, \\ \tilde{\varepsilon}_{it} &= \text{idiosyncratic error term}. \end{aligned}$$

The corresponding objective function minimises the sum of squared residuals:

$$\min_{\beta_1, \beta_2, \beta_3, \gamma} \sum_{i=1}^{N} \sum_{t=1}^{T_i} \left(\tilde{Y}_{it} - \beta_1 \widetilde{\text{loan\_sequence}}_{it} - \beta_2 \widetilde{\text{need\_label}}_{it} - \beta_3 (\widetilde{\text{loan\_sequence}}_{it} \cdot \widetilde{\text{need\_label}}_{it}) - \tilde{\mathbf{X}}_{it}' \boldsymbol{\gamma} \right)^2$$

This approach eliminates time-invariant borrower characteristics by subtracting the borrower's mean from each variable, allowing the model to isolate within borrower variation and better estimate the effects of loan dynamics over time:

TABLE III

REGRESSIONS OF WITHIN BORROWER LOG LOAN AMOUNT ON DEMEANED LOAN SEQUENCE

	Model A: Baseline FE	Model B: FE + Interaction	Model C: FE + Controls + Interaction
	(1)	(2)	(3)
Loan Sequence	0.002*** (0.000)	0.002*** (0.000)	0.001*** (0.000)
High Need Loan Dummy	-	-0.039*** (0.001)	-0.035*** (0.001)
Loan Sequence × High Need	-	-0.001*** (0.000)	-0.001*** (0.000)
Funding Speed (Days)	-	-	0.008*** (0.000)
Number of Lenders	-	-	0.019*** (0.000)
Loan Term (Months)	-	-	0.020*** (0.000)
Number of Observations	956168	956168	956151
R^2	0.001	0.002	0.341
Root MSE	0.303	0.303	0.246

Notes:
*The dependent variable is the demeaned natural logarithm of loan amount, adjusted for borrower count. All regressors are also demeaned at the borrower level, meaning each variable reflects deviations from the borrower's own historical average. This within transformation removes all borrower-level fixed characteristics (e.g., gender, baseline credit quality), and results are interpreted as within-borrower changes over time. Standard errors are robust and reported in parentheses. Statistical significance is denoted as follows: ***p < 0.01, **p < 0.05, *p < 0.10.*

Model (1) confirms that, on average, loan amounts tend to increase slightly with each subsequent loan, suggesting a modest upward growth trajectory within individual borrowers. However, this increase is only 0.2% per loan and is not economically significant.

Model (3), which introduces time-varying controls, adds nuance to this. The negative and statistically significant coefficient on the high-need dummy (−0.035) indicates that a borrower tends to receive loans that are 3.5% smaller when the textual description for that specific loan expresses more financial need than usual. Though counterintuitive, this suggests that microfinance institutions may not reward higher perceived needs with larger loans, at least not within the same borrower.

Moreover, the negative interaction between loan sequence and high-need status (−0.001) implies that high-need loans grow more slowly over time. In other words, if a borrower's loans become increasingly classified as high-need, the growth in their loan size decelerates. In contrast, longer loan terms, faster funding speeds, and a greater number of lenders are all associated with larger loans. Taken together, these results suggest that microfinance institutions may not only refrain from increasing support in response to heightened financial need but may scale down their lending to high-need borrowers over time, even when those borrowers have built a repayment history.

While these findings may seem troubling, they offer a more balanced interpretation too. Loan amounts are a proxy for institutional support, but they also reflect how much borrowers request in their own right. The declining size of high-need loans could indicate that borrowers' needs are shrinking over time, that is, they require less capital to achieve their goals. This may be interpreted as a reduction in financial burden for those who are most vulnerable. On the other hand, the small (0.1%) but persistent increases in loan size for low-need loans may reflect growing dependence rather than business expansion, especially given that "low-need" descriptions are often associated with borrowers who are already relatively secure. In this sense, small loan growth in low-need cases might not represent economic advancement but rather repeated reliance on external capital.

V. Conclusion

This project set out to examine whether microfinance institutions effectively prioritise borrower need in allocating loan amounts, and whether repeated borrowing is associated with growth or dependence. The OLS regressions reveal several important insights. First, while financial vulnerability, measured via a text-derived need label and regional poverty index (MPI), is statistically associated with lower absolute loan amounts, high-need borrowers tend to receive slightly larger loans relative to income. This suggests some institutional recognition of borrower constraints, though the effect is small and inconsistent across subgroups. Gender disparities also persist: female borrowers and mixed-gender groups consistently receive smaller loans, highlighting a potential equity gap in microloan distribution.

Longitudinal regressions tracking borrowing patterns over time offer further nuance. Individual borrowers generally see a modest increase in loan size across sequential loans, consistent with the notion of relationship lending. However, this growth is significantly slower for borrowers flagged as high-need. The interaction between loan sequence and need label is negative, implying that even when high-need borrowers return for subsequent loans, they receive smaller increases than their lower-need counterparts. This raises concerns about whether microfinance institutions reinforce dependency rather than enable upward financial mobility, particularly for the very populations they are meant to serve.

The machine learning component adds both value and complexity to the analysis. While the use of a large language model (LLM) to classify need from loan descriptions enabled scalable labelling of over one million loans, this approach introduces classification noise. Some loan descriptions may be mischaracterised due to ambiguity or linguistic subtlety, potentially leading to attenuation bias. For example, if the model misclassifies high-need loans as low-need (or vice versa), the observed relationship between need and loan amount may be underestimated. Despite this limitation, the classifier uncovered clear sectoral trends; high-need loans were concentrated in consumption-oriented sectors like health and housing, while business sectors like retail were dominated by low-need loans.

Looking forward, future research could expand this analysis by refining the classification of need, perhaps incorporating multi-label sentiment or urgency detection, or validating labels against external data. Alternatively, a more scalable LLM model could be run on the entire dataset. Further exploration of partner-level factors, such as institutional mission, tenure on Kiva, or risk ratings, could also explore cross-country variation in lending patterns. Finally, more work is needed to understand long-term borrower outcomes. Are repeat loans improving household welfare, or simply sustaining short-term consumption? Linking microfinance data to downstream indicators like business performance, education attainment, or income mobility would provide a fuller picture of microfinance's role in development.

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VII. Appendix

APPENDIX I

LLM LOAN NEED CLASSIFICATION PROMPT & MODEL

Prompt:

You are an expert in microfinance. Your task is to classify the financial need expressed in a microloan request.

A 'High Need' loan is one where the borrower appears to lack the financial resources to achieve their goal — whether that goal is essential (like food or shelter) or economic (like starting a small business). Indicators include:
- signs of financial hardship,
- dependence on the loan to proceed,
- mention of unemployment or limited income,
- or inferred urgency based on the language used.

A 'Low Need' loan is one where the borrower appears very financially secure or is seeking the loan for unessential improvements, marginal expansion, or supplemental purposes.

Do not use the loan amount or country/region to determine the need level — focus only on the description's content.

Loan Description: {text}

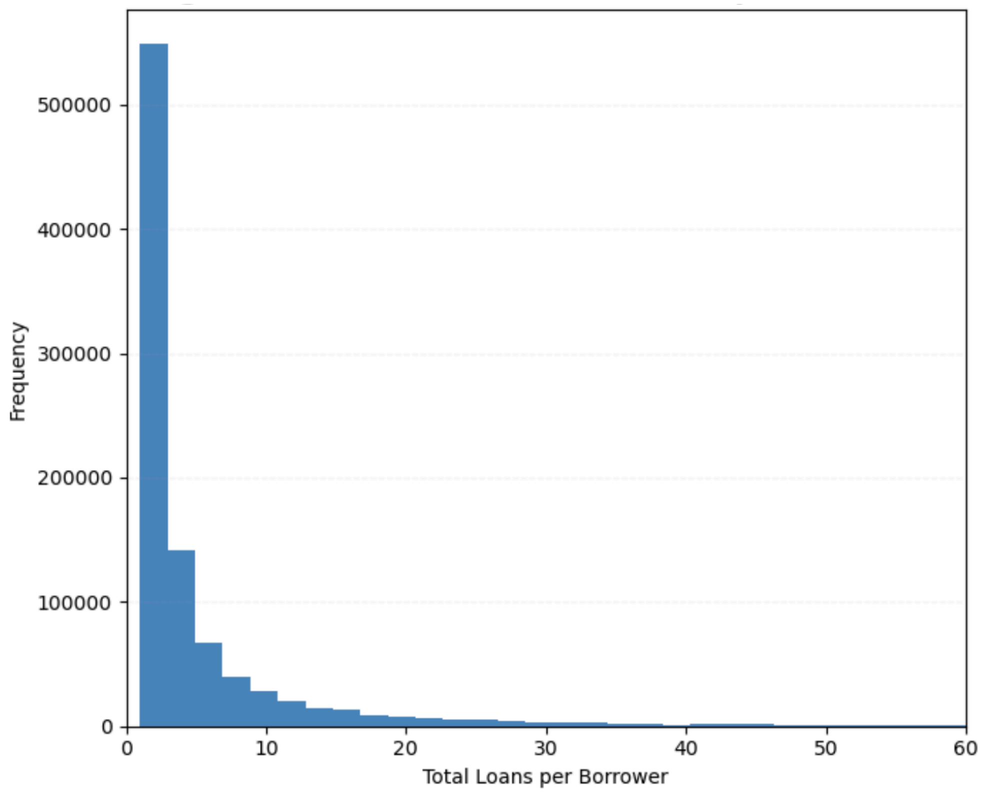
Classification:

Model:

gpt-4o-mini-2024-07-18

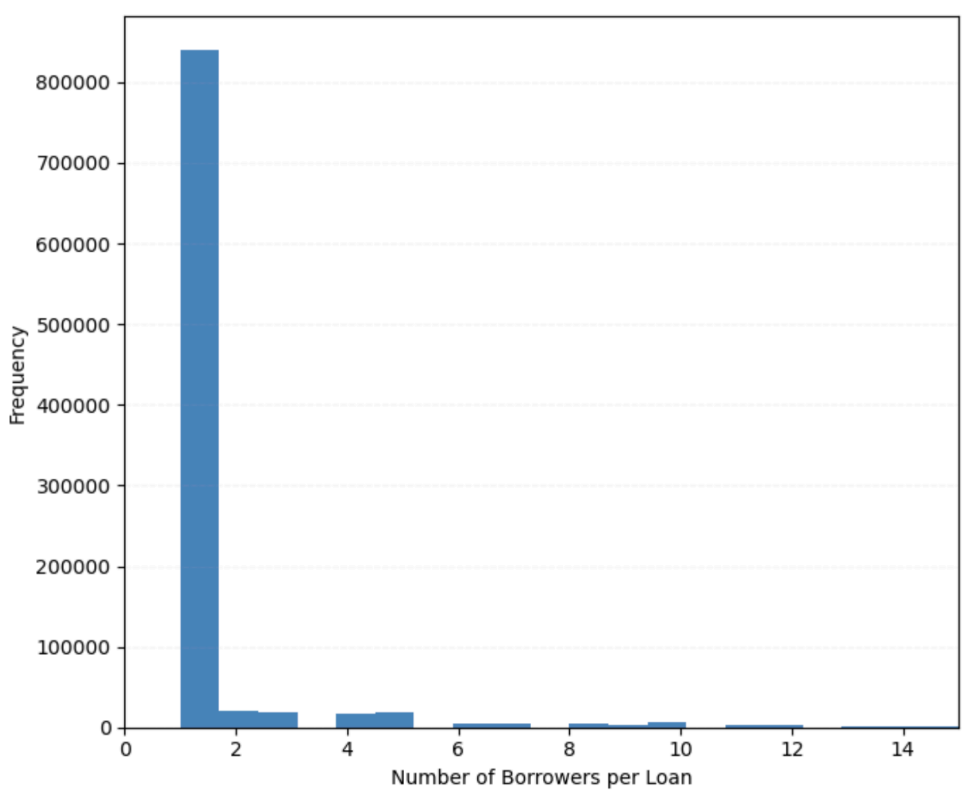
APPENDIX II

DISTRIBUTION OF TOTAL LOANS PER BORROWER



APPENDIX III

DISTRIBUTION OF BORROWER COUNT PER LOAN

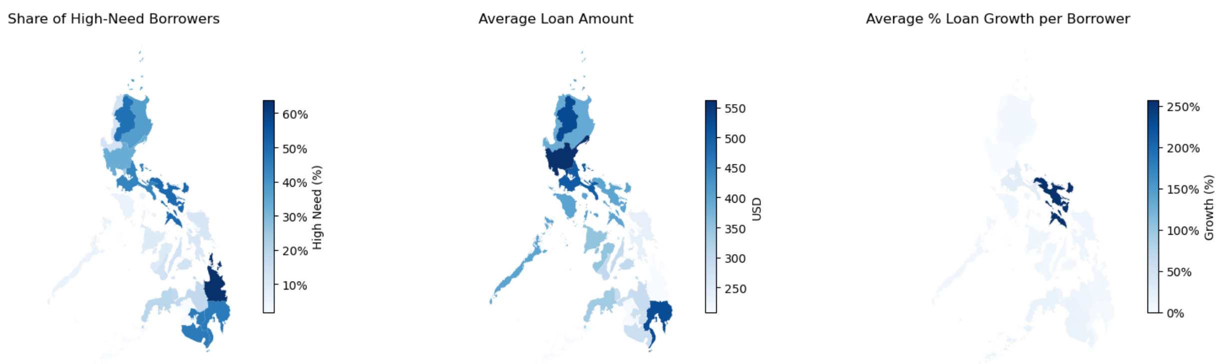


Appendix 2 displays the distribution of total loans per borrower. While most borrowers take out only a few loans, there is a long right tail with some individuals taking dozens, reflecting a small segment of highly frequent borrowers.

Appendix 3 shows the distribution of borrower count per loan. The majority of loans are made to single individuals, with multi-borrower loans being relatively rare. This supports the use of borrower-level fixed effects and the inclusion of group loan controls in regression models.

APPENDIX IV

REGIONAL MICROFINANCE INDICATORS IN THE PHILIPPINES

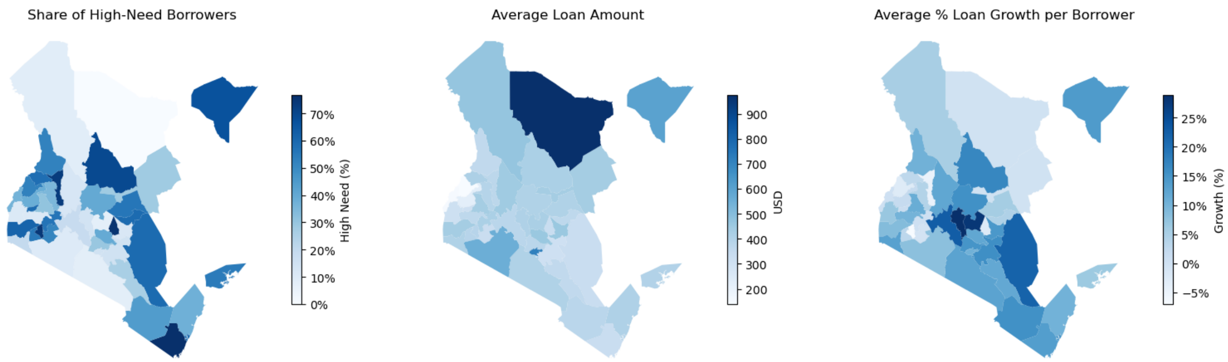


This figure presents regional patterns across the Philippines, the country with the highest loan count in the dataset (267,887 loans).

- **Left Panel:** Share of loans classified as high-need using the LLM-based classifier.
- **Middle Panel:** Average loan amount per borrower, adjusted for borrower count.
- **Right Panel:** Average percentage loan growth per borrower across borrowing sequences. Loan and borrower data are aggregated by region to visualise disparities in financial vulnerability, loan distribution, and growth trajectories.

APPENDIX V

REGIONAL MICROFINANCE INDICATORS IN KENYA



This figure summarizes microfinance indicators in Kenya (112,192 loans), the second-largest borrower country in the dataset.

- **Left Panel:** Regional distribution of high-need borrowers.
- **Middle Panel:** Average loan size per borrower.
- **Right Panel:** Average within-borrower loan growth across borrowing cycles.

  These regional aggregates help illustrate the geographic concentration of financial need and credit allocation, complementing the main paper's discussion on inequality in microfinance access.