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

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Using nearly a million Kiva loans, I test whether MFIs size credit to need and whether repeat borrowing grows over time; analysing micro-finance as a tool for inclusive development.

Research Questions

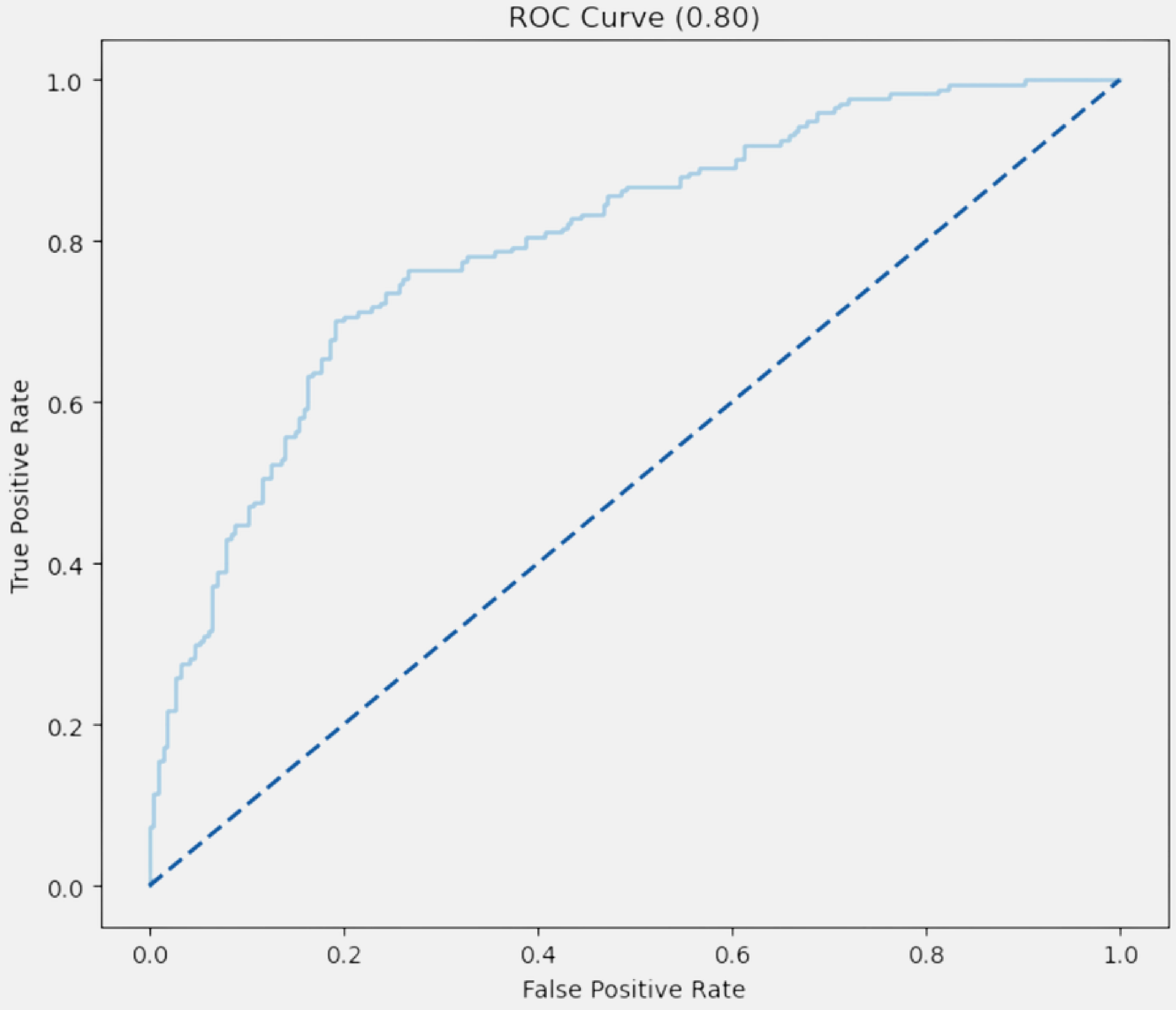
Q1: Do MFIs allocate larger loans to more vulnerable borrowers?
Q2: Does repeat borrowing grow loan size (mobility) or keep it flat (dependency)?

If credit isn't sized to need, or fails to grow with it, micro-finance can entrench, rather than ease, household vulnerability.

Diagnosing that mismatch is important, because donors funnel $100 + billion into micro-credit annually as a flagship poverty-reduction strategy.

Data & Need-Classification

ROC Curve for the Logistic Classifier



Building the High-Need label

- 2,000 loan descriptions hand-coded (LLM-assisted).
- Logistic Regression for classification

Model performance (curve on left)

- ROC AUC = 0.8
- Precision 0.73 | Recall 0.71

Group Averages by Need Label

group	High-Need	Low-Need	All
Loan amount (USD)	637.5	611.8	621.2
Loan term (months)	13.6	11.0	11.9
Funding speed (days)	12.0	11.5	11.7
Repeat borrower (%)	0.4	0.5	0.4
Female (%)	0.7	0.8	0.8
Agri+Food (%)	0.5	0.5	0.5

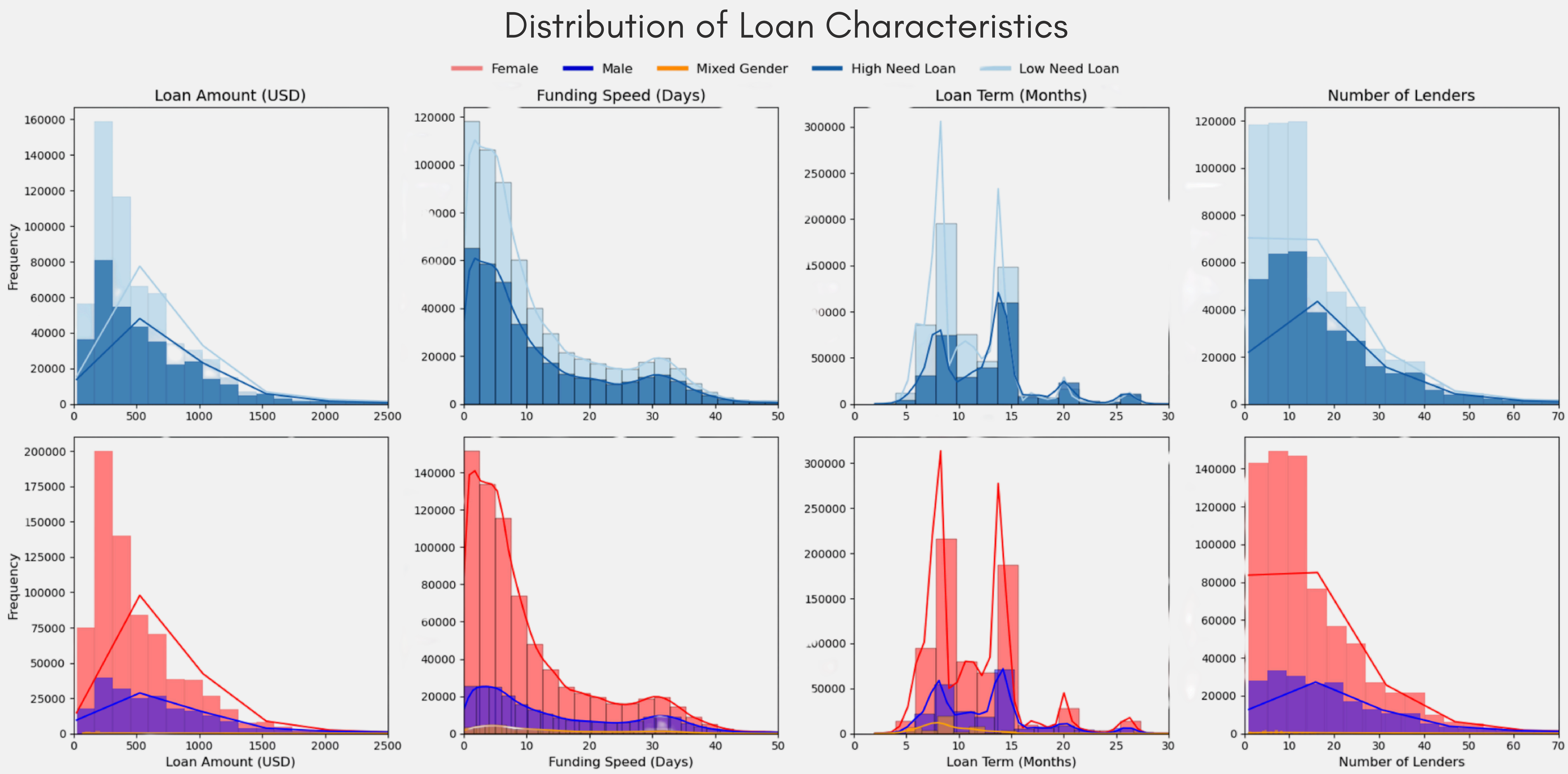
Descriptive snapshot

Summary Statistics for Key Variables

	Observations	Mean	Standard Deviation	Min	25th	50th	75th	Max
Loan Amount (USD)	956593	621.2	780.4	25.0	250.0	425.0	750.0	100000.0
GDP per Capita (USD)	956593	2638.7	1729.3	231.5	1418.3	2176.0	3153.3	12406.6
Funding Time (Days)	956593	11.7	11.6	0.0	3.4	7.3	16.7	176.6
MPI (Standardised)	956593	-0.0	1.0	-1.0	-0.6	-0.4	0.5	4.5
Borrower Loan Number	956168	4.0	11.0	1.0	1.0	1.0	3.0	347.0
Total Loans (Per Borrower)	956168	7.1	18.6	1.0	1.0	2.0	5.0	347.0
Number of Borrowers (Per Loan)	956593	1.6	2.3	1.0	1.0	1.0	1.0	50.0
Loan Terms (Months)	956576	11.9	6.5	2.0	8.0	11.0	14.0	158.0
Number of Lenders (Per Loan)	956593	17.9	22.6	1.0	7.0	13.0	22.0	3045.0

- Kiva loan-level dataset, 2004 – 2017 (N = 955 781 loans, 46 countries)
- Rapid funding: loans fill in ≈12 days on average, but speed ranges from minutes to months.

Loan Characteristics By Need & Gender



Baseline regression: Does need matter?

Regression of Log Loan Amount

	Baseline Model	Full Controls	Full + Interactions
High Need Loan Dummy	0.037*** (0.002)	-0.072*** (0.001)	-0.087*** (0.002)
MPI Value (Standardised)	-	-0.031*** (0.001)	-0.043*** (0.001)
Female Borrower Dummy	-	-0.041*** (0.001)	-0.050*** (0.002)
High Need × MPI	-	-	0.026*** (0.001)
High Need × Female	-	-	0.019*** (0.002)
Full Controls	-	✓	✓
Observations	956593	956576	956576
R^2	0.001	0.616	0.616
Root MSE	0.791	0.490	0.490

High-Need borrowers receive 9% smaller loans

- Baseline shows a naive "bonus" (3.7%), but this flips once controls are added.

Penalty weakens in poorer countries

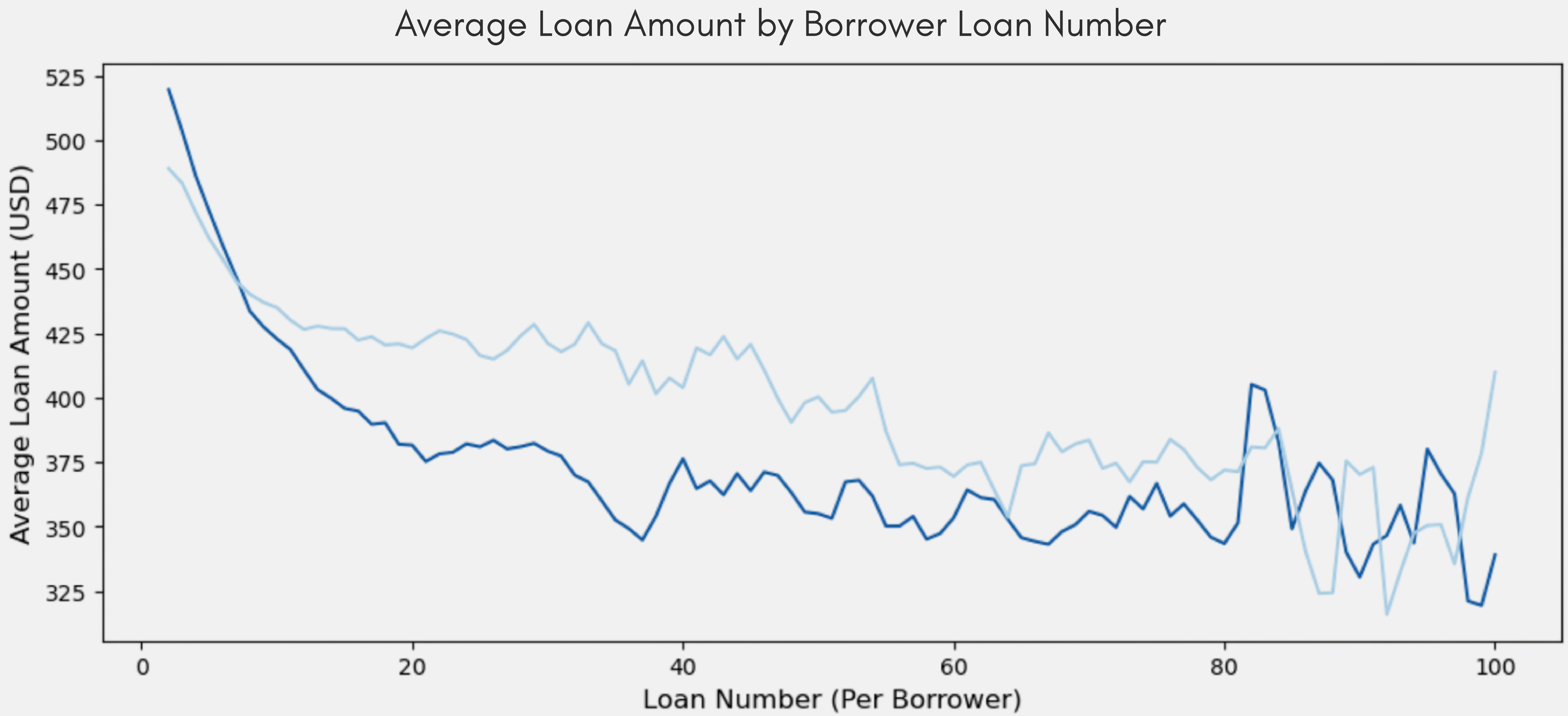
- Suggests MFIs respond more flexibly to need where poverty is widespread.

Gender amplifies the gap

- Women classified as High-Need are hit hardest

Sequential Borrowing Picture

- Loan sizes decline over time and then flatten, even across 90+ loans.
- No evidence of progressive scaling; microfinance appears static, not developmental.



Panel Model: Pooled Trends

Regression of Log Loan Amount

	Baseline Sequence Trend	Full Model w/ Controls
Loan Sequence	-0.004*** (0.000)	-0.004*** (0.000)
High Need Loan Dummy	-	-0.056*** (0.001)
Female Borrower Dummy	-	-0.066* (0.001)
Loan Sequence × Female	-	0.004*** (0.000)
Loan Sequence × High Need	-	-0.001*** (0.000)
Full Controls	-	✓
Observations	956168	956151
R^2	0.003	0.601
Root MSE	0.783	0.495

Each additional loan is associated with a 0.4% smaller loan size.

- Microfinance lending does not scale with borrower history; the sequence penalty persists.

High-Need borrowers start 5.6% lower and decline even faster.

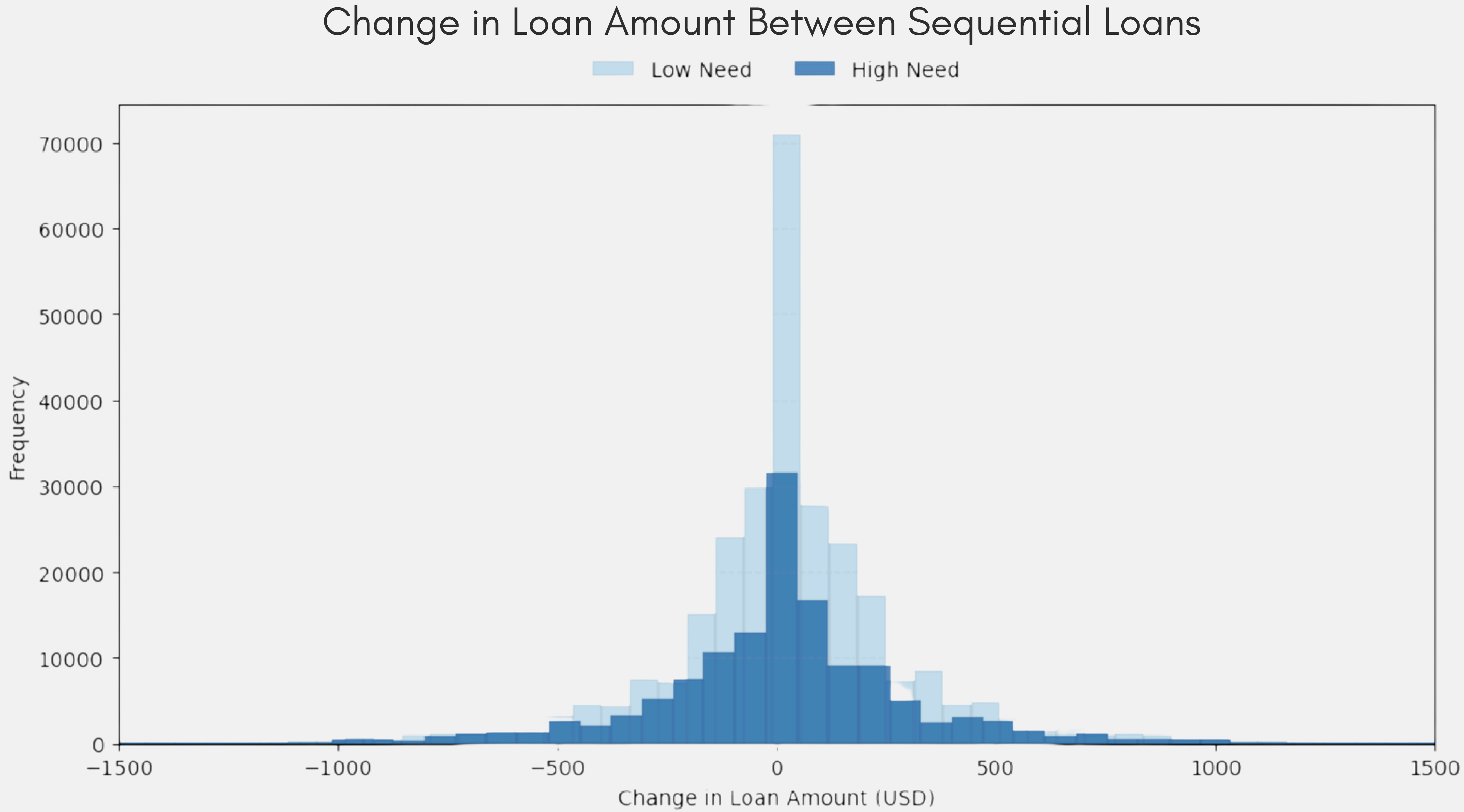
- Interaction effect (-0.1 pp per loan) suggests deepening gap over time.

Women see similar disadvantage

- Lending structures may reinforce rather than close gender gaps.

Change-in-Loan Histogram

- Loan size changes cluster tightly around zero, especially for High-Need borrowers.
- Repeat loans don’t escalate, even over dozens of borrowing rounds.



Within-Borrower Fixed Effects

Regression of Within-Borrower Log Loan Amountl

	Baseline FE	FE + Controls + Interaction
Loan Sequence	0.002*** (0.000)	0.001*** (0.000)
High Need Loan Dummy	-	-0.035*** (0.001)
Loan Sequence × High Need	-	-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	956151
R^2	0.001	0.341
Root MSE	0.303	0.246

Controlling for borrower fixed effects, loans still grow only 0.1 % per round.

- Growth is nearly flat even after accounting for personal and time-invariant traits.

High-Need borrowers see 3.5 % lower loans, and do not grow per loan.

- The gap holds within the same person over time, clear structural disadvantage.

Larger loans go to faster-funded, longer-term, more-lender-backed entries.

- Market-side variables correlate more strongly with loan size than borrower need.

Policy & Interpretation

High-need borrowers start ≈ 9 % under-funded & don't catch up

- Loan sizing fails to relieve the very constraint micro-finance claims to solve.

Repeat borrowing plateaus → risk of debt treadmill

- Tiny 0.2 % growth per loan suggests dependence rather than graduation.

Why the gap?

- Demand side (smaller requests) + supply side (risk pricing) both plausible; either way, need targeting is missing.

What could fix it?

- Integrate need scores into underwriting
- Offer graduated-size schedules or matching grants
- Track borrower outcomes, not just repayment

Takeaway

Microfinance under-delivers where it matters most.

- High-need borrowers receive 9% less upfront and see no meaningful growth over time.
- To target poverty, MFIs must rethink how loans are sized and how they evolve.

References

- Alkire, S., & Santos, M. E. (2010). Multidimensional Poverty Index. Oxford Poverty and Human Development Initiative (OPHI).
- Bangko Sentral ng Pilipinas. (2021). 2021 Financial Inclusion Survey. https://www.bsp.gov.ph/Inclusive%20Finance/Financial%20Inclusion%20Reports%20and%20Publications/2021/2021FISToplineReport.pdf
- Banerjee, A., Duflo, E., Glennerster, R., & Kinnan, C. (2015). The miracle of microfinance? Evidence from a randomized evaluation. American Economic Journal: Applied Economics, 7(1), 22–53. https://doi.org/10.1257/app.20130533
- D'Espallier, B., Guérin, I., & Mersland, R. (2011). Women's empowerment and microfinance: A global analysis. Journal of Microfinance, 13(1), 21-49. https://www.researchgate.net/publication/222639246_Women_and_Repayment_in_Microfinance_A_Global_Analysis
- Domanban, P. B. (2023). Determinants of loan sizes in microfinance institutions: Evidence from the Upper West Region of Ghana. Cogent Economics & Finance, 12(1), 2300924. https://doi.org/10.1080/23322039.2023.2300924
- Field, E., Pande, R., Papp, J., & Rigol, N. (2013). Does the classic microfinance model discourage entrepreneurship among the poor? Experimental evidence from India. American Economic Review, 103(6), 2196-2226. https://doi.org/10.1257/aer.103.6.2196
- Food and Agriculture Organization. (2024). Employment indicators 2000-2022 (October 2024 update). https://www.fao.org/statistics/highlights-archive/highlights-detail/employment-indicators-2000-2022-(september-2024-update)/en
- Hermes, N., & Lensink, R. (2011). Microfinance: Its impact, outreach, and sustainability. World Development, 39(6), 875-881. https://doi.org/10.1016/j.worlddev.2009.10.021
- Huang, Y., Li, X., & Wang, C. (2019). What does peer-to-peer lending evidence say about the risk-taking channel of monetary policy? http://dx.doi.org/10.2139/ssrn.3468021
- Muthoni, P. M., & Lewa, P. M. (2017). Influence of loan characteristics on microcredit default in Kenya: A comparative analysis of microfinance institutions and financial intermediaries. IOSR Journal of Business and Management, 19(5), 39-59. https://doi.org/10.9790/487X-1905043959
- OpenAI. (2024). GPT-4o-mini [Large language model]. https://openai.com/
- Sanz-Guerrero, M., & Arroyo, J. (2024). Credit risk meets large language models: Building a risk indicator from loan descriptions in P2P lending. arXiv preprint arXiv:2401.16458. http://dx.doi.org/10.2139/ssrn.4979155