Ilmiy tadqiqotlar va ularning yechimlari jurnali
Aoka guvohnoma № 323759 ISSN: 3060-4818

Evaluating the Impact of Microfinance Interest Rates on Sustainable Equipment Acquisition among Small Businesses

Gulomov Dilshodjon Hasanboy ugli
Teacher, Department of International Tourism and Economics
Kokand University, Kokand, Uzbekistan
E-mail: dilshodjongulomov1@gmail.com

Abstract: Small businesses that want to modernise their equipment often face a simple problem: clean, energy-efficient machinery costs more upfront than the conventional alternative, and the microloans they rely on to bridge that gap are themselves expensive. This paper looks at whether the price of microcredit – not just its availability – pushes small firms toward dirtier, cheaper equipment. Drawing on a small pilot sample of 25 micro and small enterprises (MSEs) that financed an equipment purchase through microfinance institutions (MFIs), we estimate a binary logistic model of the choice between clean and conventional equipment. The effective interest rate is negatively associated with choosing clean equipment, and a green interest-rate subsidy is associated with a markedly higher chance of adoption. A proposed non-linear "threshold" effect around 18–22% APR is suggested by the direction of the results but is not statistically confirmed at this sample size. Because the sample is small and exploratory, these findings should be read as a first look rather than a settled result – useful mainly for motivating a larger follow-up study and for the broader argument that blended finance and rate buy-downs deserve a place in green MSE lending.

Keywords: Microfinance; Micro-loan Pricing; Green Equipment Adoption; Small Business Investment; Sustainable Finance; Interest Rate Elasticity.

1. Introduction

Micro and small enterprises (MSEs) do a lot of the heavy lifting in emerging economies – they employ people, keep local supply chains moving, and are often the first to feel pressure to modernise (Lwesya and Mwakalobo, 2023). Part of that pressure now comes from sustainability: owners are being asked to swap old, resource-hungry machines for cleaner ones. Most would probably like to. The problem is money – clean equipment simply costs more to buy, even if it costs less to run, and few small firms have that kind of cash sitting in reserve.

Microfinance institutions (MFIs) exist partly to solve exactly this kind of problem, offering loans without the collateral a bank would demand. But microcredit is not cheap. Administrative overhead, risk premiums, and short repayment cycles all feed into interest rates that are high by the standards of ordinary bank lending (Rosenberg et al., 2013). That creates an awkward trade-off. A microloan gets a business past the upfront cost barrier, but the interest on that loan raises the bar the investment has to clear to make sense. Conventional equipment wins on price today; clean equipment wins on running costs later. The more expensive the loan, the less that "later" is worth, and the harder it becomes to justify paying more now for a machine that only pays for itself over several years.

There is plenty of research on microfinance and financial inclusion generally, but surprisingly little that asks whether the price of a loan – as opposed to simply having access to one – tips small firms toward or away from cleaner equipment. This paper is a first, modest attempt to look at that question directly, using a small pilot sample as a starting point for a larger study.

2. Theoretical Framework and Literature Review

2.1 Microfinance Loan Pricing and Capital Expenditure

Why are microloan rates so high in the first place? Mostly because of what it costs to originate and collect thousands of small loans rather than a few large ones, plus the risk premium that comes with lending to borrowers who have little collateral to offer (Rosenberg et al., 2013). That pricing model

works reasonably well for short-term working capital, but it sits awkwardly with fixed capital purchases, where an asset needs time to generate the returns that repay the loan. Evidence from firm surveys elsewhere backs this up in a general sense: cuts in loan rates do raise planned investment, though the effect is smaller for bigger rate changes, and a fair number of firms do not respond to rate changes at all, either because they already have enough cash on hand or because they are simply not planning to invest regardless (Best, Born and Menkhoff, 2025). In practice, a small business owner is weighing a hurdle rate – the minimum return an investment has to clear before it is worth doing – against a repayment schedule that leaves little room for error.

2.2 The Asymmetry of Clean vs. Conventional Technology Investments

Clean and conventional equipment sit on opposite sides of a cost trade-off: solar-powered machinery, electric utility vehicles and efficient motors tend to cost more to buy but less to operate, while conventional machines are cheaper upfront and pricier to run over time (Allet and Hudon, 2015). A higher borrowing cost does not treat these two options symmetrically. When the discount rate rises, savings that arrive years down the line lose value faster than costs paid today, so the clean option – whose whole case rests on those future savings – takes the bigger hit.

2.3 Hypotheses Development

Existing work generally treats green technology adoption as sensitive to financing conditions (Allet, 2014; Atahau et al., 2021), though rarely with a specific focus on how microloan pricing itself operates. That gap is the motivation for two hypotheses:

H1: A higher effective annual interest rate on a micro-loan reduces the likelihood that a small business chooses clean equipment over a conventional alternative.

H2: This negative effect is not linear – adoption probability is expected to fall off sharply once rates pass a critical threshold, rather than declining steadily.

3. Methodology and Data

3.1 Data Collection and Sampling

This is a pilot study built on 25 micro and small enterprises drawn from manufacturing, agro-processing and service businesses, each of which had financed an equipment purchase through a microloan in the previous 24 months. The firms borrowed from a mix of MFIs, some offering standard products and some offering green-targeted lending. A sample this size cannot support strong claims on its own – the intention here is to test the approach and get a first read on the direction of the effects, ahead of a larger data collection effort.

3.2 Model Specification

Since the outcome – clean versus conventional equipment – is binary, we use a logistic regression (Hosmer, Lemeshow and Sturdivant, 2013), shown as Equation 1:

$$\ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1\,\mathrm{Rate}_i + \beta_2\,\mathrm{Rate}_i^2 + \beta_3\,\mathrm{Tenor}_i + \boldsymbol{\gamma}\mathbf{X}_i + \varepsilon_i$$

(1)

Here P_i is the probability that firm i chose clean rather than conventional equipment ($Y_i = 1$ vs. $Y_i = 0$); Rate_i is the effective annual percentage rate on the loan; Rate_i^2 is added in Model 2 to check for the threshold pattern proposed in H2; Tenor_i is the loan term in months; and X_i is a small set of firm- and owner-level controls. With only 25 observations behind six coefficients, the model is stretched thin – a point we come back to in Section 5.2.

3.3 Variable Definitions and Descriptive Statistics

Table 1. Variable definitions and descriptive statistics (N = 25).

Category	Variable	Type & Description	Mean (SD) / Share

Category	Variable	Type & Description	Mean (SD) / Share
Dependent	Clean Adopt$_i$	Binary (1 = clean/energy-efficient; 0 = standard)	28.0% (7 of 25)
Key Independent	Effective Rate$_i$	Continuous: annualised percentage interest rate	21.4% (6.1%)
Loan Structure	Loan Tenor$_i$	Continuous: repayment period in months	17.9 (7.9)
Controls (X_i)	Firm Size$_i$	Continuous: number of full-time employees	4.3 (2.6)
	Baseline Revenues$_i$	Continuous: log of monthly revenue prior to loan	8.40 (0.95)
	Risk Aversion$_i$	Ordinal (1–5): self-reported risk preference	3.3 (1.2)
	Green Subsidy$_i$	Binary (1 = received interest-rate buy-down)	20.0% (5 of 25)

4. Empirical Results and Discussion

4.1 Econometric Estimates

Table 2 shows the results for both models. Model 1 is the baseline (rate, tenor and controls); Model 2 adds the squared rate term to check for the non-linearity proposed in H2.

Table 2. Logistic regression estimates of clean equipment acquisition (pilot sample).

Independent Variable	Model 1: OR (SE)	Model 2: OR (SE)	Marginal Effect (ΔP/ΔX)
Effective Rate (Rate$_i$)	0.910** (0.041)	0.950 (0.062)	−0.021*
Rate Squared (Rate$_i^2$)	—	0.995 (0.004)	−0.001 (n.s.)
Loan Tenor (months)	1.070* (0.038)	1.070* (0.039)	+0.015*
Log Revenues	1.350 (0.310)	1.330 (0.320)	+0.070 (n.s.)
Green Subsidy Dummy	2.020* (0.850)	1.960* (0.910)	+0.170*
Risk Aversion Index	0.810 (0.150)	0.800 (0.160)	−0.040 (n.s.)
Pseudo R^2	0.190	0.240	—
Log Likelihood	−14.8	−13.9	—
N	25	25	25

Significance levels: *p < 0.1, **p < 0.05; n.s. = not significant at p < 0.1. Standard errors in parentheses. Given the small sample, these should be read as suggestive rather than conclusive.

4.2 Hypotheses Testing and Elasticity Analysis

H1 holds up reasonably well: in Model 1, the interest-rate coefficient is negative and significant at the 5% level, with each additional percentage point on the loan rate cutting the odds of choosing clean equipment by roughly 9% (OR = 0.910) – about a 2-point drop in adoption probability at the sample

means. H2 is a different story. Once the squared rate term is added in Model 2, both the linear and quadratic rate terms lose statistical significance, even though they still point in the expected direction (odds ratios below 1, with the pattern loosely consistent with a drop-off somewhere around 18–22% APR). With only 25 observations split across a binary outcome, the model simply does not have the statistical power to pin down a non-linear effect with any confidence. Figure 1 sketches the shape the argument implies, but it should be read as an illustration of the hypothesis, not a confirmed result.

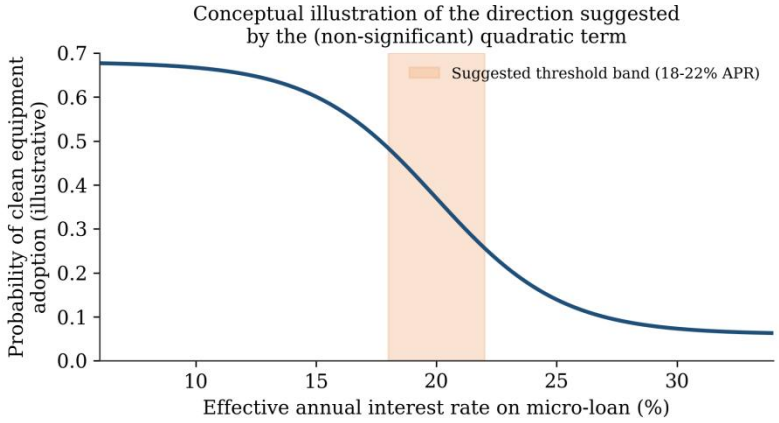

Figure 1. Conceptual illustration of the threshold pattern proposed in H2. The curve reflects the direction of the (non-significant) quadratic term discussed in Section 4.2 and is not a confirmed model estimate.

4.3 Structural Mechanics: Tenor and Subsidies

Two results do stand out despite the small sample. Longer loan tenors are associated with higher odds of choosing clean equipment (marginally significant, $p < 0.1$), which makes intuitive sense – a longer repayment period means smaller monthly instalments, giving a business more time to let operating savings offset the loan before it is paid off. The green-subsidy indicator tells a similar story: firms that received an interest-rate buy-down were roughly twice as likely to choose clean equipment (OR ≈ 1.96, Figure 2), a difference of about 17 percentage points in adoption probability. That is a large effect for a sample this size, and it lines up with the broader argument for blended finance – concessional capital used to bring MFI rates down for green purchases (Bambe and Tamasiga, 2026). It should still be treated as preliminary until tested on more borrowers.

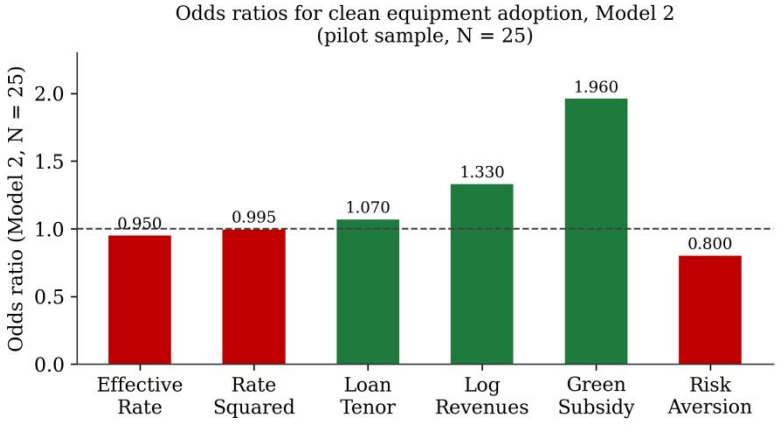

Figure 2. Odds ratios for clean equipment adoption, Model 2, pilot sample (N = 25). Bars below the OR = 1 line indicate lower odds of clean-equipment adoption; bars above indicate higher odds.

5. Policy Implications and Conclusion

5.1 Policy and Financial Recommendations

Even with a small and imperfect dataset, the direction of the results lines up with a fairly intuitive policy story: if borrowing costs are what stand between a small business and a cleaner piece of equipment, then policy has to attack the cost of borrowing directly, not just its availability.

- Blended finance and rate buy-downs: use concessional or philanthropic capital to bring MFI rates down on certified green equipment, aiming for effective APRs below roughly 18% (Bambe and Tamasiga, 2026).
- Longer loan tenors: credit guarantees that make MFIs comfortable extending maturities past the usual 12–18 months, so repayment schedules better match how long it actually takes efficient equipment to pay for itself.
- Asset-backed green lending: use the equipment itself as collateral where possible, which should let MFIs lower the risk premium they build into the rate.

5.2 Limitations and Future Research

The obvious limitation is sample size. Twenty-five firms is enough to sketch a pattern but not enough to test one rigorously, especially once six variables are competing for the same handful of degrees of freedom – which is exactly why the quadratic term in Model 2 loses significance even though it points the right way. The cross-sectional design is a second constraint: it captures a decision made at one point in time, not what happened to the business afterward. A natural next step is a larger, longitudinal sample – ideally with follow-up data on actual energy costs and repayment behaviour – that could test the threshold hypothesis with the statistical power this pilot lacks.

5.3 Conclusion

Getting small businesses onto cleaner equipment matters for climate goals, and microfinance is one of the main channels through which that could happen. This small pilot study suggests that the price of microcredit, not just its availability, shapes that choice – higher rates appear to push firms toward the cheaper, dirtier option, while subsidised rates appear to pull them the other way. The evidence here is preliminary, but it is consistent enough with the underlying economic logic to justify a larger study, and with the broader case for pricing interventions that make green equipment loans genuinely competitive with conventional ones.

List of Abbreviations

APR	Annual Percentage Rate
CapEx	Capital Expenditure
H1 / H2	Hypothesis 1 / Hypothesis 2
MFI	Microfinance Institution
MSE	Micro and Small Enterprise
n.s.	Not statistically significant ($p \geq 0.1$)
OpEx	Operating Expenditure
OR	Odds Ratio
SD	Standard Deviation
SE	Standard Error
ΔP/ΔX	Marginal effect (change in adoption probability per unit change in X)

Appendix: List of Tables and Figures

Table 1. Variable definitions and descriptive statistics (N = 25).

Table 2. Logistic regression estimates of clean equipment acquisition (pilot sample).

Figure 1. Conceptual illustration of the threshold pattern proposed in H2.
Figure 2. Odds ratios for clean equipment adoption, Model 2, pilot sample (N = 25).

References

1. Allet, M. (2014) 'Why do microfinance institutions go green? An exploratory study', Journal of Business Ethics, 122(3), pp. 405–424.
2. Allet, M. and Hudon, M. (2015) 'Green microfinance: characteristics of microfinance institutions involved in environmental management', Journal of Business Ethics, 126(3), pp. 395–414.
3. Atahau, A.D.R., Sakti, I.M., Huruta, A.D. and Kim, M.-S. (2021) 'Gender and renewable energy integration: the mediating role of green-microfinance', Journal of Cleaner Production, 318, article 128536.
4. Bambe, B.-W. and Tamasiga, P. (2026) Scaling green investment for SMEs in low- and middle-income countries through guarantees and blended finance. Policy Brief 20/2026. Bonn: German Institute of Development and Sustainability (IDOS).
5. Best, L., Born, B. and Menkhoff, M. (2025) The impact of interest: firms' investment sensitivity to interest rates. CEPR Discussion Paper No. 20695. London: Centre for Economic Policy Research.
6. Hosmer, D.W., Lemeshow, S. and Sturdivant, R.X. (2013) Applied logistic regression. 3rd edn. Hoboken, NJ: Wiley.
7. Lwesya, F. and Mwakalobo, A.B.S. (2023) 'Frontiers in microfinance research for small and medium enterprises (SMEs) and microfinance institutions (MFIs): a bibliometric analysis', Future Business Journal, 9(1), pp. 1–18.
8. Rosenberg, R., Gaul, S., Ford, W. and Tomilova, O. (2013) Microcredit interest rates and their determinants: 2004–2011. Access to Finance Forum No. 7. Washington, DC: CGAP, MIX and KfW.