

The Quantity and Size of Microloans Follow Different Development Logics: Evidence from Kiva

Kexing Yan

University of Toronto

July 9, 2026

Abstract

I study how Kiva microfinance activity relates to economic development across an 84-country panel (2013–2017), testing whether lending follows the inverted-U (“middle-income peak”) pattern suggested by early descriptive plots, and at which of three margins. Conditional on Kiva already lending in a country, total volume shows no significant nonlinearity (quadratic $p = 0.179$), confirmed by a formal Lind–Mehlum (2010) shape test. At the loan level, individual loan size follows a significant *U-shape* ($p < 0.001$), the opposite sign, which the same formal test confirms decisively. At the *extensive* margin — whether Kiva operates in a country at all, on a global panel including zero-lending country-years — a Logit model finds significant concavity (quadratic $p = 0.023$), but the same shape test shows the initial rise in entry probability among the poorest countries is not statistically distinguishable from flat, so a completed inverted-U is not formally established. The contribution is documenting this three-way divergence while holding every margin, including the paper’s most favorable-looking result, to one formal shape-test standard rather than reading significance off a single quadratic coefficient.

JEL Codes: G21, O16, O12

Keywords: microfinance; Kiva; economic development; extensive margin; PPML; U-test

1 Introduction

Microfinance is often described as a tool for expanding credit access where formal banking systems are thin, but the empirical literature does not support a simple view that more poverty automatically implies more successful microfinance. Early survey and review work emphasizes both the promise and the limits of microfinance, especially the tension between outreach to poor borrowers and the operational realities of lending in weak institutional environments ([Morduch, 1999](#)). A second strand of work studies microfinance institutions directly and argues that financial sustainability, commercialization, and outreach often move together only imperfectly. [Cull et al. \(2007\)](#) and [Cull et al. \(2009\)](#) show that institutions can scale, but doing so may involve trade-offs between profitability and reaching poorer clients. [Hermes et al. \(2011\)](#) similarly find that deeper outreach can be associated with lower operating efficiency.

A third strand asks whether microcredit actually improves welfare for poor households. Some influential studies report gains in access to credit and business activity but more limited average effects on broader welfare outcomes. [Banerjee et al. \(2015\)](#), [Angelucci et al. \(2015\)](#), [Tarozzi et al. \(2015\)](#), and [Karlan and Zinman \(2011\)](#) all contribute to a more cautious consensus: microcredit may help some borrowers and relax constraints, but average poverty effects are not universally large or immediate. This more skeptical perspective is reinforced by replication and reanalysis work such as [Roodman and Morduch \(2014\)](#), which highlights how sensitive headline claims can be to identification choices and model specification. At the same time, classic work on financial access and poverty, such as [Pitt and Khandker \(1998\)](#) and [Burgess and Pande \(2005\)](#), keeps attention on the idea that credit access can matter, especially when it expands into underserved places. Platform-mediated peer-to-peer giving of the kind Kiva popularized adds a further wrinkle: lender-side motivations and platform design shape which borrowers and loan types get funded in ways that are distinct from traditional microfinance institutions ([Galak et al., 2011](#)).

Taken together, this literature offers three recurring lessons that motivate the empirical strategy below. First, outreach to poor borrowers and financial sustainability are not automatically aligned, so where and how intensively a lender operates cannot be read off a single summary statistic. Second, the average treatment effects documented at the household level do not by themselves say anything about the geographic allocation of

lending activity across countries at different stages of development — a platform can expand into a country for reasons that have little to do with the marginal welfare gain to any individual borrower there. Third, the RCT literature’s emphasis on careful identification of a single causal object stands in useful contrast to a question this paper treats as explicitly non-causal and multi-object: not “does microcredit help,” but “at which of several distinct margins does microfinance activity vary with development, and in which direction.”

These papers are highly relevant, but most focus on either household-level treatment effects or institution-level performance. This paper asks a different question at the country-year and loan level: where is platform-based microfinance most active across countries, and does the answer depend on whether “activity” is measured by whether Kiva operates there at all, by total volume, or by the size of individual loans? Country-level Kiva lending data capture the geographic allocation of microfinance activity rather than only average borrower outcomes or the internal efficiency of a single lender; a global panel that adds zero-lending country-years lets the same question be asked about the *extensive* margin (does Kiva operate in a country at all); and loan-level data let it be asked about the *intensive* margin — how large a loan Kiva borrowers receive, conditional on receiving one.

The analysis uses an $X \rightarrow Y \rightarrow Z$ framework, with three versions of Y . The first, *Kiva presence*, captures whether Kiva lends in a country-year at all. The second, *total lending volume*, captures how much Kiva activity a country receives conditional on Kiva being present. The third, *individual loan size*, captures how large a typical loan is once a loan has been made. The main explanatory variable X is economic development, proxied by log GDP per capita. The mechanism Z is institutional quality and financial access, which may shape whether development translates into more or less microfinance activity. Kiva lending data are combined with World Bank macroeconomic indicators, governance variables, and country-level population measures to build all three panels.

Initial descriptive plots (Section 3) suggest a possible middle-income hump in total lending volume, which motivated an original hypothesis that lending follows an inverted-U pattern peaking in lower-middle income countries. That hypothesis does not survive formal regression testing at the country level (Section 5.1) conditional on Kiva already operating there: the quadratic term is never significant, a conclusion confirmed by a

formal shape test (Section 5.4). What the data *do* support, robustly, is a divergence across margins: whether Kiva enters a country at all is significantly concave in development, with entry probability falling steeply with income, though the initial rise among the very poorest does not pass the formal low-end slope test; total lending volume conditional on entry trends flat-to-downward with development; and the size of individual loans follows a significant U-shape — falling and then rising with income. The remainder of the paper develops these three results, checks their robustness, and discusses limitations, including that the size and quantity margins remain descriptive, non-causal analyses of countries and loans that Kiva has already chosen to serve.

2 Data

2.1 Construction

The central empirical question is whether Kiva lending activity is concentrated in the poorest countries, clusters at intermediate development levels, or instead varies with development in some other way — and whether that answer changes depending on whether “activity” means total volume or typical loan size. The main dataset begins with Kiva loan-level posting records ([Kiva.org](https://kiva.org), 2018) and aggregates them to the **country-year** level for 2013–2017: loan amounts and loan counts are summed within each country-year and merged with country-level development and institutional variables. A second, loan-level file keeps each individual loan as its own observation and merges in the same country-year covariates.

The country-year panel’s main variables are: **quantity** (total Kiva lending activity, log total loan amount); **size** (individual loan size, loan level only, log loan amount); **development** (X , log GDP per capita); **institutional environment** (Z , an institutional-quality principal component, with an alternative index and a financial-access index as robustness measures); and **controls**, especially log population, to account for country size. Poverty rate is used only in a limited-sample descriptive check, given substantial missingness; a broader cleaned dataset also carries measures such as the Human Development Index, life expectancy, and gross national income where available, though these are not part of the main regression battery. Before estimation, the merged panel is audited for duplicate country-year keys, variable missingness, and within-country variation, since

the analysis depends on correct country-code/year merges and some merged variables are available for fewer observations than the Kiva outcome itself; this audit step matters in practice, since it is what first flags that the institutional-quality series are the most missingness-prone inputs into the regressions below, well before any model is estimated.

2.2 External Data and Merging

These outside datasets are essential because the Kiva records describe lending activity but do not by themselves measure cross-country development, institutional quality, or population size. The Kiva panel is enriched with three external sources from the World Bank’s World Development Indicators ([World Bank, 2018](#)), merged at the country-year level by country code and year. First, GDP-per-capita data (constant 2015 USD) construct the main development regressor. Second, governance and financial-development indicators construct the institutional-quality principal component and its two alternative measures; these capture dimensions of institutional strength, governance quality, and access to formal financial infrastructure, and play the role of the mechanism variable Z . Because these series are incomplete or nearly time-invariant over 2013–2017 for some countries, all three measures are reported and compared rather than relying on a single one. Third, country-level demographic and development controls, especially population, are merged in; population is particularly important because raw loan totals partly reflect country size, so per-capita measures are needed to avoid conflating scale with lending intensity. The panel audit described above reports duplicate country-year keys, missingness after merging, and within-country variation in the merged variables, which is why the three institutional measures are compared side by side rather than treated as interchangeable.

2.3 Sample Period: Is 2013 Comparable?

The panel begins in 2013, when Kiva’s own posting volume was still ramping up, so before treating the 2013–2017 year fixed effects in Section 5 as evidence of anything, it is worth checking directly whether 2013 is a genuinely comparable observation year. A decision rule, applied mechanically before looking at any regression results, treats 2013 as *incomplete* and drops it if either (a) fewer than 10 of 12 months are represented in the raw loan-posting dates, or (b) loan counts are below 40% of 2014’s *and* country coverage is clearly lower than 2014’s. Table A4 in the Appendix, built directly from

raw loan-posting timestamps rather than the aggregated panel, shows 2013 has complete 12-month coverage, loan counts 80.4% of 2014’s (above the 40% threshold), and country coverage of 74 versus 81 in 2014 (not “clearly lower”). Neither disqualifying condition is met, so the full 2013–2017 sample is retained, with lower 2013 activity levels read as genuine platform growth rather than a partial-year artifact. This motivates including year fixed effects in the preferred specifications rather than treating them as a nuisance control; Section 6 re-estimates the preferred specifications on the 2014–2017 subsample only as a direct check on this judgment call.

3 Descriptive Evidence

Table 1 reports summary statistics for the core regression variables. The sample spans substantial variation in both development and lending intensity: log GDP per capita covers low-income through relatively rich economies, log total loan amount shows Kiva lending is far from uniform across countries, and the institutional and financial-access variables display meaningful cross-country dispersion. A first, purely descriptive cut splits total lending by development tercile (Table A1, Appendix): the middle-development tercile has the highest mean log lending (13.436) compared to the low- (12.806) and high-development terciles (12.776). This raw, bivariate pattern is the origin of the original middle-income-peak hypothesis and motivates taking it seriously as a starting point, but as Section 5.1 shows, it does not survive as a statistically significant nonlinear relationship once the regressions control for institutions, population, and year effects and formally test the quadratic term.

Figure 1 plots the main bivariate relationship between development and total lending volume, with a quadratic fit and a LOWESS smoother overlaid on the raw country-year scatter. Both curves bend downward at higher income levels, which is the descriptive origin of the middle-income-peak hypothesis and is worth taking seriously as a starting point. This is, however, still purely unconditional evidence: it does not control for institutions, population, or year, and Section 5.1 shows the same curvature is not statistically significant once those controls and a formal shape test are added. Figure 2 shows the distribution of the dependent variable itself, which is far from tightly clustered — substantial heterogeneity in lending across country-years is what gives the later regressions

meaningful cross-country variation to work with, rather than only a handful of outlying observations driving the result. Figure 3 shows the distribution of log GDP per capita across the sample, confirming that the panel covers a wide development range, from low-income to relatively rich economies; that breadth is necessary for asking whether the development–microfinance relationship is monotonic, nonlinear, or different across the quantity and size margins in the first place.

Figure 4 rescales lending by population, using loan amount per 100,000 people rather than raw country totals, which reduces the risk of mechanically reading large countries as high-lending simply because they are large; the per-capita pattern is broadly similar in shape to Figure 1. Figures 5–7 then map average lending, development, and institutional quality across countries over 2013–2017. The goal of the maps is not causal identification but a check that the geography of microfinance is visually consistent with the bivariate patterns above: Figure 5 maps the per-capita outcome, Figure 6 maps the main development regressor, and Figure 7 maps the institutional mechanism. All three are built using the underlying shapefile’s alternate ISO code field rather than its primary one, because the primary field codes several territories with complex sovereignty status (including Kosovo, which is Kiva-active in this panel) as a single non-standard placeholder value; using the alternate field restores those countries’ outlines to the map rather than leaving unexplained holes in the choropleth, so that grey areas on the map can be read as genuine “no Kiva data” rather than a plotting artifact.

Table 1: Summary Statistics (Country-Year Panel)

Variable	N	Mean	SD	Min	Median	Max
Log Total Loan Amount	357.000	12.955	1.933	7.151	13.137	16.602
Log GDP per capita	351.000	7.834	1.067	5.539	7.776	10.971
Institutional quality (PCA1)	352.000	-0.132	0.884	-2.551	-0.085	1.955
Institutional quality index	352.000	-0.115	0.803	-2.325	-0.075	1.898
Financial access index	323.000	0.069	1.095	-0.945	-0.145	6.861
Log population	354.000	16.640	1.617	12.188	16.588	21.067
Poverty Rate	151.000	11.797	17.016	0.000	4.800	75.800

Country-year panel, $N = 357$ observations across 84 countries, 2013–2017.

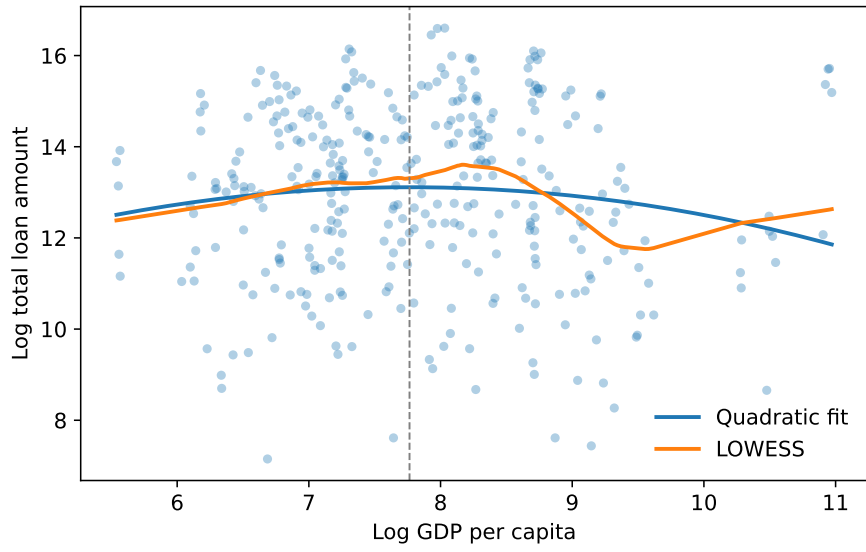


Figure 1: Development and total lending volume. Each point is one country-year; the solid curve is a quadratic fit and the dashed curve a LOWESS smoother, both fit without controls. The vertical dashed line marks the quadratic fit's implied turning point.

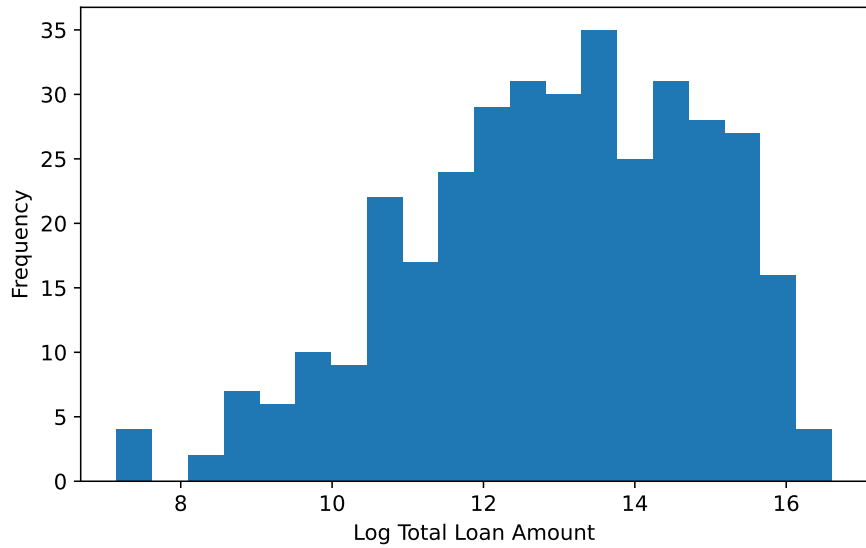


Figure 2: Distribution of log total Kiva lending volume across country-years in the sample.

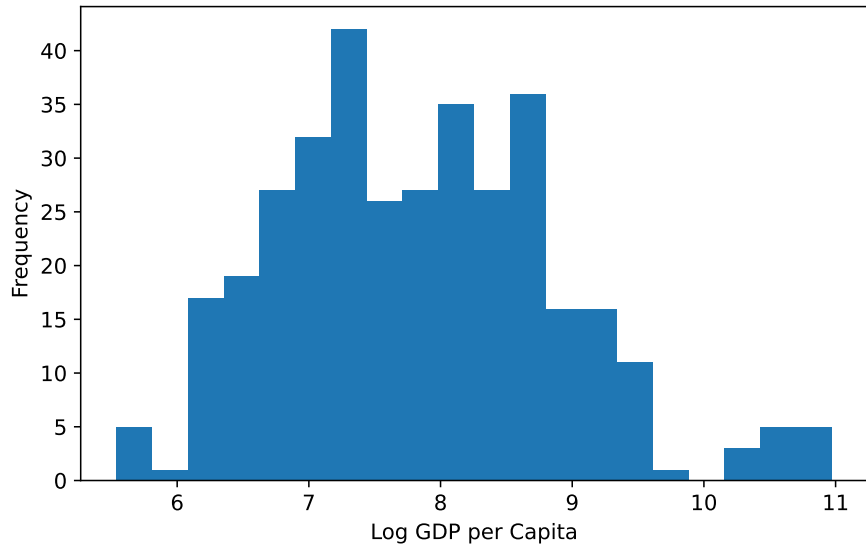


Figure 3: Distribution of log GDP per capita across country-years in the sample.

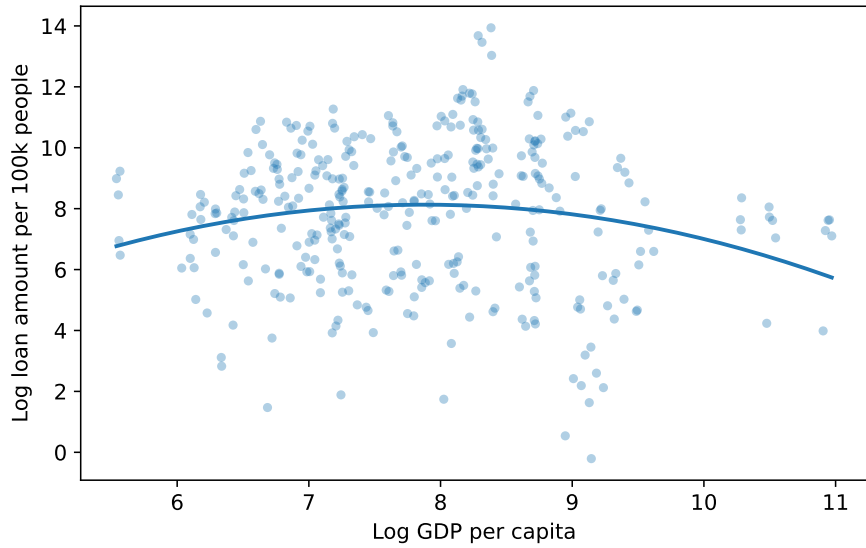


Figure 4: Development and per-capita microfinance lending. Each point is one country-year; the vertical axis is log Kiva loan volume per 100,000 people, with a quadratic fit overlaid.

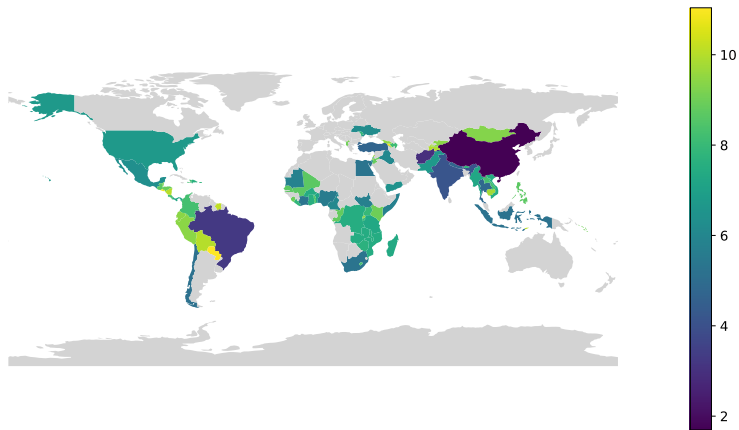


Figure 5: Average microfinance lending per 100,000 people by country, 2013–2017. Grey indicates no Kiva-lending observations for that country in the panel.

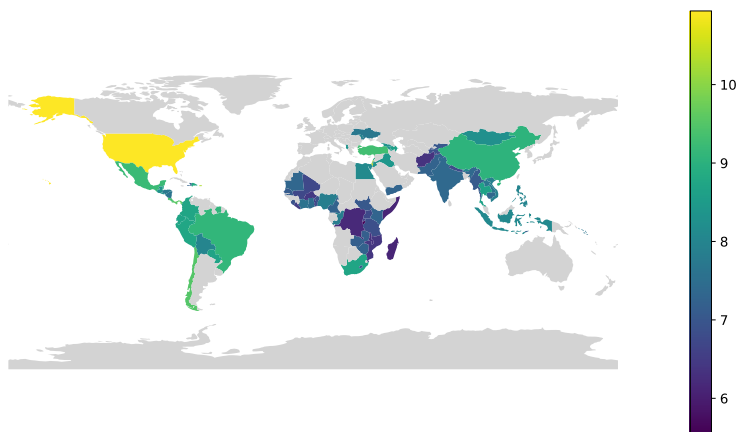


Figure 6: Average log GDP per capita by country, 2013–2017.

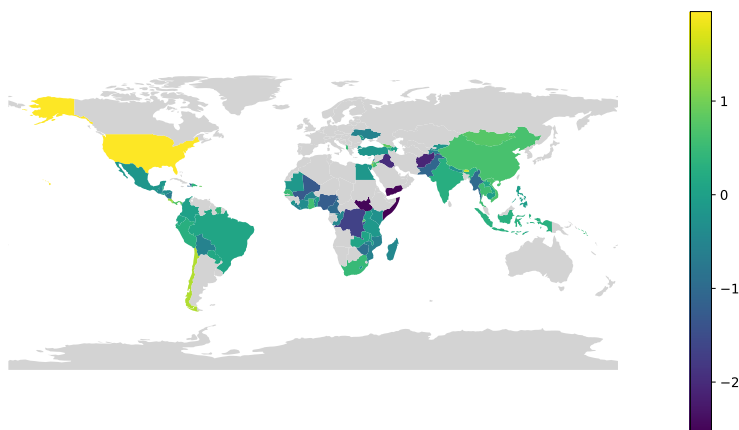


Figure 7: Average institutional-quality index by country, 2013–2017.

4 Empirical Strategy

The regression analysis tests whether the descriptive patterns in Section 3 survive formal specifications, at both the country-year and loan level. Two families of models are estimated, one per outcome: **quantity models** (Section 5.1), dependent variable log total lending volume, country-year panel, country-clustered standard errors; and **size models** (Section 5.2), dependent variable log loan amount, loan-level panel, country-year-clustered standard errors (with a country-clustered robustness check in Section 6). For each outcome, four linear/interaction specifications are estimated — a linear benchmark; linear plus institutions; adding year fixed effects; and adding an interaction between development and institutional quality — followed by four quadratic/robustness specifications that add a squared development term (centered on the sample mean, to ease interpretation of the linear term), then swap in year fixed effects and alternative institutional measures. Both outcomes are tested with the same battery so that any divergence between them reflects a difference in the underlying relationship, not a difference in specification.

Because a squared term can fit noise as readily as a genuine peak, the analysis treats *statistical significance of the quadratic term* as a necessary, not sufficient, criterion: Section 5.4 adds a formal test of whether the implied curve actually turns within the observed data range, applied uniformly to every shape claim in the paper, including the extensive margin.

Two further design choices apply across every specification. First, log GDP per capita is centered on its sample mean before squaring, so that the linear term in every quadratic specification can be read directly as the slope of the curve at a representative point in the sample rather than at an arbitrary and substantively meaningless zero. Second, every model is estimated with clustered standard errors at the level appropriate to where the regressor of interest actually varies: country-clustered for the country-year panel, since log GDP per capita is fixed within a country-year and repeated observations of the same country over time are not independent draws; country-year-clustered for the loan-level panel, since the same development regressors are repeated across every loan made in a given country-year cell. Getting the clustering level wrong in either direction would overstate the precision of the development coefficients specifically, which are the coefficients the paper’s central claims depend on — so Section 6 checks the loan-level

choice directly against the coarser alternative.

5 Results

5.1 Country-Year: Total Lending Volume

Table 2 reports linear and interaction specifications for log total lending volume. The coefficient on log GDP per capita is small, negative, and never statistically significant across the linear models, which is itself informative because it suggests a one-directional specification is not obviously the right functional form. Adding an interaction between development and institutional quality, the delta-method marginal effect of development is negative at the 25th percentile, mean, and 75th percentile of institutional quality and is not statistically significant at any of them, so the sample does not support a sign flip across institutional environments.

Table 2: Country-Year: Linear and Interaction Specifications (Total Lending Volume)

	(1)	(2)	(3)	(4)
Log GDP per capita	-0.060 (0.150)	-0.181 (0.158)	-0.179 (0.169)	-0.130 (0.165)
Institutional quality (PCA1)		0.251 (0.189)	0.273 (0.208)	2.213 (1.475)
Log population	0.112 (0.094)	0.134 (0.097)	0.145 (0.110)	0.156 (0.116)
Log GDP per capita $\times$ institutional quality				-0.252 (0.195)
Constant	11.605*** (2.068)	12.213*** (1.968)	9.801*** (2.171)	9.351*** (2.400)
Year fixed effects	No	No	Yes	Yes
Observations	348	348	348	348

Dependent variable: log total Kiva lending volume, country-year level. Standard errors in parentheses.

Country-clustered standard errors. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 4 is the direct test of the middle-income-peak hypothesis at the country level, and it does **not** support it. The squared development term is negative in all four specifications, ranging from -0.155 to -0.201 (models 5–8), but is not statistically distinguishable from zero in any of them (p from 0.102 to 0.181, standard errors around 0.12–0.13). The point estimate in the preferred specification implies a concave curve with a turning point at log GDP per capita ≈ 7.456 (about \$1,731 in constant 2015 USD), inside the sample range, but because the quadratic coefficient itself is not significant, the data cannot reject

a simpler description — a flat or monotonically declining relationship — over the “peak” shape implied by the point estimate. The linear component evaluated at the sample mean is also negative in every specification, so the estimated relationship with development is a decline across most of the observed income range, not a rise to a peak, and this pattern is stable across all three institutional-quality measures and whether or not year fixed effects are included. **The country-level quadratic pattern is therefore not treated as evidence of a middle-income peak in total lending volume;** the more defensible summary is that total Kiva lending volume tends to be lower, not higher, in richer countries within this sample, without strong evidence of a rise-then-fall shape.

Table 3: Marginal Effect of Log GDP per Capita on Log Total Lending Volume (Model 4)

	Institutional quality level	Marginal effect	SE	p-value
25th percentile	-0.568	0.012	0.198	0.950
Mean	-0.132	-0.097	0.167	0.560
75th percentile	0.417	-0.235	0.184	0.201

Delta-method marginal effects of log GDP per capita at percentiles of institutional quality, model (4).

Table 4: Country-Year: Quadratic and Robustness Specifications (Total Lending Volume)

	(5)	(6)	(7)	(8)
Log GDP per capita (centered)	-0.117 (0.153)	-0.111 (0.165)	-0.121 (0.167)	-0.162 (0.237)
Log GDP per capita ² (centered)	-0.155 (0.116)	-0.168 (0.125)	-0.170 (0.125)	-0.201 (0.123)
Institutional quality (PCA1)	0.274 (0.185)	0.297 (0.204)		
Institutional quality index			0.338 (0.224)	
Financial access index				0.305 (0.286)
Log population	0.154 (0.100)	0.166 (0.114)	0.161 (0.112)	0.114 (0.105)
Constant	10.655*** (1.663)	8.233*** (1.899)	8.318*** (1.870)	9.034*** (1.739)
Year fixed effects	No	Yes	Yes	Yes
Observations	348	348	348	319

Dependent variable: log total Kiva lending volume, country-year level. Log GDP per capita is centered. Standard errors in parentheses. Country-clustered standard errors. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Year fixed effects in the preferred specification rise from the omitted 2013 baseline by roughly 2.3 to 2.9 log points in 2014–2017, with no further monotonic increase after

2014 — consistent with Kiva’s total lending volume genuinely expanding over this period (total dollar volume rises from about \$133.0M in 2013 to \$175.6M in 2017, per Table A4) rather than with a sample-composition change, since country coverage grows far less (74 to 76 countries) than dollar volume does. This supports reading the year effects as a platform-growth control rather than as evidence bearing on the development–lending relationship itself.

5.2 Loan Level: Individual Loan Size

The country-year regressions preserve the main macroeconomic story, but the number of observations is mechanically limited by the number of countries and years (348 in the regression sample). To test the same nonlinearity question on the intensive margin, the same eight specifications are estimated at the **loan level**, using 917,955 individual Kiva loans merged to the same macro covariates. The dependent variable becomes log loan amount, so these coefficients describe how country-year development conditions are associated with the *size of a typical loan*, not aggregate lending volume — a distinct question, not a higher-powered re-estimate of Section 5.1. Because development varies at the country-year level while loan size varies at the loan level, the main specifications use country-year clustered standard errors, with a country-clustered version reported as a robustness check.

The linear and interaction specifications (Table A2, Appendix) mirror Table 2: the development coefficient is negative, and the delta-method marginal effect from the interaction specification is negative across the range of institutional quality, though with far tighter standard errors given the much larger sample. With roughly 900,000 loans rather than 348 country-years, these models have far more power to detect a nonlinear pattern if one exists. The squared development term is **positive and statistically significant at the 1% level** (0.245, $p < 0.001$, preferred specification) in every quadratic specification. This is a **U-shape, not an inverted-U**: individual loan size is estimated to fall as development rises from the low end of the sample, reach a minimum, and then rise again at higher development levels — the opposite sign from the (statistically insignificant) country-level pattern. This is not a contradiction, because the two outcomes measure different objects: a country can plausibly receive less total lending as it develops (fewer, larger loans crowd out many small ones, and formal banking substitutes for Kiva overall)

while the loans that *are* still made through Kiva get smaller in lower-middle income settings — where Kiva serves a high volume of very small borrowers — before rising again as remaining Kiva borrowers in richer countries use it for larger, more bank-like loan sizes. Sections 5.1 and 5.2 should therefore be read as two separate, both well-supported findings about different margins of microfinance activity, not as two tests of one shared hypothesis.

Table 5: Marginal Effect of Log GDP per Capita on Log Loan Size (Model 4, Loan Level)

	Institutional quality level	Marginal effect	SE	p-value
25th percentile	-0.290	0.189	0.057	0.001
Mean	-0.147	0.225	0.055	0.000
75th percentile	-0.012	0.259	0.054	0.000

Delta-method marginal effects of log GDP per capita at percentiles of institutional quality, loan-level model (4).

Table 6: Loan-Level: Quadratic and Robustness Specifications (Loan Size)

	(5)	(6)	(7)	(8)
Log GDP per capita (centered)	0.201*** (0.050)	0.206*** (0.049)	0.209*** (0.050)	0.166*** (0.064)
Log GDP per capita ² (centered)	0.245*** (0.030)	0.245*** (0.028)	0.245*** (0.028)	0.211*** (0.050)
Institutional quality (PCA1)	-0.091 (0.066)	-0.094 (0.066)		
Institutional quality index			-0.110 (0.075)	
Financial access index				0.043 (0.082)
Log population	-0.207*** (0.028)	-0.204*** (0.027)	-0.201*** (0.026)	-0.203*** (0.028)
Constant	9.713*** (0.455)	9.764*** (0.451)	9.718*** (0.445)	9.778*** (0.473)
Year fixed effects	No	Yes	Yes	Yes
Observations	913,128	913,128	913,128	891,246

Dependent variable: log individual loan amount. Log GDP per capita is centered. Standard errors in parentheses. Country-year-clustered standard errors. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

5.3 Two Margins: Extensive versus Intensive

Sections 5.1 and 5.2 both condition on Kiva already lending in a country-year: countries with no Kiva presence simply do not appear in the country-year panel at all. That means Table 4’s insignificant quadratic term cannot distinguish two very different stories: devel-

opment has no nonlinear relationship with Kiva activity at any margin, or development *does* have a nonlinear relationship with **whether Kiva is active in a country at all** (the extensive margin), but that pattern is invisible in Table 4 because the regression only ever sees countries where the answer is already yes.

To test this, a **global country-year panel that includes true zeros** is built: every economy with World Bank GDP-per-capita and population data for 2013–2017 is outer-merged with Kiva country-year loan totals built directly from raw loan-posting data, so that country-years with no matching Kiva loans get a lending total of zero and a Kiva-active indicator of zero rather than being dropped. Country codes are harmonized to a common three-letter standard for the merge, since Kiva’s own loan records use two-letter codes while the World Bank series use three-letter codes; this resolves cleanly for every one of Kiva’s 90 country codes, including territory-style codes such as the one used for Kosovo. The World Development Indicators classify 217 economies as actual countries, excluding regional and income-group aggregates such as “Sub-Saharan Africa.” Of the resulting 1,085 candidate country-year cells, 65 are dropped for missing GDP per capita or population (mostly small territories and a few years of state fragility), leaving **1,020 country-years covering 206 countries**, of which **374 (36.7%) are Kiva-active**. Because institutional and financial-access variables are only available for the roughly 90–96 countries Kiva already covers, they are heavily missing in the global sample and are not used as controls in the global regressions; institutional quality is reintroduced only in the Kiva-only intensive-margin column, where coverage is adequate.

Two models are estimated on this global panel. The **extensive margin** is modeled with **Logit** (country-clustered standard errors, reporting both coefficients and average marginal effects). The **intensive margin** is modeled with **PPML** (Poisson pseudo-maximum-likelihood; Santos Silva and Tenreyro, 2006), because the outcome now includes true zeros and a log-linear OLS model is not an option — dropping zeros would simply reproduce Section 5.1’s selected sample. PPML is estimated both on the full global sample including zeros and on the Kiva-only subsample, so the same functional form can be compared with and without the zero-lending country-years.

Table 8 (with full Logit coefficients and average marginal effects in Table 7) shows where the strongest evidence for development-related nonlinearity lives, with an important qualification from the formal test in Section 5.4. The **extensive margin is signifi-**

Table 7: Extensive Margin: Logit Coefficients and Average Marginal Effects

	Coefficient	Average marginal effect
Log GDP per capita (centered)	-1.026*** (0.204)	-0.157*** (0.024)
Log GDP per capita ² (centered)	-0.260** (0.114)	-0.040** (0.017)
Log population	0.399*** (0.086)	0.061*** (0.011)
Year fixed effects	Yes	Yes
Observations	1,020	1,020
Pseudo R^2	0.301	

Dependent variable: indicator for Kiva active in a country-year, global panel including zero-lending country-years. Country-clustered standard errors in parentheses. Log GDP per capita is centered. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 8: Two Margins: Logit (Extensive) vs. PPML (Intensive), Development Terms

Covariate	Logit coef.	Logit p	Logit AME	PPML (global) coef.	PPML (global) p	PPML (Kiva-only) coef.	PPML (Kiva-only) p
Log GDP per capita (centered)	-1.0265	0.0000	-0.1569	-0.5407	0.1611	-0.0055	0.9808
Log GDP per capita ² (centered)	-0.2603	0.0226	-0.0398	-0.2318	0.2417	-0.0698	0.5300

Logit: global panel including zero-lending country-years, country-clustered SE. PPML (global): same sample; PPML (Kiva-only): restricted to Kiva-active country-years. All models include year fixed effects and log population; PPML (Kiva-only) also includes institutional quality.

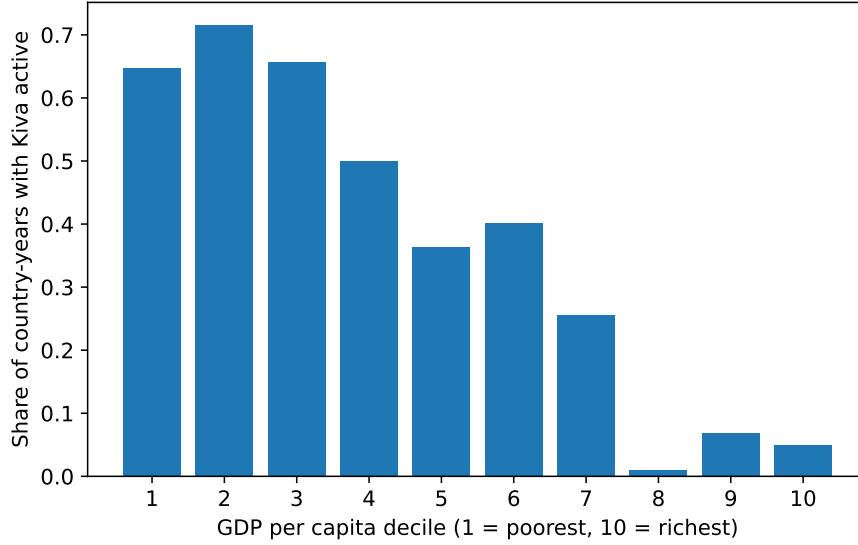


Figure 8: Share of country-years with Kiva active, by decile of log GDP per capita (1 = poorest decile, 10 = richest decile), global panel including zero-lending country-years.

cantly concave: the Logit quadratic term is negative and significant (coefficient -0.260 , $p = 0.023$; average marginal effect -0.040 , $p = 0.018$), and Figure 8 shows the pattern directly in the raw data — Kiva’s entry rate is roughly two-thirds across the poorest three deciles, falls to half by the fourth decile, and declines steeply to between 1% and 7% in the top three deciles. The implied turning point is at log GDP per capita ≈ 6.79 (about \$893 in constant 2015 USD), very close to the low end of the sample. Applying the same Lind–Mehlum test used for the other margins (Section 5.4), the high-end decline is unambiguous but the low-end *rise* is not individually significant ($t = 1.07$, one-sided $p = 0.143$), so the data confirm concavity and a steep decline with development, not a completed rise-then-fall within the observed range.

The **intensive margin does not show this pattern, whether or not zeros are included**. PPML on the full global sample gives a quadratic coefficient of -0.232 ($p = 0.242$); PPML restricted to the 369 (of 374) Kiva-active country-years with complete institutional controls gives -0.070 ($p = 0.530$). Both are statistically indistinguishable from zero, echoing the OLS-in-logs result in Table 4 even though PPML uses a completely different estimator and, in the global specification, a completely different zero-inclusive sample. Development therefore matters most visibly for *whether* Kiva operates in a country, with entry probability significantly concave in income and falling steeply as countries develop; but that is not the same as a confirmed inverted-U, because the initial rise at the very bottom of the income distribution cannot be statistically distinguished from a flat start. The three-margin picture is therefore: (1) whether Kiva enters a country — significantly concave, steeply declining, peak unconfirmed; (2) how much a country receives in total, conditional on entry — flat/declining, not significant; (3) how large an individual loan is — U-shaped, significant and formally confirmed. These are three distinct empirical objects, and the original middle-income-peak intuition survives, at most, in weakened form at the first of them.

5.4 Formal Test for Nonlinearity: The Lind–Mehlum U-Test

Throughout Sections 5.1–5.3, whether the quadratic term is statistically significant has been the main criterion for taking a nonlinear pattern seriously. That criterion is necessary but not sufficient: a significant quadratic coefficient does not by itself guarantee that the curve actually turns within the observed data range, because a significant coefficient

combined with a turning point far outside the sample would imply an essentially monotonic relationship over the range actually observed. [Lind and Mehlum \(2010\)](#) formalize the correct test: a genuine U-shape (or inverted-U) requires that the slope of the curve be significantly negative (positive) at the low end of the sample and significantly positive (negative) at the high end, evaluated at the sample’s actual minimum and maximum of X , not just that the quadratic coefficient differs from zero at the sample mean.

Concretely, for a fitted quadratic $\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x + \hat{\beta}_2 x^2 + \text{controls}$, the slope at any point is $\hat{\beta}_1 + 2\hat{\beta}_2 x$. This slope is computed at $x_{\min}$ and $x_{\max}$ (the sample extremes of centered log GDP per capita), with its standard error obtained via the delta method,

$$\text{SE}(\hat{\beta}_1 + 2\hat{\beta}_2 x) = \sqrt{\text{Var}(\hat{\beta}_1) + (2x)^2 \text{Var}(\hat{\beta}_2) + 2(2x) \text{Cov}(\hat{\beta}_1, \hat{\beta}_2)}, \quad (1)$$

using each model’s full clustered covariance matrix so the covariance term is not assumed away, and both slopes are tested individually. Following Lind and Mehlum’s intersection-union logic (closely related to [Sasabuchi, 1980](#)), the overall test statistic is the **weaker of the two individual t -statistics** in absolute value: the shape is confirmed only if both ends pass, so the binding constraint is whichever end is less significant. A [Fieller \(1954\)](#) confidence interval is also reported for the turning point $x_0 = -\hat{\beta}_1/(2\hat{\beta}_2)$, which correctly accounts for x_0 being a ratio of two estimated, correlated coefficients; if the quadratic term is not precisely estimated relative to the critical value, the Fieller interval is unbounded, which is itself informative.

This test is applied to all three shape claims in the paper: **m6** (country-year, total lending volume), **lm6** (loan-level, individual loan size), and the **extensive-margin Logit** (Section 5.3), the last evaluated on the linear-index (log-odds) scale where the quadratic functional form lives.

Table 9: Lind–Mehlum (2010) U-Test: m6, lm6, and the Extensive-Margin Logit

Model	Slope (low)	t (low)	Slope (high)	t (high)	U-test p	Confirmed?	Fieller 95% CI
m6 (country-year, volume)	0.659	1.080	-1.162	-1.478	0.140	No	Unbounded
lm6 (loan-level, size)	-0.893	-5.752	1.766	10.954	0.000	Yes	[-0.730, -0.198]
Logit (global, extensive margin)	0.654	1.065	-2.742	-3.028	0.143	No	[-10.384, -1.216]

Slopes evaluated at the sample minimum and maximum of (centered) log GDP per capita, with delta-method standard errors using each model’s full clustered covariance matrix. The U-test statistic is the weaker of the two end t -statistics (one-sided); shape is confirmed only if both ends are individually significant at the 5% level with opposite-signed slopes. The Logit row is evaluated on the linear-index (log-odds) scale.

Table 9 confirms, formally, what the p-value-only discussion above already suggested

informally. For **m6**, the slope at the low end of the sample is positive but only $t \approx 1.08$, well short of conventional significance, so the weaker-end test statistic fails decisively (one-sided $p \approx 0.140$), and the Fieller confidence interval for the turning point is **unbounded** — the data are consistent with a turning point essentially anywhere, including outside the observed range. This is independent confirmation that the country-level “peak” should not be treated as an established finding.

For **lm6**, the result is the opposite in every respect: the slope is significantly negative at the low end ($t \approx -5.75$) and significantly positive at the high end ($t \approx 10.95$), both comfortably clearing the bar, so the U-test **confirms** the shape (one-sided $p < 0.001$). The Fieller confidence interval for the turning point is tight and lies well inside the sample range, at roughly log GDP per capita ≈ 7.05 – 7.59 (about \$1,150–\$1,970 in constant 2015 USD), bracketing the point estimate of ≈ 7.36 (\$1,577). This is the formal, quantitative basis for treating the loan-level U-shape as the paper’s central confirmed nonlinear finding and the country-level curvature as unsupported.

For the **extensive-margin Logit**, the test delivers a split verdict. The high-end slope is strongly negative and individually significant ($t = -3.03$), confirming the steep decline in entry probability among richer countries. But the low-end slope, while positive, is not individually significant ($t = 1.07$, one-sided $p = 0.143$), so the intersection-union test fails and the inverted-U is not formally confirmed: the data cannot rule out that entry probability is simply flat at the very bottom of the income distribution before declining. This is the same discipline that the country-level curvature was held to, applied symmetrically to the paper’s most favorable-looking result: the extensive margin is reported as significant concavity with a steep decline, not as an established peak.

6 Robustness

6.1 Clustering Choice

The loan-level main specifications cluster standard errors at the country-year level, because the country-year development regressors are mechanically repeated within every country-year cell of loans, so treating each loan as an independent observation for inference would overstate precision. As a direct check on that choice, the preferred loan-level specification is re-estimated with standard errors clustered at the coarser country level

instead (Table A3, Appendix). The standard errors on the development terms are of similar magnitude under both choices, so the significance of the loan-level quadratic term is not an artifact of the finer country-year clustering.

6.2 Sample Period: Does Including 2013 Matter?

Section 2.3 concluded that 2013 is a complete year of genuine, if smaller, Kiva activity and should be kept in the main sample. As a direct check on that judgment call, the preferred quadratic specifications — **m6** (country-year, total volume) and **lm6** (loan-level, loan size) — are re-estimated on the 2014–2017 subsample only, dropping 2013 entirely, and the development terms are compared side by side with the full-sample results (Table 10).

Table 10: Sample-Period Robustness: Full Sample vs. 2014–2017 Only

Specification	Linear coef.	p	Quadratic coef.	p (sq.)	N
m6, full sample (2013-2017)	-0.1106	0.5018	-0.1676	0.1795	348.0000
m6, 2014-2017 only	-0.0947	0.5945	-0.1760	0.1594	294.0000
lm6, full sample (2013-2017)	0.2055	0.0000	0.2447	0.0000	913128.0000
lm6, 2014-2017 only	0.1874	0.0008	0.2456	0.0000	776306.0000

m6: country-year volume model; lm6: loan-level size model, both with year fixed effects.

Both conclusions are unchanged: at the country level, the quadratic term moves from -0.168 ($p = 0.179$, full sample) to -0.176 ($p = 0.159$, 2014–2017 only) — still negative, still far from significant; at the loan level, the quadratic term is virtually identical (0.245, $p < 0.001$ in both the full sample and the 2014–2017-only subsample), with the linear term also stable (0.206 versus 0.187). The paper’s two central conclusions do not depend on the decision to keep 2013 in the sample.

6.3 Loan-Level Robustness: Alternative Specifications of the Size Margin

The loan-level U-shape is the paper’s central confirmed nonlinear finding, so it is worth stress-testing directly rather than only checking the clustering choice and the sample period above. The preferred loan-level specification is re-estimated under three additional variants (Table 11), with the formal shape test applied to each (Table 12): excluding the United States, since US-based Kiva loans are a qualitatively different product (small-business loans in a high-income economy) rather than the poverty-lending use case the rest of the panel represents, and could be driving the “rises again” half of the U-shape

by themselves; a relative-loan-size measure that deflates the nominal loan amount by local GDP per capita, to check whether the U-shape partly reflects price- or income-level scaling rather than a real change in typical loan size; and sector fixed effects, since Kiva’s raw data classify every loan into one of fifteen sectors and richer and poorer countries in the sample could differ systematically in which sectors are active, which would make an apparent size U-shape partly a compositional artifact rather than a within-sector pattern.

Table 11: Loan-Level Robustness: lm6 Under Four Specifications

Specification	Linear coef.	p	Quadratic coef.	p (sq.)	N
(1) Baseline (lm6)	0.2055	0.0000	0.2447	0.0000	913128.0000
(2) Excluding US	0.2289	0.0000	0.3322	0.0000	904855.0000
(3) Relative loan size	-0.7945	0.0000	0.2447	0.0000	913128.0000
(4) Sector fixed effects	0.1925	0.0001	0.2340	0.0000	913128.0000

(3) Relative loan size regresses $\log(\text{loan amount} / \text{local GDP per capita})$ on the same controls; because $\log$ GDP per capita already enters linearly, this reproduces (1) by a Frisch–Waugh–Lovell identity and is not independently informative about curvature (see text). All columns use country-year-clustered standard errors.

Table 12: Lind–Mehlum U-Test Applied to All Four Loan-Level Robustness Variants

Specification	t , low end	t , high end	U-test p	Shape confirmed
(1) Baseline (lm6)	-5.752	10.954	0.000	Yes
(2) Excluding US	-4.868	7.129	0.000	Yes
(3) Relative loan size	-12.194	4.750	0.000	Yes
(4) Sector fixed effects	-5.650	11.071	0.000	Yes

One-sided U-test statistics for each column of Table 11.

Excluding the United States barely matters and if anything strengthens the pattern: US-based loans are only 0.9% of this sample, and the quadratic term rises slightly to 0.332 (still $p < 0.001$) once the US is dropped, so the “richer countries get larger loans again” half of the U-shape is not a US-specific artifact. **Relative loan size** (loan amount deflated by local GDP per capita) requires a genuine caveat: the quadratic coefficient in this column is numerically identical to the baseline’s (0.245 in both, to three decimal places) because $\log(\text{loan amount}/\text{GDP per capita})$ is algebraically $\log(\text{loan amount}) - \log(\text{GDP per capita})$, and $\log$ GDP per capita is already the model’s own linear regressor. By the Frisch–Waugh–Lovell theorem, subtracting a variable already in the design matrix from the dependent variable can only shift that variable’s own coefficient (here, by exactly -1) and leaves every other coefficient, including the quadratic term, mechanically unchanged; this specification, as given, cannot actually test whether the nominal-dollar U-shape survives deflating by local price levels, since it is guaranteed

to reproduce the original quadratic term regardless of the true data-generating process. A supplementary check that removes the self-cancelling linear control shows the quadratic term **attenuates but survives**: 0.148 (down from 0.245), still significant at $p = 0.002$. The honest reading is that some, but probably not all, of the nominal-dollar U-shape’s magnitude reflects local price- or income-level scaling, while a statistically significant U-shaped pattern in the deflated measure remains. **Sector fixed effects** leave the quadratic term essentially unchanged (0.234 versus 0.245 in the baseline, both $p < 0.001$), so compositional shifts across Kiva’s fifteen lending sectors are not driving the result. Table 12 confirms with the formal shape test that all four variants pass decisively, including the relative-size column for the mechanical reason just explained, which is why that particular “pass” should not be read as additional independent evidence beyond what the supplementary, linear-control-free check already provides.

7 Limitations

The results above are subject to several limitations that bear directly on how much weight to place on each of the three margins. Some are fully resolved by the paper’s own design choices (building the global zero-inclusive panel, running the formal shape test uniformly); others are only partially addressed and are flagged as such below, rather than smoothed over.

Sample selection (partially addressed). The country-year and loan-level panels (Sections 5.1–5.2) cover only the countries in which Kiva was already active between 2013 and 2017; whether Kiva enters a country at all is itself a decision shaped by local infrastructure, regulation, and partner-organization availability, and that entry decision is not modeled in those two panels. Section 5.3 directly addresses part of this by building a global panel that includes zero-lending country-years and modeling entry with a Logit, but it still cannot say *why* Kiva enters some countries and not others beyond the reduced-form relationship with GDP per capita and population.

Zero-lending country-years and the log transform (addressed at the country level, not the loan level). Log total lending volume and log loan size are well-defined and strictly positive for every row in their respective panels, since there are no zero-loan country-years or zero-dollar loans within the Kiva-only samples. Section 5.3’s

global panel resolves this at the country level by including true zeros and modeling them with a Logit rather than dropping them; there is no loan-level analogue of this concern, since individual realized loans are by definition non-zero.

Short panel. The panel spans only five years (2013–2017). Some of the observed variation may reflect the global expansion of the Kiva platform over this period rather than only structural differences across countries; Section 2.3 checks that 2013 is not a partial or incomplete year and Section 6 confirms the main results are unchanged if 2013 is dropped, but the panel remains short relative to typical macro panels, and year fixed effects only partially absorb platform-growth effects that may themselves vary by country.

Price-level and currency-conversion effects (partially addressed). Section 6 shows that a naive test of whether the loan-level U-shape survives deflating by local GDP per capita is mechanically guaranteed to reproduce the original result, and that a corrected version of the same test shows the U-shape attenuates but remains significant. This suggests part, but apparently not all, of the nominal-dollar loan-size U-shape reflects local price-level scaling rather than a real change in relative loan size — a distinction future work could pursue further with a proper purchasing-power-parity or local-currency deflator.

Descriptive, not causal. All specifications are estimated by OLS, Logit, or PPML on observational data. Development, institutional quality, and Kiva lending are jointly determined by many unobserved factors, so the coefficients reported here should be read as conditional associations, not treatment effects.

8 Conclusion

This paper set out to test whether Kiva microfinance lending activity follows an inverted-U relationship with economic development, peaking in lower-middle income countries. The country-year evidence does not support that hypothesis: the quadratic term is negative but statistically indistinguishable from zero in all four specifications ($p > 0.10$), and the linear component is negative on average, so the more defensible reading is that **total lending volume tends to decline with development** across most of the sample, without strong evidence of a rise-then-fall shape. The formal Lind–Mehlum test confirms this is not just a significance-testing artifact: the slope at the low end of the sample is

not even individually significant ($t \approx 1.08$), and the Fieller confidence interval for the implied turning point is unbounded.

At the loan level, a different and much better-supported pattern emerges: the quadratic term is **positive and significant at the 1% level**, implying that individual loan size follows a **U-shape** — falling and then rising with development — the opposite sign from the (insignificant) country-level curvature. The formal test confirms this shape decisively, with a Fieller turning-point interval of roughly \$1,150–\$1,970 that lies comfortably inside the sample range, and this survives excluding the US, sector fixed effects, and (with attenuated but still significant magnitude once a mechanical cancellation is correctly accounted for) deflating by local price levels.

A third margin resolves an ambiguity in the first two: because the country-year panel only contains country-years where Kiva was already active, it cannot distinguish “no nonlinearity anywhere” from “the nonlinearity is in whether Kiva enters a country at all.” Building a global panel that includes true zero-lending country-years and estimating a Logit for Kiva’s extensive margin shows **significant concavity with a steep decline**: the probability that Kiva is active in a country is highest among the poorest deciles and falls to near zero among the richest countries, though the initial rise at the very bottom fails the formal low-end slope test, so a completed inverted-U is not established. PPML on total lending volume, both including zeros and restricted to Kiva-active country-years, shows no such pattern, consistent with the OLS-in-logs result.

Because total volume, Kiva presence, and loan size measure three different objects — aggregate country-level volume, whether Kiva operates in a country at all, and the size of a single realized loan — these are not competing estimates of one underlying relationship. They are three distinct findings about three different margins of microfinance activity:

1. **Extensive margin (country level, whether Kiva is active at all)**: significantly concave — entry probability declines steeply with development; the raw-data peak in the second income decile is suggestive, but the initial rise is not statistically confirmed by the Lind–Mehlum test.
2. **Quantity margin (country level, conditional on Kiva being active)**: not robustly nonlinear in development; if anything it declines as countries get richer within this sample, and fails the formal shape test.

3. **Size margin (loan level):** robustly and significantly U-shaped in development, confirmed by the formal shape test and by four separate robustness variants.
4. These are not three tests of the same claim. A country can be less likely to receive any Kiva lending as it develops, while conditional on receiving some, the total volume and the typical loan size follow different, and in one case opposite-signed, patterns.

Both results are conditional on the sample-selection and short-panel limitations discussed in Section 7, and both are descriptive rather than causal. The extensive-margin analysis addresses part of the original excluded-zeros limitation directly, but the loan-level findings remain conditional on a loan having been made. Future work could usefully model Kiva’s entry decision more richly (for example, with partner-organization availability as a covariate), extend the panel beyond five years, and examine borrower-level heterogeneity within the loan-level file to test whether the size U-shape reflects compositional shifts in borrower type or loan purpose as countries develop, beyond the sector and price-level checks already performed here.

More broadly, the methodological point of this paper travels beyond Kiva specifically: whenever a lending, giving, or allocation platform is studied only within the set of markets it already serves, a quadratic term estimated on that selected sample cannot distinguish a genuinely flat relationship from one whose curvature lives entirely at the unobserved entry margin. The three-margin decomposition used here — extensive, quantity, and size — and the discipline of holding every resulting shape claim to the same formal test, including the one that looks most favorable to the original hypothesis, are both directly portable to other platform-mediated markets where entry and intensity are jointly determined but usually analyzed as if they were one outcome.

References

- Angelucci, M., Karlan, D., and Zinman, J. (2015). Microcredit impacts: Evidence from a randomized microcredit program placement experiment by compartamos banco. *American Economic Journal: Applied Economics*, 7(1):151–182.
- Banerjee, A., Duflo, E., Glennerster, R., and Kinnan, C. (2015). The miracle of microfinance? Evidence from a randomized evaluation. *American Economic Journal: Applied Economics*, 7(1):22–53.
- Burgess, R. and Pande, R. (2005). Do rural banks matter? Evidence from the Indian social banking experiment. *American Economic Review*, 95(3):780–795.
- Cull, R., Demirgüç-Kunt, A., and Morduch, J. (2007). Financial performance and outreach: A global analysis of leading microbanks. *The Economic Journal*, 117(517):F107–F133.
- Cull, R., Demirgüç-Kunt, A., and Morduch, J. (2009). Microfinance meets the market. *Journal of Economic Perspectives*, 23(1):167–192.
- Fieller, E. C. (1954). Some problems in interval estimation. *Journal of the Royal Statistical Society, Series B*, 16(2):175–185.
- Galak, J., Small, D., and Stephen, A. T. (2011). Microfinance decision making: A field study of prosocial lending. *Journal of Marketing Research*, 48(SPL):S130–S137.
- Hermes, N., Lensink, R., and Meesters, A. (2011). Outreach and efficiency of microfinance institutions. *World Development*, 39(6):938–948.
- Karlan, D. and Zinman, J. (2011). Microcredit in theory and practice: Using randomized credit scoring for impact evaluation. *Science*, 332(6035):1278–1284.
- Kiva.org (2018). Kiva loan data snapshot. Kiva Microfunds, San Francisco, CA. Loan-level posting records (loan amount, sector, country, and posting timestamp) for loans funded through the Kiva platform, 2013–2017.
- Lind, J. T. and Mehlum, H. (2010). With or without U? The appropriate test for a U-shaped relationship. *Oxford Bulletin of Economics and Statistics*, 72(1):109–118.

- Morduch, J. (1999). The microfinance promise. *Journal of Economic Literature*, 37(4):1569–1614.
- Pitt, M. M. and Khandker, S. R. (1998). The impact of group-based credit programs on poor households in Bangladesh: Does the gender of participants matter? *Journal of Political Economy*, 106(5):958–996.
- Roodman, D. and Morduch, J. (2014). The impact of microcredit on the poor in Bangladesh: Revisiting the evidence. *Journal of Development Studies*, 50(4):583–604.
- Santos Silva, J. M. C. and Tenreyro, S. (2006). The log of gravity. *The Review of Economics and Statistics*, 88(4):641–658.
- Sasabuchi, S. (1980). A test of a multivariate normal mean with composite hypotheses determined by linear inequalities. *Biometrika*, 67(2):429–439.
- Tarozzi, A., Desai, J., and Johnson, K. (2015). The impacts of microcredit: Evidence from ethiopia. *American Economic Journal: Applied Economics*, 7(1):54–89.
- World Bank (2018). World development indicators. World Bank Group, Washington, DC. GDP per capita (constant 2015 US\$, series NY.GDP.PCAP.KD), total population (series SP.POP.TOTL), and governance and financial-access indicators, accessed for the 2013–2017 panel.

Appendix

Table A1: Lending Activity by Development Tercile

Development tercile	N	Mean log lending	Mean log GDP p.c.	Mean institutional quality	Mean log population
Low development	116.000	12.806	6.708	-0.619	16.598
Middle development	116.000	13.435	7.755	-0.229	16.845
High development	116.000	12.776	9.020	0.437	16.575

Terciles of log GDP per capita, country-year panel.

Table A2: Loan-Level: Linear and Interaction Specifications (Loan Size)

	(1)	(2)	(3)	(4)
Log GDP per capita	0.275*** (0.060)	0.278*** (0.058)	0.283*** (0.058)	0.262*** (0.054)
Institutional quality (PCA1)		-0.011 (0.076)	-0.014 (0.076)	-2.028*** (0.356)
Log population	-0.199*** (0.035)	-0.200*** (0.036)	-0.197*** (0.034)	-0.207*** (0.032)
Log GDP per capita $\times$ institutional quality				0.252*** (0.041)
Constant	7.584*** (0.850)	7.561*** (0.835)	7.581*** (0.808)	7.857*** (0.712)
Year fixed effects	No	No	Yes	Yes
Observations	913,128	913,128	913,128	913,128

Dependent variable: log individual loan amount. Standard errors in parentheses.

Country-year-clustered standard errors. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A3: Loan-Level Standard Errors: Country-Year vs. Country Clustering

Covariate	Country-year-clustered SE	Country-clustered SE
Log GDP per capita (centered)	0.0493	0.0925
Log GDP per capita ² (centered)	0.0280	0.0561
Institutional quality (PCA1)	0.0665	0.1341
Log population	0.0267	0.0566

Coefficients are from model (6) of Table 6 (lm6); only standard errors differ by clustering level.

Table A4: Year and Month Coverage of Raw Kiva Loan-Posting Data (2013–2017)

Year	N loans	Total loan amount (USD)	N countries	Months covered (of 12)	Min monthly loans	Max monthly loans	N loans,
2013	140034.0	133018800.0	74.0	12.0	9658.0	13357.0	80.4
2014	174234.0	152924550.0	81.0	12.0	11735.0	16484.0	100.0
2015	181833.0	157622925.0	77.0	12.0	12405.0	16369.0	104.4
2016	197236.0	164434750.0	74.0	12.0	13559.0	18474.0	113.2
2017	224618.0	175581800.0	76.0	12.0	16114.0	22954.0	128.9

Coverage diagnostics computed directly from Kiva’s raw loan-posting timestamps.