IBN HALDUN UNIVERSITY
SCHOOL OF GRADUATE STUDIES
DEPARTMENT OF ECONOMICS

PH.D. THESIS

AN INQUIRY INTO THE EFFECTS OF MICROFINANCE ON SOCIAL DISTRUST LEVELS AMONG THE POOR

SYED MUHAMMAD USMAN MASOOD

THESIS SUPERVISOR
PROF. RASİM ÖZCAN

ISTANBUL, 2023

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by
SYED MUHAMMAD USMAN MASOOD

A thesis submitted to the School of Graduate Studies in partial fulfillment of the requirements for the degree of Ph.D. in Economics

THESIS SUPERVISOR
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ISTANBUL, 2023

APPROVAL PAGE

This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Doctor of Philosophy in Economics.

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Title - Name Surname	Opinion	Signature
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This is to confirm that this thesis complies with all the standards set by the School of Graduate Studies of Ibn Haldun University.

Date of Submission   Seal/Signature

ACADEMIC HONESTY ATTESTATION

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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Signature:

ÖZ

MİKROFİNANSIN YOKSULLARIN TOPLUMSAL GÜVENSİZLİK DÜZEYLERİNE ETKİSİNE İLİŞKİN BİR ARAŞTIRMA

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Şubat, 2023, 94 Sayfa

Bu tez mikrofinans literatürüne üç katkıda bulunmaktadır. Mikrofinans ve sosyal sermaye hakkındaki kanıtları sentezleyerek, grup kredisine dayalı mikrofinans ve sosyal sermayenin nasıl etkileşime girdiğine dair bir anlayış geliştirmektedir. Literatürdeki boşluklardan yola çıkarak, toplum için neyin (aslında) işe yaradığını anlamak için sosyologlar ve ekonomistler tarafından benimsenen yaklaşımlar arasında köprü kuran disiplinler arası araştırmalara duyulan ihtiyacı vurgulamaktadır. Daha sonra, ülkeler arası analizler için üç yeni mikrofinans (yaygınlık) yoğunluğu ölçütü önerilmektedir. Bu yeni ölçütlerin mevcut ölçütlerden daha kesin olduğunu, mevcut ölçütlerle yüksek korelasyona sahip olduğunu ve daha yüksek varyans gösterdiğini gösteriyoruz. Bu özellikler, yeni ölçümlerin ülkeler arası heterojenliği daha iyi kullanmasına olanak tanımaktadır. Son olarak, mikrofinans yoğunluğu ile sosyal güvensizlik arasındaki ilişki analiz edilmiştir. Yirmi yılı aşkın bir süreyi kapsayan verileri kullanarak, 2001, 2007, 2012 ve 2019 yıllarına karşılık gelen Dünya Değerler Anketi'nin son dört dalgasını kullandık ve ampirik Bayes, 2 Aşamalı En Küçük Kareler ve zayıf enstrümanlar-güçlü regresyonlar dahil olmak üzere çeşitli kontrollere dayanıklı önemli bir ilişki bulduk. Bu ilişki sadece toplumun düşük gelirli kesimlerinde mevcut olup zengin kesimlerinde görülmemektedir; bu da mikrofinansın yoksul kesimleri hedef alması nedeniyle bu ülkelerde mikrofinansın etkisini düşündürmektedir. Mikrofinans, sosyal sermayenin teminat altına alınması nedeniyle topluluklar içindeki güvensizlik düzeylerini etkileyebilir. Müteselsil sorumluluk

mekanizması, geçmişte birçok nitel çalışma tarafından rapor edildiği üzere sosyal sürtüşme yaratmakta ve bu da toplumdaki güven seviyelerini kırmaktadır. Bu tez, mikrofinansın güven(siz)liği nasıl kötüleştirdiğini kamuya açık verileri kullanarak ampirik olarak gösteren ilk çalışmadır. Çalışmanın teori ve uygulamada mikrofinans için önemli çıkarımları vardır: sonuçlar, tipik grup temelli mikrofinansın teşvik yapısının, tasarımının doğasında bulunan sosyal maliyetleri daha iyi hesaba katmak için yeniden gözden geçirilmesi gerektiğini göstermektedir; finansal içerme, sosyal bağlar ve güven pahasına gelmemelidir.

Anahtar Kelimeler: Finansal Katılım, Güven, Grup Kredisi Müşterek Sorumluluk, Mikrokredi, Sosyal Sermaye..

ABSTRACT

AN INQUIRY INTO THE EFFECTS OF MICROFINANCE ON SOCIAL DISTRUST LEVELS AMONG THE POOR

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February 2023, 94 pages

This thesis makes three contributions to the microfinance literature. It synthesizes the evidence on microfinance and social capital, developing an understanding of how group lending-based microfinance and social capital interact. Drawing on gaps in the literature, it highlights the need for interdisciplinary research that bridges the approaches taken by sociologists and economists for understanding what (actually) works for society. Next, three novel measures of microfinance (prevalence) intensity for cross-country analyses are proposed. We show that these new measures are more precise than existing ones, are highly correlated with the existing measures, and show a higher variance. These characteristics allow the new measures to better exploit cross-country heterogeneity. Lastly, the association between microfinance intensity and social distrust is analysed. Utilizing data extending over two decades, we use the four recent waves of the World Values Survey, corresponding to the years 2001, 2007, 2012, and 2019, and find a significant relationship, robust to various checks, including empirical Bayes, 2-Stage Least Squares, and weak instruments-robust regressions. The relationship is present only in the low-income strata of the society and not in the rich, suggestive of the effect of microfinance in these countries, as microfinance targets the poor strata. Microfinance may affect distrust levels within communities because of the collateralization of social capital. The joint-liability mechanism creates social friction, as has been reported by many qualitative studies in the past, which fractures the levels of trust in society. This thesis is the first to show how microfinance worsens (dis)trust empirically using publicly available data. The study has important implications for microfinance in theory and practice: the results suggest that the incentive structure of the typical group-based microfinance needs revisiting to better account for the social costs inherent in its design; financial inclusion should not come at the expense of social ties and trust.

Keywords: Financial Inclusion, Group-Lending. Joint Liability, Microcredit, Social Capital, Trust.

DEDICATION

To those
who had faith,

to those
who kept faith,

but especially to those
who whirl on and on
in Faith…

ACKNOWLEDGMENT

I would like to extend my warmest thanks to my supervisor, Prof. Dr. Rasim Özcan, for his immense support, guidance, and encouragement throughout the course of my doctorate. My deep gratitude goes to Dr. Şerife Genç İleri and Dr. Sadullah Yıldırım for being a part of my Ph.D. Committee and insightful advice at every step. I am grateful to all members of the jury for taking the time to assess the thesis.

A special thanks is due to Dr. Asad ul Islam Khan for his guidance and crucial advice, especially towards the latter parts of the thesis, where much of the thought work was to be converted into papers. A very special thanks to Prof. Dr. Mohamad Lutfi Hammour for enlightening discussions at the incubation time of the thesis: his trust, guidance, and encouragement gave me the confidence to get going. I thank Mr. Muhammad Moiz, Dr. Naeem Nawaz, Dr. Abdur Rehman Cheema, Mr. Ali Moin, Dr. Wajid Hussain, Mr. Ayuba Napari, Mr. Jamie Turner, and Mr. Hassan Asghar for the useful discussions we had and their support during this journey.

I am indebted to Mr. Imtiaz Hussain, Mr. Kareem Masood, Mr. Naveed Ashraf, Mr. Tariq Siddique, Dr. Hafiz Muhammad, Dr. Mansoor Khan, and Mr. Mubeen Ahmad Khan for always being there whenever I needed it. A sincere thanks to all my early teachers, but especially Mr. Ghulam Ali, Mr. Ashfaq Ahmad, Mr. Hasan Ashraf Khan, Mr. Bakhtiar Muhammad, Ms. Huma Arif, Ms. Shireen, Ms. Reshma, Mr. Munir, and Mr. Younus.

My sincerest gratitude is due to Dhammo Gaga and Noor Gaga for pretty much making me who I am today. I am indebted to my father for his love, immense support, and guidance during the whole journey, which made all the difference. I would sincerely like to thank my brother, sister, baji, bhabi, and phuppo, whose support and encouragement helped me navigate through the ups and downs of the Ph.D.

I cannot thank my wife enough for her immense support, warmth, patience, and encouragement throughout my Ph.D. This thesis could not have been possible without her. I thank my son for “patiently” waiting for my doctorate to finish (so that I can play with him) and my little daughter for excusing me (hopefully!) for not opening the door even to her “*baa baa*.”

Lastly, I’d like to thank my late mother, who I am sure must have put great effort in instilling in me the values that brought me here, and my late Professor Abdul Qayyum Saba for his love, trust, and mentorship, which continues to illuminate everything I come across.

No debt, least spiritual, moral, emotional, or intellectual, can perhaps ever be repaid. But a ‘thank you’ makes things beautiful. This page is meant just to do that. Otherwise, I remain in your debt—and in debt of the Almighty.

I would be remiss in not mentioning the generous scholarship and teaching fellowship offered by Ibn Haldun University that made this doctorate possible. All the deficiencies and errors that remain in the thesis are mine.

Syed Muhammad Usman MASOOD

ISTANBUL, 2023

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CHAPTER I

INTRODUCTION

Thanks to group lending, the emblematic models of microfinance - Village Banking in Latin America and Grameen Bank in South Asia - offered mechanisms to tap social capital within communities in novel ways, making financial inclusion of the poor much easier. Joint liability, which the typical microfinance models employ (Lehner, 2009), solved multiple problems from the lending institution's perspective. It provided a mechanism to avoid the problem of costly state verification (utilizing peer monitoring), adverse selection (by relying on peer screening), and moral hazard (using the threat of financial and social exclusion), which had held back financial institutions from providing unsecured credit to poor (Aniket, 2009; de Quidt et al., 2016).

Yet the question of optimal leveraging of social capital for better wellbeings was elusive - and perhaps tedious to solve - and was left to credit markets (Cull & Morduch, 2009; Haldar & Stiglitz, 2016). On the one hand, microfinance institutions tweaked the parameters of the original models to make microfinance commercially viable (de Quidt et al., 2018). On the other, the poor, diffuse, credit-constrained borrowers welcomed the new profusion of loans, thanks to the immediate relief they offered, but without the requisite financial sophistication (Banerjee & Duflo, 2010). The findings on the effectiveness of microfinance in terms of financial well-being and income growth, or other related outcomes such as human development and women empowerment, are mixed (Banerjee et al., 2015; Batista et al., 2021; Cavoli et al., 2021; Duvendack & Mader, 2019; Morduch, 1999; Zulfiqar, 2017a, 2017b).

A crucial element of the group-lending model, relatively understudied in economics, is the effect of the substitution of physical by social collateral (Bateman, 2013; Taylor, 2012). With any physical capital to pledge absent, a poor borrower in the group-lending model effectively pledges her social capital to obtain a loan. This means that a social cost is programmed into the model, which takes effect in case of delinquency or default. Crucially, this is different from the individual economic cost associated with a default (Abbass et al., 2021) in conventional, secured credit, where only the physical collateral is at stake.

This study focuses on one such social cost of microfinance: social distrust (henceforth, distrust). Distrust may be a direct consequence of within-group default by a struggling member. With repayments required as frequently as every week, a borrower can easily fall behind schedule and default. This triggers the peer pressure mechanism, which results in intense coercion by other members and even social sanctions. Thus, the incentive structure of the typical joint-liability micro-loan forces a credit-constrained borrower to convert a social relationship into an economic arrangement, which, when it derails, fractures the trust levels of borrowers, potentially affecting the possibility of future cooperation (Karlan, 2007).

Specifically, the question this thesis seeks to answer is, "Is microfinance prevalence (intensity) associated with social distrust among the low-income strata in a country?" in addition to investigating evidence of a causal link between microfinance causing distrust. Using data from the most recent, 7th wave/round (2017-2022) of the World Values Survey and European Values Survey integrated dataset (WVS-EVS) (*WVS Database*, n.d.) for cross-sectional ordinary least squares (OLS), and the 4th to the 7th waves of the World Values Survey (WVS) for empirical Bayes panel analysis, we find the relationship between microfinance prevalence and distrust to be statistically significant for poor as well as the ultra-poor (jointly, referred to as 'low-income' in this study). The relationship is not statistically significant for the rich, as expected, as microfinance targets only low-income households. We use a novel instrument, i.e., percentage yield on microfinance loans adjusted for its stability (yield divided by its standard deviation) to account for possible endogeneity issues. The results for two-stage least squares (2SLS) and weak instruments-robust, coverage-corrected instrumental variable tests confirm the findings of the OLS and empirical Bayes.

The question explored in this study falls in the realm of an emerging strand in economics research which focuses on the social effects of economic interventions. Heß, Jaimovich, and Schündeln (2021) studied the effects of a community-driven development program in Gambia in randomly selected treatment villages and found a significant reduction in informal economic interactions. They caution that development projects "can have unintended consequences for the economic and social networks of villages" (Heß et al., 2021). Similarly, Comola and Prina (2021) demonstrate that networks "may rewire" due to changes in the economic environment, including financial interventions; thus, the results of an intervention should take such changes in networks into account while interpreting results. According to Binzel et al. (n.d.), access to formal credit, such as the availability of microfinance in an area, can similarly affect social networks, with institutional credit access substituting for informal arrangements, reducing peer borrowing and gift exchange within the community.

A fascinating work most closely related to our study is by Banerjee et al. (2021b), which focuses on microfinance specifically and finds social network shrinkage in two independent, empirical settings. In the first setup, which is rural, they find that communities that got access to microfinance experienced a shrinkage in social networks, even among individuals unlikely to borrow. They replicate these findings in a subsequent urban setup in a randomized controlled trial. Microfinance exposure affected links even between non-borrowers - those who did not borrow from the MFI - showing global spillovers. While the evidence offered by these studies is rigorous, experimental studies are sometimes criticized for their external validity (Deaton & Cartwright, 2018; Levitt & List, 2009; Ogden, 2020).

The current study adds to the literature on the social effects of financial interventions by offering evidence on the relationship between microfinance and distrust. We use publicly available secondary datasets, which precludes the possibility of a correlation between outcomes of interest and any measurement errors or biases in the data collection process. This advantage, and using cross-country data, makes the results relatively generalizable. The hypothesis itself—of a potential effect of microfinance on distrust in the low-income strata—has not been previously studied to the best of our knowledge.

We follow the empirical approach of Kai and Hamori (2009); Imai et al. (2012); and Hermes (2014), among others, who study aggregate, country-level effects of microfinance (Ahlin et al., 2011; Fadikpe et al., 2022; Lacalle-Calderon et al., 2019).

Imai et al. (2012), for instance, study the impact of microfinance on poverty levels across countries and find microfinance intensity to be associated with poverty reduction. Similarly, Hermes (2014) uses cross-country data to study the effect of microfinance on inequality, finding modest effects.

Our study follows the overall approach of these studies as we regress distrust levels on microfinance prevalence (henceforth, microfinance intensity, following the convention in literature). However, we make our measurements more specific. For the dependent variable, distrust, we distinguish between distrust among the poor, the ultra-poor, and the rich. This distinction helps us pin down the relationship for specific income strata. Similarly, for the explanatory variable, microfinance intensity in a country, we introduce a new measure, namely, the ratio of microfinance gross loan portfolio to the total domestic private credit in the country. We think this measure of microfinance intensity represents an improvement on measures previously used in literature because of its higher precision as a measure of the microfinance industry's size in a country. Notwithstanding, we report results for two intensity measures well-established in studies of the aggregate effects of microfinance (Hermes, 2014; Imai et al., 2012).

Lastly, a clarification is in order before we proceed to the study: we use the broader term "microfinance intensity" to refer to what could more precisely be termed "microcredit intensity." We acknowledge this difference but use "microfinance" to situate the study seamlessly in the relevant literature and improve its discoverability, following earlier studies (Hermes, 2014; Imai et al., 2012; Lacalle-Calderon et al., 2019). But the focus of the study, in particular, is on microfinance *loans* only, i.e., microcredit.

The thesis progresses as follows: chapter II surveys the literature on the social effects of microfinance and endeavors to show where the literature is generally converging and where it is not. It also identifies the research gap. The need for more research at the intersection of economics and sociology, accounting for the social effects that group-based microfinance lending can have, is highlighted. Chapter III lays out the data sources and discusses the methodological issues. First, we show the need for new measures of microfinance intensity that reflect the prevalence of microfinance in a country more precisely. After developing these new measures and comparing them with the earlier ones, Chapter IV discusses the tests we use to assess the effect of microfinance intensity across countries on social distrust levels. We specify the model and discuss the tests - ordinary least squares (OLS), Pooled OLS, Random Effects Model, Empirical Bayes, and 2-Stage Least Squares, there. The novel instrument we use for microfinance intensity, namely, the volatility-adjusted yield of microfinance loans in a country, to take potential endogeneity concerns into account, is developed here. Chapter V presents and interprets the results of the OLS, Pooled OLS, Random Effects Model, Empirical Bayes, 2-Stage Least Squares, and weak instruments-robust conditional IV tests. Chapter VI, finally, offers concluding remarks of the thesis, discussing the mechanisms that drive the results obtained and their implications for responsible financial inclusion. We discuss the contributions of this study and the implications for future research in the last section. It may be noted that a part of this study has been published (Masood et al., 2023). Moreover, this thesis was originally written in the three articles format common in economics departments but had to be converted to a monograph format to meet university requirements.

1.1. Background

Since the beginnings of microfinance, sometimes attributed to Dr. Akhtar Hameed Khan, a development practitioner from Pakistan, in the 1960s (Bateman, 2010), and its innovative scaling-up and popularisation by Dr. Muhammad Yunus of Bangladesh, microfinance has grown into a mammoth financial institution for the credit-constrained, especially the poor individuals. It has 140 million active borrowers worldwide, of which 80% are women and 65% are rural. Dr. Muhammad Yunus and his Grameen Bank were awarded the Nobel Peace Prize in 2006 for the transformative idea and its successful execution. Today, there are about 916 Microfinance Institutions (MFIs) the world over (García-Pérez, 2020).

Still, microfinance remains a polarising subject for social scientists, and the debate on its effectiveness is far from settled. At one extreme are studies demonstrating a correlation between microfinance and suicide rates, for instance. On the other end, there are glossy reports with glowing faces telling the stories of changed fortunes that began with a micro-financed cow. Social scientists have found limited evidence of the success of microfinance, especially regarding an increase in income and entrepreneurship (Banerjee et al., 2015). In various related strands of literature, ongoing research explores how microfinance programs may be designed better (Field & Pande, 2008; Field et al., 2013), how behavioral biases can affect outcomes (Heidhues & Kőszegi, 2017), how consumer protection laws can improve welfare (Garz et al., 2020), and how debt burden could translate into a debt trap (Lui & Roth, 2020).

Here, we focus on the social costs arising from financial distress in social collateral-based loans. Financial distress may come in the form of serial borrowing, delinquency, loan rollovers, renegotiation, and the like. A poor borrower with limited or no experience faces the problem of asymmetric information (compared to an expert lender), present bias, optimism bias, and other pitfalls, which affect her judgment. Even if perfectly rational and sophisticated, she could still suffer from limited outside options in less-developed credit markets; should a contract have to be renegotiated, she would have minimal bargaining power compared to the firm. This asymmetry is critical in the case of a within-group default in which a defaulting borrower is sometimes encouraged to hide the default even by the microfinance institution staff to keep the reported repayment schedule on track in the MFI's books. This pits the borrower in financial distress against the lending institution and alienates him from other group members, who pressure him to repay if they find out about the default. Thus, the mechanism that was supposed to build social capital – the group-lending model with unsecured credit – harms social capital.

Given such issues, one alternative to the standard microcredit model could be an equity-based, micro-partnership model based on risk-sharing (rather than risk-transferring from lender to borrower). Patently, there is no single microcredit model which can represent microcredit the world over. But we think that barring a few alternative models, such as Akhuwat in Pakistan, microcredit models are very similar considering the characteristics we are concerned with here. Akhuwat – and other similar models – are successful, yet it is primarily a donation-based model which relies on heavily subsidized credit. An equity-based model in the spirit of participatory finance, which is also self-sustaining, may be useful for MFIs, investors, and borrowers. Also, as the equity-based model spreads the risk between the borrowers and the lending institution more evenly, it should have a lower default rate and social costs.

Such a model could be evaluated in the field using a pipeline study, a quasi-experimental evaluation, or a randomized controlled trial. However, the design of the study will depend on the proposed model and its critical characteristics. For now, it may be safe to say that such a model should be analyzed considering the profitability of the lender, the increase in income of the borrower, and the mitigation of financial distress and the overall well-being of the borrowers. The work that most closely matches these criteria is by Bari et al. (2021), where investigators partner up with Akhuwat to see the effects of a hire-purchase/rent-to-own (in the spirit of Diminishing Musharakah-Ijarah hybrid) on financial well-being compared to the usual Akhuwat loans. They find that the participatory finance model is better in terms of increasing assets and consumption compared with the Akhuwat loan. However, it may be noted that the size of the loans in the treatment group is different from the control group: USD 1,900 vs. USD 475.

This thesis aims to study the social costs associated with conventional microfinance models to provide a fuller picture of the socioeconomic repercussions of group-based micro-loans. To this end, it is imperative to develop a basic understanding of financial distress: the nature of the debt trap that emerges from debt rescheduling, rollover, or outright default in credit markets; understanding the literature on debt rollover to understand the credit market conditions that the creditor and a poor debtor face; and how these conditions shape the nature of contracts. We try to corroborate the theory with the empirical studies to offer a prescriptive review and an alternative, equity-based financing model for poor individuals, which hinges on risk-sharing and does not have adverse social effects. The avoidance of interest, and the ballooning of debt from rollover, may be avoided by a micro-partnership model, which involves the sharing, instead of the transference, of risk. Such a model, we conjecture, will be more conducive to "self-correcting" and returning to a high-return stable equilibrium rather than locking the transacting parties in a low-return, ballooning-debt equilibrium. The precise nature of the model, however, remains beyond the scope of this thesis, which focuses on the social costs of microfinance. Here, we aim to provide new evidence on the social costs that any potential microfinance model should consider.

A model may be developed later. Once such a model is made, a rigorous study design for evaluating the new model in the field, comparing the outcomes of interest in a conventional model vis-a-vis "micro partnership" is imperative. The gold standard in development economics for such evaluations is a randomized controlled trial, with as clean randomization as is feasible to test how the outcomes of interest play out in the field over time which goes further than simply the graduation of the poor from the program.

For the alternative mechanisms, it is important to develop a model that is feasible and sustainable for micro-entrepreneurs. By implication, it may be replicated and should have the groundwork for a larger model of credit; but that is beyond the scope of this study, even if a direct implication of the findings presented here. Lastly, the field experiment should aim to find the different nature of the burden of indebtedness, the likelihood of delinquency, and other outcomes of interest widely used to measure the effectiveness of microcredit in poor and ultra-poor households of less-developed countries.

1.2. Issues in Credit and Microfinance

Whether or not consumer markets oversupply credit is far from settled (Zinman, 2013), but the question becomes more sensitive in the case of microcredit, where borrowers are generally the poor. In a survey conducted as part of the seminal study on the effectiveness of microfinance, Banerjee et al. (2010) came across a remarkable statistic: 30% of the households reported repaying the old loan to get a new one. Should the borrowers have been screened better, to begin with?

Banerjee et al. (2015), in their concluding remarks in a review of 6 randomized trials, state, "...understanding distributional effects is important in a world with growing concerns about debt traps and here the increasing potential to develop screening and targeting technologies that maximize benefits while minimizing harm offers exciting possibilities." This is especially important because situations, and repeated interactions, in which learning by consumers about their own biases would be expected may not result in such learning adequately (Ali, 2011; Eil & Rao, 2011; Schwartzstein, 2011).

1.2.1. Overborrowing Due to Behavioural Biases

A strand of literature focuses on behavioral tendencies within borrowers who borrow more than they can afford, unaware of the limitations of their judgment. This may be because the firms are more sophisticated in the design and comprehension of contracts than the individual consumers, for whom the borrowing or purchase decision may not be so oft-repeated, or simply due to inherent behavioral biases of the consumers (DellaVigna and Malmendier, 2004; DellaVigna, 2009).

Ellison & Ellison (2009) find evidence of deliberate obfuscation by online retailers to make purchase decision complex, and Ellison (2006) points, in a similar vein, "...it is also hard to imagine that the complex fee schedules, in small print on the back of credit card, offers could not be made simpler." Grubb (2015) provides a comprehensive review of the obfuscation, but more generally, the literature on consumers' manipulation.

A borrower’s behavioral vulnerabilities are especially exposed in the case of payday loans, which typically have triple-digit Annualised Percentage Rates (APR). “Ten million American households borrowed on payday loans in 2002. Typically, to receive two weeks of liquidity from these loans, households paid annualized (compounded) interest rates over 7000%” (Skiba & Tobacman, 2008). They find suggestive evidence of *naive* quasi-hyperbolic discounting, where borrowers borrow repeatedly and delay default, even though the cost of a delayed default is higher. *Naive* here refers to the unawareness of an individual to their self-control problem, as opposed to *a sophisticated* individual, who is cognisant of, and can moderate, the effect of quasi-hyperbolic discounting and hence be less present-biased (Camerer, 2003). For credit card borrowing in particular, Meier and Sprenger (2009) ran an experiment estimating the Individual Discount Factors (IDF) and found that present-biased individuals are more likely to have credit card debt and a higher one.

Further, the important study by Skiba and Tobacman (2019) uses regression discontinuity design to study 145,000 applicants and finds that access to payday loans increases personal bankruptcy rates. This finding is striking, as access to payday loans is only a small constituent of the financial health of any borrower but still "has an economically significant effect on bankruptcy, a cumulative financial outcome."

Allcott et al. (2020) demonstrate that payday loans are not as problematic as is sometimes contended. Yet they find that inexperienced borrowers underestimate the likelihood of borrowing, and "[r]ollover restrictions could increase welfare by inducing faster repayment in line with long-run preference" (Allcott et al., 2020).

1.2.2. Delinquency and Financial Distress

The issue is further complicated when the financial distress may not be explicit, as in the case of a default, but what may be called implicit, as in the case of delinquency, a loan rollover, a rescheduling, forced renegotiation at maturity (Nikolaev 2012), or even some ad hoc alternative loan arrangement, possibly involving some other lender, to meet the repayment schedule. Ad-hoc/informal arrangement to meet the repayment timeline is a distinct case, which can only be estimated but not accurately measured. Yet, it is crucial as it may be used as a cover-up for a present-biased individual who is engaging in borrowing from multiple lenders.

In essence, this is similar to the 'informal bankruptcy' pointed out by Dawsey and Ausubel (2004), a term Dawsey and Ausubel use for delinquency in which no formal bankruptcy application is filed. They find that informal bankruptcy (or delinquency) is correlated with a lower cost of such a move. Thus, the more distressed borrowers resort to informal rather than formal bankruptcy in the absence of strict garnishment laws, as in some US states. The interaction of borrowers with multiple lenders makes the issue even more complex, but it is still an under-researched area, as almost all models assume that a debtor borrows from only one creditor at a time (Livshits, 2015).

But even the more straightforward "delinquency" is difficult to measure, and MFIs may exaggerate the health of their loans (Rosenberg, 1999). This is why we emphasize the distinction between implicit as opposed to explicit default, which is crucial not just for the true picture of the debt profile of a creditor but even more so for the poorer borrowers, who may resort to temporary an alternative arrangement for timely repayment, but be just looking forward to a bigger loan, getting further "entrapped," as discussed later in the study.

From the borrower's point of view, successive loan rollovers may morph into a debt trap. We have already discussed some of the major behavioral studies. Here, we review the works relying purely on economic forces and incentives rather than psychological slippages.

One plausible explanation for a somewhat spontaneous making of a debt trap is the inability of credit to bring about a growth in profits. The negligible correlation between availing microcredit and business profitability has been extensively documented, and there is a near consensus that the incomes of borrowers do not grow, at least, in a transformative way (Karlan & Zinman 2011; Aggarwal et al. 2012; Meagher, 2019). Banerjee et al. (2020), however, show that more experienced entrepreneurs can benefit from microcredit, also indicated by Meagher (2019). Still, this result holds for a very limited subset of micro borrowers, and it is relatively under-researched yet.

1.2.3. Theory of Debt Trap

The conditions of a contract of credit between a creditor and a debtor are governed by a multitude of factors. This means that both parties are constrained by each other as well as the environment in which the contract is taking place. According to Peterson and Rajan (1995), henceforth PR, a creditor is more likely to lend to credit-constrained firms when the creditor has more market power. The creditor can back-load the interest payments by extracting greater rents later. This is difficult in a competitive credit market. The creditor can foresee that the borrower has—and will have—more options to shop around for credit, and thus the time horizon of the relationship is smaller. This may lead to a higher price/cost of credit, which discourages the borrower from getting credit. Thus, the borrowers stay in a poverty trap.

Lui & Roth (2020), henceforth LR, put forth a theory of debt trap. They argue that it is in the interest of the lender to offer a relatively restrictive contract to a poor entrepreneur to keep them captive. While the richer entrepreneurs are offered better contracts, the poorer entrepreneurs may be offered contracts that stall their business growth to the point that their growth is worse than it could have been without credit. Thus, in a way, the poverty trap follows from the debt trap.

So, while PR model why a credit-constrained entrepreneur cannot get credit, LR model how an entrepreneur can have access to credit, albeit only under a restrictive contract. In PR as well as LR models, incomes don't grow, but the incentives used to explain the stagnation are different. The difference in the reasoning of PR vs LR indicates the complexity and unresolved nature of the working of economic forces in credit contracts.

It should be noted here that back-loading credit contracts to extract rents later has also been theorized in the behavioral literature, which focuses on such contracts which result in the non-sophisticated or naive borrowers delaying repayment without understanding that the decision to be costlier (Heidhues & Koszegi, 2017). This is because the “lender chooses the repayment options so that when deciding how to repay in the future, the consumer will be indifferent between the front-loaded and back-loaded schedule (Koszegi, 2014).” Figure 1.1 presents a summarized schematic representation of important papers in the realm.

Figure 1.1. Financial Distress in Conventional Credit (Literature)

1.3. Current State of Empirical Knowledge on Microfinance

Let us now proceed to the purely empirical evidence on microfinance. The one problem that limits the validity of most non-experimental studies is selection bias. If the people who borrowed from the MFI are systematically different from the people who did not borrow, then the outcome of interest may be influenced by some of these unobserved characteristics. The borrowers may be grittier, for example, and the success of their venture, which a study attributes to microcredit, may be due to their grit, at least in part.

Randomized controlled trials (RCTs) have been criticized for being expensive, morally controversial, and less precise than their proponents claim. Yet RCTs are still considered to be more robust than any other techniques for impact evaluation, not least because they allow the researcher to avoid selection bias. According to Duvdendack et al. (2011), they are more 'internally valid' than pipeline designs, with/without comparisons, natural experiments (although this is a wide category by itself), and general-purpose surveys.

An early study with sound randomization is Karlan & Zinman (2008), as also noted by Duvendack (2011). They randomly assigned applicants to credit who were slightly above and slightly below the cut-off and randomized the offered interest rates. Although some of their allocations were rejected by the loan staff, they minimized the noise in results with Intention-to-Treat. They found that high-interest rates may discourage loan take-up and repayment. Also, they found evidence of moral hazard: the borrowers who were offered an incentive – such as a further loan at discounted terms – if they made timely repayments, complied better.

The seminal paper of Banerjee et al. (2015) intervened with a microcredit offer in 54 out of 104 slums in Hyderabad, India. Spandana, the participating firm, agreed to offer loans to only 54 intervention slums, but other MFIs could still lend there. About 65 households from each neighborhood were surveyed from a total of 6,850 households at baseline and were surveyed again after two years. They found low loan take-up. Households were only 8.8% more likely to take loans than the control group after 15-18 months. The intervention group was no more likely to start a new business and did not show any change in expenditure. Still, those with existing businesses did invest more in them.

Banerjee et al. (2020), in continuation of the Banerjee et al. (2015) experiment, ventured into studying whether overall average results may be masking group heterogeneity. This is because people with already existing businesses were found to invest more when they had access to credit, according to Banerjee et al. (2015). Banerjee et al. (2020), find that "'gung-ho entrepreneurs' (GEs), households who were already running a business before microfinance entered, show persistent benefits that increase over time. Six years later, the treated GEs own businesses that have 35% more assets and generate double the revenues as those in control neighborhoods." Yet they did not find this effect among the "non-gung ho entrepreneurs.” Thus, they showed that microcredit could help experienced entrepreneurs help escape the poverty trap.

1.4. Scientific Contribution of the Thesis

This study synthesizes the literature on the social effects of microfinance, which is a somewhat ignored area of research, especially in economics. Next, this thesis develops novel measures of country-level microfinance prevalence intensity and shows the effectiveness of these new measures. These measures, which we find to be more precise than earlier measures used in literature, may be used for future studies assessing the effects of microfinance intensity on various social and economic indicators.

Third, this thesis provides empirical evidence showing higher distrust levels (lower trust levels) in countries with a higher prevalence of microfinance, based on publicly available datasets and alternative measures of microfinance intensity. We use data from different datasets and employ a battery of tests to study the hypothesis. While publicly available datasets can constrain the researcher from conducting the study in several ways, they do have the advantage that the outcomes of interest are highly unlikely to be correlated with data collection design or other survey issues. Also, this approach is more transparent.

This is the first study to bring forth evidence of the potential effects of microfinance loans - which heavily rely on social instead of physical collateral – on (dis)trust levels in society. The results of the study imply that microfinance can fracture social relationships, and it may have gone too far in leveraging social capital. While leveraging social capital — which acts as a substitute for physical capital — may have enabled extending unsecured credit to the poor — who lack credit history and physical collateral — it may have come with negative social effects, including a higher generalized distrust in societies. This may be expected because of high default levels within groups — the kinds of delinquency and default which may not show up in microfinance institutions' books as they are hidden by the loan-group members and MFI staff but can affect within-group social ties adversely.

CHAPTER II

LITERATURE REVIEW

According to at least the received wisdom, the fundamental problem which had kept the poor out of formal credit markets was the lack of collateral and credit history. At one end, the poor farmers faced exorbitant interest rates from local moneylenders; at the other, they were forced to sell their products as quickly as possible, even if this meant getting a low price. Akhtar Hameed Khan pioneered a novel model of credit for the poor, which relied on cooperatives to get around these problems. Teams of village members would get together under a leader and form a borrowing and savings group. Because the village members knew each other, they could select the right peers, and as they used to meet every week, they could monitor one another's activities. These village-level teams were, in turn, part of a larger multi-village cooperative (Yousaf, 2009). This new model of credit, termed the Comilla model—named after Comilla, the city in present-day Bangladesh where it was first implemented—solved several problems from the lender's standpoint. As loans were given to groups, it reduced transaction (processing) costs per loan, at the same time, taking care of problems arising from information asymmetries between the borrower and the lender. The function of monitoring was transferred from the lending institution to the borrowing institution itself—somewhat of a watershed moment in the history of financial inclusion.

Whatever the exact mechanism, the spirit behind the Comilla model was social capital. It was targeted at utilizing and creating a sense of solidarity and tapping social capital to unlock formal credit for the poor. The Grameen Bank, which won the Nobel Peace Prize in 2006, along with its founder, Dr. Muhammad Yunus, optimized the model for providing credit to groups of poor women, and so did BRAC (Mader, 2015).

There is no consensus on how microfinance eventually fared for social capital. Ito (2003) has gone as far as questioning the question itself, demonstrating the complexity of issues in solving the riddle of the relationship between microfinance and social capital. Nevertheless, that has not stopped inquisitive researchers from venturing into the arena. Some studies claim microfinance has affected social capital negatively, while others have argued it to be a force to strengthen social capital. Empirical evidence, as is its nature, gives all kinds of answers depending on the specific question asked, the social context, the program(s) being studied, the data collection design, the model, and the hypothesis testing methods. This study takes the daunting task of diving into the literature on microfinance and social capital, nevertheless endeavoring to find where the consensus seems to be headed (though not necessarily claiming that consensus would be closer to “truth”).

2.1. The Nature of Social Capital

Since the popularisation of the term “social capital” by Putnam (1995), it remains an involved concept with no consensus on its definition (Conrad, 2008). While some scholars have contended the use of “capital” with social, arguing that social capital does not have the characteristics of capital proper, that is, physical capital (Solow, 1999; Robison et al. 2002), others have pointed out the inherent reductionism in simplifying a concept as nuanced as “social capacity” into a form of “capital,” "urging citizens to become social capitalists" (Smith & Kulynych, 2002).

While the debate on the aptness of the term continues, the wide use of the 'social capital' in social sciences reflects the gravity of the concept, particularly the benefits that society can accrue from interpersonal trust and social cohesion.

But what is social capital? In the words of Putnam (1995), social capital constitutes "features of social organization such as networks, norms and social trust that facilitate coordination and cooperation for mutual benefit." According to Fukuyama (2002), “Social capital is shared norms or values that promote social cooperation, instantiated in actual social relationships.”

Social networks may be conceived as the "structural" manifestation of social capital (Stone, 2001), while trust reflects its qualitative aspect, which may be referred to as its "spirit." Social capital, as well as social networks and trust, are linked with better well-being and economic outcomes.

When confined within groups, however, social capital can be socially undesirable. For example, in-group trust (trust between people you know, generally, friends and family) has been noted in networks that exclude others, cults, and criminal gangs (Meier, 2016). Glaser, Sacerdote, and Scheinkman (1995) find an association between social interactions and the seriousness of crimes, with the group size being correlated with the seriousness of crimes. Interestingly, their results also show higher interactions between criminals in cities with more female-headed households, which they suggest may be because of a lower number of intact family units.

While social networks are generally formed for their intrinsic reward – the positive feeling one derives from social interaction – they may be formed intentionally for economic reasons by participating agents or may be facilitated and/or designed by governments or institutions. Hence, Arrow (1999) questions, "Are these a form of social 'capital' with the same consequences as self-organizing 'spontaneous' social networks?". (The question is important from the point of view of microfinance loan groups.)

2.2. How Microfinance Utilized Social Capital?

Group-lending models of microfinance that started with some form of cooperative credit schemes rose to prominence with the Comilla model, and culminated – in popularity – with the Grameen Bank and its founder winning the Nobel Peace Prize, have social capital at their heart (Nobel Prize, 2006). Where physical collateral was absent, group lending provided a mechanism to collateralize social capital (Postelnicu et al., 2014). Because group lending entailed joint liability, the social/peer pressure ensured that every member would make timely repayments. Rathore (2015, 2017) provides a review of this literature.

A defaulting member could face social sanctions and social exclusion. The threat of punishment would keep repayments on track. Consequentially, the group-lending model solved multiple problems arising from information asymmetries. It could act as a screening device, where potential group members with better knowledge of each other self-select with the advantage of local information (Tassel, 1999; Ghatak, 2000). Stiglitz (1990) shows how, even with risk getting transferred from the lending institution to the borrower, peer monitoring can increase borrower welfare (though subject to some conditions, discussed at length in his article). Group lending, coupled with sequential financing (Chowdhury, 2005), has the advantage of incentivizing repayment due to dynamic returns – the prospect of further loans from the microfinance institution (MFI) and the threat of social sanctions in case of individual default. But it can also incentivize default for a member who would be otherwise willing to repay the loan when most of the other group members are likely to default (Besley and Coate, 1995). Ghatak and Guinnane (1999) show how joint liability helps avoid adverse selection and moral hazard and helps mitigate the problem of costly state verification.

Gomez and Santor (2001) find empirical evidence supporting the hypothesis that microfinance-related self-employment flourishes more in high social capital environments. Karlan (2007) uses quasi-experimental evidence and finds social connections – in culturally and spatially closer groups – to be associated with higher repayment rates, higher savings, and lower default rates. Postelnicu & Hermes (2018) use cross-country data to show that the social and financial performance of microfinance is associated with higher levels of social capital.

The complexity surrounding 'social capital' in microfinance is reflected in this comment:

> Social capital as wielded in financial self-help organizations is a powerful tool because of the implicit threat of physical violence and the confiscation of household utensils. The threats seem to work very efficiently and limit the incidence of default… It is assumed that relying on social capital, including peer pressure, will cover the risks of default... Here… social capital is seen as a powerful instrument (Smets and Bahre, 2004).

2.3. Does Microfinance Help Build Social Capital?

Microfinance models have been noted for utilizing, and even creating it in conditions where the market had failed (Dowla, 2006). Larance (2001) studied a Grameen Bank center and found the group borrowers to have higher levels of social capital. Feigenberg et al. (2010) find that the frequency of group meetings is associated with more interaction between clients and more informal risk-sharing, which they interpret as increased social capital. In particular, they find that microfinance-induced higher interpersonal interaction is associated with more cooperation, reciprocity, better repayment discipline, and lower defaults.

Basargekar (2010) studies 217 women Self Help Group (SHG) members and finds a positive effect of microfinance on self-reported social capital measures, but cautions that the creation of social capital is not an automatic process and needs to be helped by supporting activities. Xu (2020) finds that social trust is positively associated with financial services as well as digital technologies in finance targeted at financial inclusion. Thus, a short but significant strand of literature reports microfinance as not just utilizing, but also creating social capital.

2.4. Can Microfinance Negatively Affect Social Capital?

Haldar and Stiglitz (2016) argue that the relationship between the Grameen Bank's model and how it utilized social capital was nuanced in that the model had evolved organically according to the dynamics of the communities and therefore was socially embedded. While institutional features such as joint liability might have helped, the social context was no less important. Companies like SKS in India, which picked up some elements of the model and tried to install its commercialized version mechanically, were therefore unsuccessful. How SKS precipitated a suicide crisis in Andhra Pradesh state in India has a strand of literature on its own (see Priyadarshee and Ghalib, 2011; Taylor, 2011; Ashta et al., 2011; Mader, 2013; Pole et al., 2014). Bateman (2013) notes that the SKS crisis was just one in a series of similar crises in other parts of the world, where the poor were being exploited, with *Compartamos* in Mexico, *Mikrofin* in Bosnia, and *Capitec* in South Africa. He argues that microfinance institutions were ‘anti-development’ in social as well as economic terms.

Hulme and Maitrot (2014) argue that microfinance "lost its moral compass" by over-indebting the poor and using extreme coercive means to recover loans. They contend that it is not social capital but these threats that result in repayments. Maitrot (2014) reports violent threats, sexual harassment, coercion by neighbors, verbal abuse, and humiliation as common strategies used by loan officers.

The following is a selected list of channels through which social capital may be affected.

2.4.1. Within-Group Hidden Default

A somewhat understudied issue in microfinance is the problem of within-group delinquency or default, which can severely affect social relations. The microfinance repayment rate on the ground may not be as high as they appear to be in the MFIs' balance sheets. Sometimes, the accounting conventions MFIs follow avoid reporting overdue loans for up to a year (Montgomery, 1996). Informal arrangements are not uncommon where one borrower could pay on behalf of another borrower to meet the repayment schedule; sometimes, the MFI staff can give a loan to a defaulting member to show 100% repayment on official books so as not to affect their job performance indicators (Rutherford 1993 in Montgomery, 1996; Kiiru, 2007); at times, the loan group leader can themselves intervene and dig into the savings of the group to pay on behalf of defaulting member (Kevane, 1996); all these cases of default/delinquency remain off-books.

Moreover, the poorest members of the community are either excluded from the loans or are the first ones to exit (Marr, 2015). This exposes them disproportionately to social and economic sanctions, including confiscation of assets (Montgomery et al., 1996; Marr, 2015). Also, they end up in deeper debt, often resorting to getting loans from moneylenders, worsening their financial position (Marr, 2015).

At the other extreme are studies that report peer pressure not to be effective and loan-group members avoiding monitoring and 'spying' on other members, being fearful of the social cost (Diagne, 2000). Similarly, Marr (2015) finds that peer monitoring levels are low, and the quality of peer audits, when present, deteriorates over time.

However, not all MFIs interpret joint liability as restricted to the group strictly. One loan center can have many small loan groups, forming a bigger secondary group. Often, the joint liability of a primary group can fall on a secondary group, even if not part of a formal loan clause (Roodman and Qureshi, 2006). Field staff can pressure the defaulter to get a loan from the Secondary group or even from any other source to meet the repayment schedule on MFI's books (Jaine and Moore, 2003). Similarly, the staff signals the secondary group members to exert pressure on a defaulting member (Ito, 2003). Whole villages could be black-listed because of group default, which results in intense social pressures (Solli et al., 2015).

2.4.2. Name and Shame

Roodman and Qureshi (2006) argue that group-lending substitutes conventional collateral with reputation, collateralizing a borrower's reputation in effect. XacBank in Mongolia posts the names of defaulters on its walls for shaming, for instance (Frankiewicz and Sousa-Shields, 2005 in Roodman and Qureshi, 2006). Sometimes, even more, aggressive measures to recover loans can include threatening a borrower's social standing and dignity, what Karim (2008) calls a whole "economy of shame," using shaming women borrowers as an instrument of social control. According to Karim (2008), "Poor men who lack physical collateral 'give' their women in membership to NGOs as economic reassurance. In reality, *the collateral that Grameen and all other NGOs extract from the poor is the Bangladeshi rural woman's honor and shame*". In these societies, men control the use of money, but this vital information is glossed over by NGOs to show they are empowering women, fulfilling the 'Western aid mandate' to keep the money flowing. Many women can even become secondary moneylenders, getting a loan and just working from home (following tradition) and lending at double the rate of primary microfinance loans, which already can be around 60%. For the defaulting women, other women borrowers can march up to her house, shame her, snatch her gold nose-ring (a symbol of her marriage in rural Bangladesh), confiscate stored grains and livestock, and even sell off her house. Karim (2008) reports several instances of house-breaking. In a subsequent study, Karim (2011) interviewed women about loan recovery, and 75% of the interviewees reported verbal or physical abuse by group members, NGOs, or their husbands.

Engel and Pedersen (2019) relate shaming of the kind studied in Karim (2008) to the poorer psychosocial well-being of borrowers as well as their families, sometimes worsening to the point of making the defaulter commit suicide. Defaulting women "are also left with few avenues for addressing shame in a microfinance group as it permeates their familial and social relations," reflecting the huge costs of "personalizing and socializing" debt relations (Engel & Pedersen, 2019). Rahman (1998) studied 294 households in Bangladesh in 1994-1995 and found increasing dominance of men over women, more violence in society, and extreme measures for loan recovery, including excruciating shaming. An anecdote noted by Rahman, told to him by an informant, narrates the story of a woman who was brought to the lending bank by her peer; the staff locked her up in a room in the building, where she eventually committed suicide by hanging to the fan using her *sari* (cloth).

2.4.3. Changes in Social Network

Microfinance-induced linkages are also complex. New relationships built around financial cooperation may come at the cost of old relations. While it is easier to refer to such a disruptive phenomenon as 'creative destruction' (Schumpeter, 1942) in the case of machines, such a utilitarianist view of social change may be devoid of nuance.

Rao (2005) finds that social inclusion brought about by microfinance initiatives may be horizontal, at the cost of vertical, for instance, when borrowers form groups based on religion or caste, undermining vertical linkages (Rao, 2005). Such an increase in bonding social capital, as opposed to bridging, can transform non-excludable into excludable goods (Patulny & Svendsen, 2007). Too much in-group trust, like within criminal networks, could be damaging to society (Portes, 1998; Putnam, 2000; Nannestad et al., 2007).

Other studies find microfinance can negatively affect even within-group social capital due to social vulnerabilities arising from excessive indebtedness and default (Banerjee & Jackson, 2017). In this context, Griffin and Husted (2015) find that cultivating harmonious social relations is more effective in increasing repayment rates than social sanctions, like the threat of exclusion from social gatherings and future loans. Karlan (2007), in a rigorous study, finds that group lending, particularly with culturally and geographically proximate members, can help cut down on default rates. But when there is a default, the relationships and trust levels between members deteriorate, also reducing economic transactions. One striking finding is that the friendship and trust levels of current members with their group mates in previous cycles deteriorated even when previous members had not defaulted. The question Karlan asked was, “Has your trust in this person become stronger, the same, or weaker?” now, compared to when they were in the loan group.

A more recent strand of literature tries to tease out the effect of financial interventions on social networks. Heß, S., Jaimovich, D., & Schündeln, M. (2021) studied the effects of a community-driven development program in Gambia in randomly selected treatment villages and found a significant reduction in informal economic interactions. They caution that development projects “can have unintended consequences for the economic and social networks of villages.”

Similarly, Comola and Prina (2021) demonstrate that networks "may rewire" as a result of a change in the economic environment, including financial interventions, and thus the results of an intervention should take such changes into account while interpreting results. New links can form, old links can disappear, and new network topologies can emerge.

Access to formal credit, such as the availability of microfinance in an area, can similarly affect social networks. Formal credit access can substitute for informal arrangements, reducing informal borrowing and gift exchange as "the risk-sharing capacity of informal networks falls, and villagers are less likely to share resources with network members in non-anonymous dictator games" (Binzel et al., 2013).

Banerjee et al. (2021) find in two different locations in different empirical settings in India. In the first setup, a rural one, they find that communities that got access to microfinance experienced a shrinkage in social networks, even among individuals unlikely to borrow at all. They replicate these findings in an urban setting in a randomized controlled trial.

2.5. Gap in Literature

It may be simplistic to conclude that microfinance is either 'good' or 'bad' for social capital. The terms of a contract, the nature, and sharing of risk, the degree to which social collateral gets leveraged, the nature of joint liability, the overall socioeconomic environment, the policies of the lender, legal environment are all important components that affect economic as well as social outcomes. Yet one tendency present in literature is that studies in sociology are critical of microfinance, and the consensus within the subject seems to be not in favor of the industry. From the standpoint of social capital, these studies perhaps bear more weight than economics research. Early in the life of the microfinance industry, especially since Grameen Bank caught the limelight, economics literature was focused on modeling and explaining the success of Grameen Bank in the financial inclusion of the poor and poverty alleviation, while few studies were questioning this success. Later literature has focused on studying various elements of the incentive structure used by microfinance programs and how they are correlated with economic and social outcomes, but the evidence here is mixed. Lastly, the latest strand of economics literature, which has relied on game-theoretic approaches and empirically validating these with experimental evidence, has tended to again produce mixed results concerning various aspects of microfinance loan designs. Though, studies in the third strand can tease out the differential impact of microfinance more clearly. The consensus this strand is moving towards is that microfinance programs can affect social networks in ways that may not be conducive to societal well-being. More research is needed to verify the effects of microfinance on various aspects of social capital and social psychology, but also to unearth the mechanisms by which various microfinance loan contracts lead to these outcomes.

Unfortunately, like much else today, research on microfinance suffers from the extreme compartmentalization between subjects and their sub-specialized fields. The polarization that has emerged as a by-product of such over-focused research has made the relatively clear facts about phenomena getting lost in debates about methodological differences, probably actually grounded in ideological inclinations. There is a wide chasm between studies of microfinance in economics and those in sociology in the questions asked, the way these are approached, and the results they have reached. On the one hand, economics has focused on game-theoretic modeling, experimental and quasi-experimental techniques, analysis of empirical data, and overall *average* outcomes. On the other hand, studies in sociology have tended to emphasize the social effects of microfinance on individuals, families, friends, and communities, deriving conclusions from participant observation, surveys, and in-depth interviews, among other methods. It may be argued that this is what these two disciplines do and may be expected to do. But human beings cannot be torn apart into these selves—economic, social, or any other—and research that just gives a part of the picture sometimes distorts rather than helping the big picture, assuming that the whole is necessarily a whole sum of parts. Human well-being, emotions, and society have layered interactions which are much more complex than a simple summation of parts. This study contributes to filling this gap, bringing forth evidence at the intersection of economics and sociology, using a quantitative approach to study the effects of microfinance on social distrust levels in societies.

CHAPTER III

METHODOLOGY

3.1. The Need for New Measures

Since the relatively modest beginnings of microfinance by Akhtar Hameed Khan in Pakistan in the 1960s (Yousaf, 2009) and its innovative scaling-up by Dr. Muhammad Yunus in Bangladesh, microfinance has grown into a huge industry, offering credit to poor people. It has 140 million active borrowers worldwide, of which 80% are women and 65% are rural. Dr. Muhammad Yunus was awarded the Nobel Peace Prize in 2006, along with Grameen Bank, for the successful execution of an idea variously attributed to different people and organizations. Today there are 916 Microfinance Institutions (MFIs) in the world (García-Pérez et al., 2020).

The economics literature has mixed findings regarding the effects of microfinance on the income of borrowers, assets, entrepreneurship, and human capital (Brau & Woller, 2004; Banerjee et al., 2015; Duvendak & Mader, 2020). More recent work has zeroed in on specific elements of microfinance, including how microfinance programs may be designed better (Karlan, 2007; Field & Pande, 2008; Field et al, 2013; Flatnes & Carter, 2016; Weber & Musshoff, 2017).

The individual pieces of the puzzle provided by these studies make a crucial contribution to solving the riddle of the ‘success’ of microfinance. Still, evidence on the *aggregate effects* of microfinance, for example, on a country or area level, can be as critical to understanding the overall picture (Sseruyange & Klomp, 2021). Even the micro-level effects need to be contextualized within the changes in the overall macro-environment if microfinance does have such an impact.

Over the last decade, new literature has emerged which tries to achieve this. Various studies investigate the effects of microfinance intensity in a country on poverty (Imai et al., 2012; Bangoura et al., 2016), on inequality (Hamori & Kai, 2009; Hermes, 2014; Lacalle-Calderon et al., 2018, Lacalle-Calderon et al., 2019; Miled et al., 2022), and on other measures of wellbeing, such as aggregate welfare and women empowerment (Ahmed and Kitenge, 2022). While the data for the dependent variable in these studies is obtained from various established datasets, microfinance intensity data is often constructed following some conceptualization. It is important to note that microfinance varies substantially from country to country and from time to time. Thus, the precision of results obtained by these macro-oriented studies hinges on the accuracy of estimates of the true, underlying intensity of microfinance in relevant population strata.

We explore the rationale behind previously used measures and propose three new measures for quantifying microfinance prevalence intensity at a country level with greater precision. We show that the three alternative measures proposed here are highly correlated with the three classic measures used in the literature previously but provide greater variation and more precision at the same time.

The following section lays out the data sources and essential definitions; section 3 explains the construction of new measures; section 4 provides an analysis of new measures, and section 5 provides concluding comments on the measures proposed.

3.2. Data for the New Measures

We obtain microfinance data from the Microfinance Information Exchange (MIX) dataset hosted by the World Bank. MIX is the largest publicly available dataset of microfinance, where microfinance institutions (MFIs) voluntarily report data according to determined standards. We obtain data on two measures, (i) gross loan portfolio (GLP) of loans in a given year and (ii) no. of active loan borrowers in a given year, from MIX. The GLP constitutes "[a]ll outstanding principals due for all outstanding client loans. This includes current, delinquent, and renegotiated loans, but not loans that have been written off" (MIX, n.d.). Meanwhile, 'Active Borrowers' are "[t]he number of individuals who currently have an outstanding loan balance with the financial institution or are primarily responsible for repaying any portion of the gross loan portfolio. Individuals who have multiple loans with a financial institution should be counted as a single borrower” (MIX, n.d.)

For other measures, we use the World Development Indicators (WDI). Thus, the data on the poverty headcount ratio (according to national poverty lines), the population of a country in a given year, the gross domestic product (GDP), and total credit to the private sector as a percentage of GDP are obtained from WDI. It is important to clarify here that domestic credit to the private sector refers to

> … financial resources provided to the private sector by financial corporations, such as through loans, purchases of nonequity securities, and trade credits and other accounts receivable, that establish a claim for repayment. For some countries, these claims include credit to public enterprises. The financial corporations include monetary authorities and deposit money banks, as well as other financial corporations where data are available (including corporations that do not accept transferable deposits but do incur such liabilities as time and savings deposits). Examples of other financial corporations are finance and leasing companies, money lenders, insurance corporations, pension funds, and foreign exchange companies (World Bank, n.d.).

We use data for all countries for which data is available. The list of countries is given in Table 3.1.

Table 3.1. List of Countries

List of Countries (novel measures of microfinance intensity)				
Afghanistan	Congo, Dem. Rep.	Indonesia	Nicaragua	Suriname
Albania	Congo, Rep.	Iraq	Niger	Syrian Arab Republic
Angola	Costa Rica	Israel	Nigeria	Tajikistan
Argentina	Cote d'Ivoire	Jamaica	North Macedonia	Tanzania
Armenia	Croatia	Jordan	Pakistan	Thailand
Azerbaijan	Dominican Republic	Kazakhstan	Panama	Timor-Leste
Bangladesh	Ecuador	Kenya	Papua New Guinea	Togo
Belarus	Egypt, Arab Rep.	Kosovo	Paraguay	Tonga
Belize	El Salvador	Kyrgyz Republic	Peru	Trinidad and Tobago
Benin	Eswatini	Lao PDR	Philippines	Tunisia
Bhutan	Ethiopia	Lebanon	Poland	Turkey
Bolivia	Fiji	Liberia	Romania	Uganda
Bosnia and Herzegovina	Gambia, The	Madagascar	Russian Federation	Ukraine
Brazil	Gabon	Malawi	Rwanda	United States
Bulgaria	Georgia	Malaysia	Samoa	Uruguay
Burkina Faso	Ghana	Mali	Senegal	Uzbekistan
Burundi	Grenada	Mexico	Serbia	Vanuatu
Cambodia	Guatemala	Moldova	Sierra Leone	Venezuela, RB
Cameroon	Guinea	Mongolia	Slovak Republic	Vietnam
Central African Republic	Guinea-Bissau	Montenegro	Solomon Islands	West Bank and Gaza
Chad	Guyana	Morocco	South Africa	Yemen, Rep.
Chile	Haiti	Mozambique	South Sudan	Zambia
China	Honduras	Myanmar	Sri Lanka	Zimbabwe
Colombia	Hungary	Namibia	St. Lucia	
Comoros	India	Nepal	Sudan	

3.3. Measuring Microfinance Intensity

In this paper, we suggest three new measures of microfinance prevalence intensity that measure the intensity or salience of microfinance in a country, improving upon earlier measures.

3.3.1. Loans Per Poor Person (GLP/Poor)

3.3.1.1. Rationale

Perhaps, the most widely used measure of microfinance intensity in a country is GLP to population ratio. GLP/population gives a reasonable estimate of the possible social significance of microfinance, giving an estimate of microfinance loans per capita.

But as the careful reader would notice, income distribution varies widely from country to country, and there is considerable heterogeneity in the target market of MFIs. Thus, Country A having a higher population can have a low percentage of poor, while Country B can have a lower population with a high proportion of poor. The estimates of GLP/population will be reasonable predictors of microfinance intensity in the population in Country B but not in Country A. For Country A, the estimates will be biased upwards.

As microfinance loans target the relatively poor population, which traditionally has not had access to formal credit markets, it is reasonable to have the poor population instead of the total population in the denominator. Thus, we suggest GLP divided by poor population as a measure of microfinance intensity (henceforth, GLP/poor). This measure does not have the limitation of bias arising from the heterogeneity in poverty rates between countries, and it provides a relatively accurate picture of the social significance of microfinance for the poor population, giving an estimate of loans per poor person.

3.3.1.2. Construction

The critical variable in the construction of GLP/poor is the poverty rate. The poverty rate typically refers to the poverty headcount ratio in a region or simply the number of poor as a proportion of the population. Various studies rely on different definitions of poverty to calculate the poverty headcount ratio. Some define poverty as a relative measure. For example, the United Kingdom considers the population living on an income that is below 60% of the median income of the country as poor. Such measures are insightful but not generalizable. Some measures of poverty are absolute, defining persons living below a certain income level as poor. The cut-off the World Bank uses for the whole world, for instance, for 'extreme poverty,' is $2.15. Standardizing the poverty line based on an absolute income level makes it generalizable but does not account for country-level differences.

We try to strike a middle ground by relying on not one relative or absolute definition of poverty but using the national-level definition of poverty lines, which may be relative or absolute. This subtle difference is crucial from the perspective of microfinance institutions, which extend loans to those who typically don't have access to traditional banks. However, the exact income dynamics of the borrowers vary from country to country.

We obtain population-weighted poverty rate data according to the national poverty lines from the World Bank, Poverty, and Inequality platform. We multiply the poverty rate of a given country by its population that year, which renders an estimate of the number of poor. As country-level poverty rates are not available every year, and the data are not continuous, making it impossible to extrapolate, the data for the number of poor also has missing values.

Next, we divide GLP in a given year by the number of poor for that year to arrive at GLP/poor. As the data has missing values, we divide the GLP by the no. of poor in the nearest year. Because the no. of poor is not likely to change significantly from year to year, the assumption seems plausible. We suggest studies define a threshold for the "nearest year." This approach could entail completely ignoring the values with missing data, tolerating a one-year deviation, or tolerating a two years difference. It is up to the researcher to weigh the gain in precision from accommodating more data against the cost of ignoring potential data points altogether.

3.3.2. Active Borrowers as a Proportion of the Poor Population (Borrowers/Poor)

3.3.2.1. Rationale

'Active borrowers' in the Mix Market dataset refers to individuals with outstanding loan balances. Borrowers, who have a payable amount but multiple loans, are counted only once. The no. of active borrowers in a country gives a reasonable estimate of the intensity of microfinance in that country. To make these estimates more accurate and comparable across countries, studies involving microfinance intensity divide active borrowers by the population to get standardized estimates that make comparisons easier.

3.3.2.2. Construction

Similar to proposing the use of GLP/poor instead of GLP/population, we suggest Active Borrowers as a percentage of the poor as a better measure of microfinance intensity than Active Borrowers as a percentage of the overall population. Borrowers/poor gives a better estimate than borrowers/population, as the non-poor population is not the target market for a typical MFI.

Borrowers/poor is arrived at using the same approach as GLP/poor. First, we multiply the poverty rate in a given country in a particular year by its population that year to get the number of poor. Next, we divide active borrowers' data acquired from MIX by the number of poor to get borrowers/poor.

3.3.3. Microcredit as a Percentage of Total Credit (GLP/Credit)

3.3.3.1. Rationale

Many macro-oriented studies of the aggregate effects of microfinance adopt another approach for standardizing gross loans on a country level. The GLP – which represents total microfinance loans - is divided by the GDP. This calculation yields a measure of GLP as a proportion of GDP, indicating the economic quantum of microfinance in a country. Like other measures, this is a good measure that makes GLP/GDP comparison across countries possible. Still, microfinance makes up a tiny proportion of the GDP, and this measure, while it is sound, may still be improved.

We suggest a new measure, namely, GLP as a percentage of total private sector credit, which yields a more precise estimate of the economic quantum of microfinance. It gives a measure of microcredit as a percentage of the Total Private credit in the economy, thus accounting for the size and development of the financial sector of a country as well.

3.3.3.2. Construction

The private sector credit data is available in the World Development Indicators database as a percentage of GDP. To obtain GLP/credit, we divide credit by GLP, both in percentage-of-GDP terms.

3.4. Analysis of Measures

Table 3.2 shows the descriptive statistics for the classic and new measures in our sample. It may be useful to compare GLP/capita with GLP/poor, to begin with. The GLP/capita is about $84.5 on average. This figure somewhat understates the intensity of microfinance, as it is not targeting the whole population. Our new measure GLP/poor more accurately reflects the quantum of microfinance for the relevant population, which is about $386.7, considerably higher than GLP/capita. Similarly, 3% of the population is an active borrower of loans, according to borrowers/capita. But this again understates the prevalence of microfinance on average, which is much higher when we take into account only the relevant, poor population. GLP/poor shows that 17.6% of the poor are likely borrowers of microfinance loans.

The third measure introduced in this study, GLP/credit (microcredit as a proportion of credit) shows a slightly higher figure than GLP/GDP as well, of about 0.06 compared to 0.02. This reflects the scale of microfinance as being 6% of total private sector credit, and about 2% of the GDP. This figure needs to be interpreted with care, however, as some countries may have higher GLP/GDP numbers higher than GLP/credit. This does not necessarily reflect the imprecision of GLP/credit, but the fact that credit prevalence varies a lot from country to country, with some countries having credit figures higher than the GDP itself. This is reflected in the higher data variation here, with the range (difference between Max and Min) of GLP/credit being higher than GLP/GDP. The key here is that GLP/credit is normalized for the size of the financial market instead of the whole economy, yielding more precise estimates of the salience of microcredit in the financial system.

Lastly, it should be noted that all three measures we introduce here have higher dispersion around the mean, reflected in higher standard deviations. This allows for more inter-country variation, providing a hopefully cleaner picture of the relationship of microfinance intensity with other measures of interest in cross-country analyses. It is for the same reason, however, that logs could give more stable results, which are reported in Table 3.2 and are used for further analysis in this paper.

Table 3.2. Descriptive Statistics of Measures of Microfinance Intensity

Variable	**Obs.**	**Mean**	**Std. dev.**	**Min**	**Max**
GLP/capita	89	54.458	145.819	0.000	1020.420
Borrowers/capita	83	0.023	0.033	0.000	0.165
GLP/GDP	87	0.018	0.053	0.000	0.382
GLP/poor	60	272.715	552.059	0.032	2704.953
Borrowers/poor	56	0.124	0.159	0.000	0.803
GLP/credit	80	0.056	0.100	0.000	0.465
Log GLP/capita	89	2.001	2.703	-11.310	6.928

Table 3.2. (cont.)

Log Borrowers/capita	83	-4.877	1.917	-11.111	-1.804
Log GLP/GDP	87	-5.766	2.412	-15.082	-0.961
Log GLP/poor	60	3.727	2.411	-3.442	7.903
Log Borrowers/poor	56	-3.248	1.998	-9.588	-0.219
Log GLP/credit	80	-4.545	2.566	-13.795	-0.766

Table 3.3 shows the pairwise correlation matrix of new (first 3 in column/row) and classic measures (last 3) of microfinance intensity. It may be noted that all microfinance intensity measures are correlated with each other at a significance >99.99% and a Pearson correlation coefficient of greater than or equal to about 0.75. In particular, the correlation coefficient for the three measures suggested in this study and the classic measures (shown in bold) is >0.95.

Table 3.3. Pairwise Correlation of Old and New Measures

Variables	1	2	3	4	5	6
(1) Log GLP/capita	1					
(2) Log Borrowers/capita	0.82	1				
	(0.000)					
(3) Log GLP/GDP	0.919	0.783	1			
	(0.000)	(0.000)				
(4) Log GLP/Poor	**0.963**	0.788	0.847	1		
	(0.000)	(0.000)	(0.000)			
(5) Log Borrowers/poor	0.779	**0.945**	0.727	0.826	1	
	(0.000)	**(0.000)**	(0.000)	(0.000)		
(6) Log GLP/credit	0.817	0.679	**0.958**	0.715	0.632	1
	(0.000)	(0.000)	**(0.000)**	(0.000)	(0.000)	

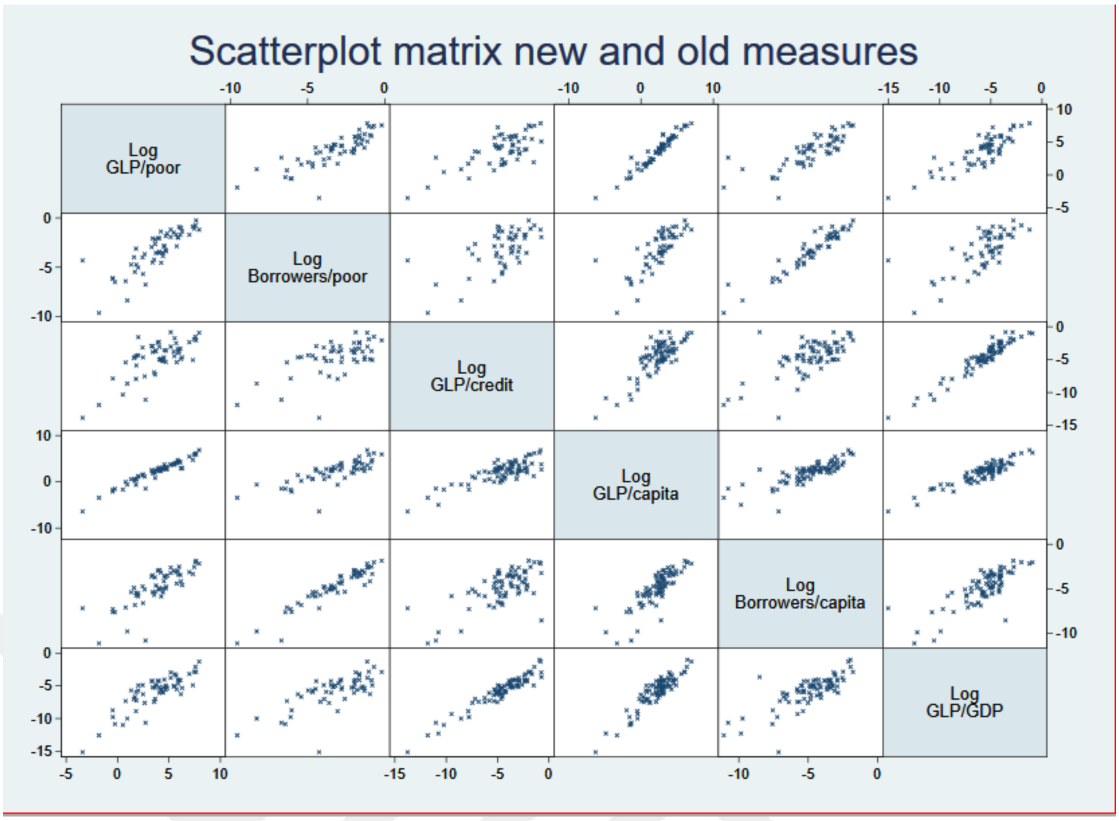

Figure 3.1. Scatterplot Matrix New and Old Measures

Figures 3.2, 3.3, and 3.4 show the scatterplot matrices of each of the new measures and the classic measures. Figure 3.2 shows plots of log GLP/poor against log GLP/capita, log borrowers/capita, and log GLP/GDP. It may be seen that log GLP/poor shows a tight distribution for log GLP/capita, with which it is most closely related conceptually, but also log GLP/GDP. Log GLP/poor is correlated with log borrowers/capita as well, though the correlation is less sharp due to a different numerator and a different denominator, both of which are originally measured in completely different units. In that respect, this correlation may be more remarkable.

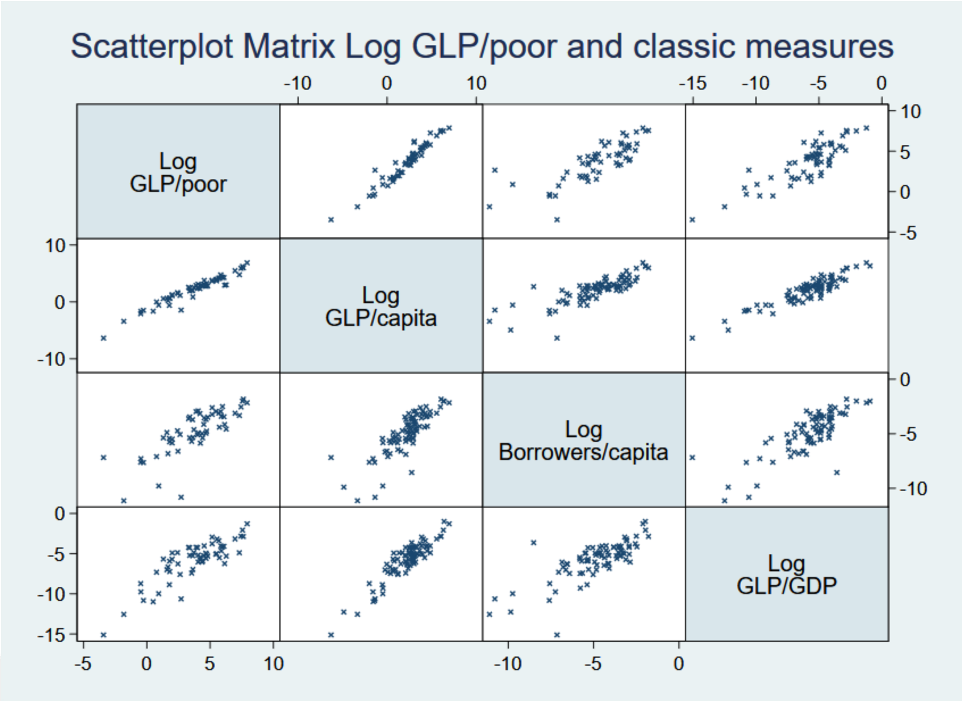

Figure 3.2. Scatterplot Matrix of Log GLP/Poor and Classic Measures

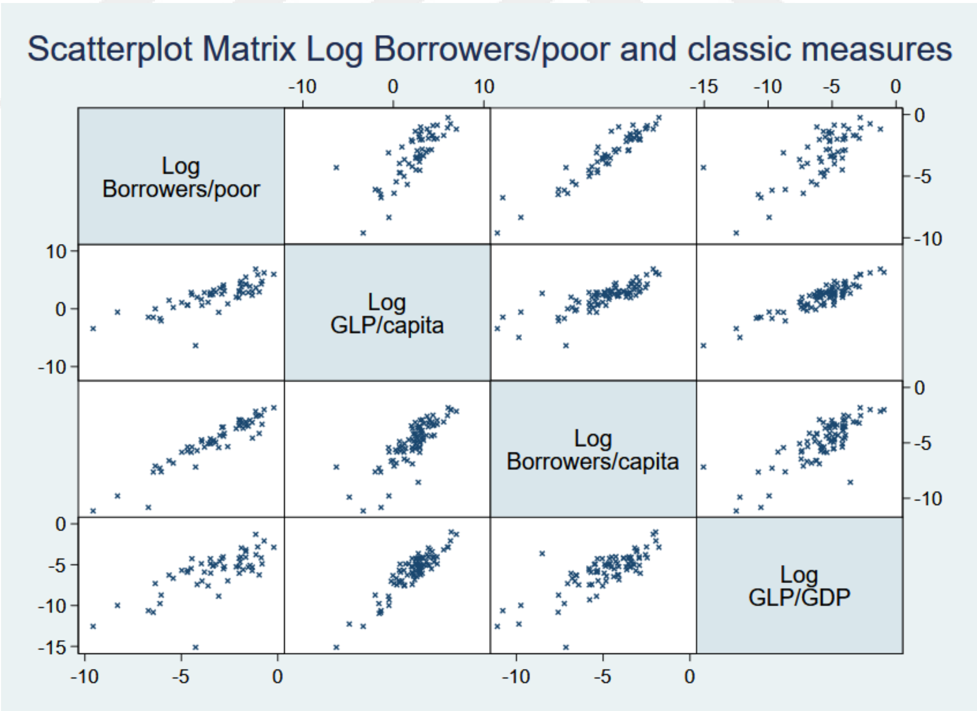

Figure 3.3. Scatterplot Matrix Log Borrowers/Poor and Classic Measures

Figure 3.3 shows the scatter of the second measure, log borrowers/poor. Except for one outlier, it shows a close correlation with log GLP/capita and log GLP/GDP. The plot of log borrowers/poor and log borrowers/capita, meanwhile, shows a very high correlation.

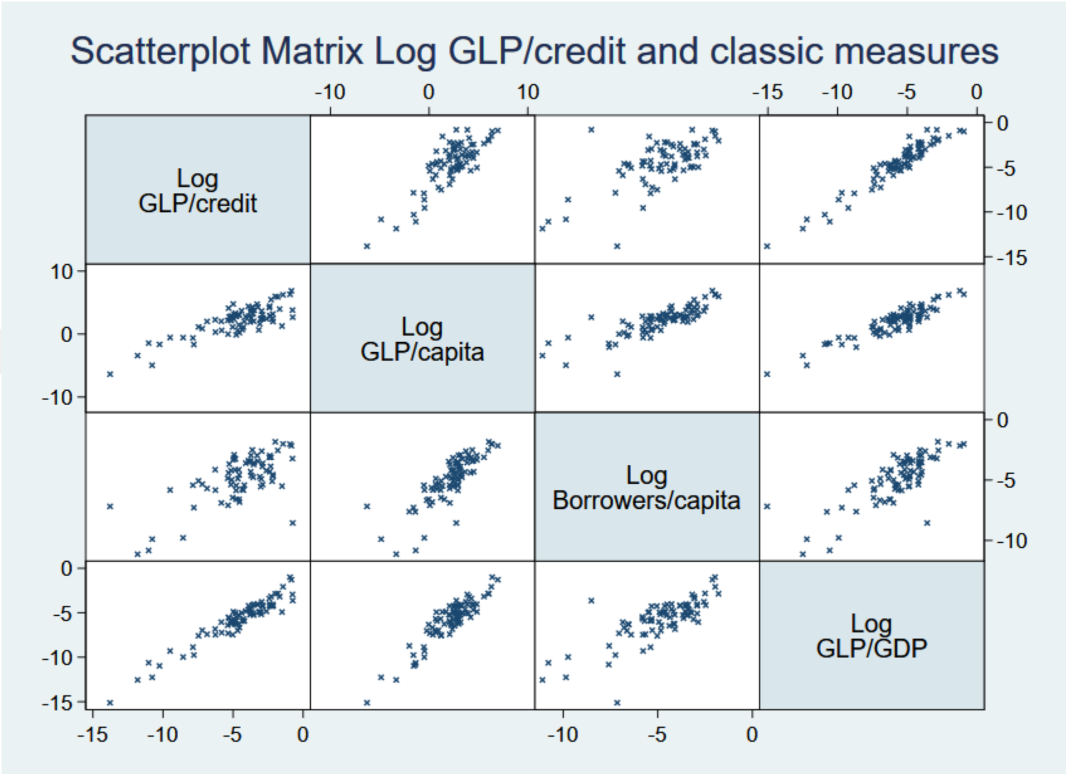

Figure 3.4. Scatterplot Matrix Log GLP/Credit and Classic Measures

Figure 3.4 shows the scatterplot matrix of log GLP/credit and classic measures. Log GLP/credit shows a close correlation with log GLP/GDP as well as log GLP/capita, though the correspondence between log GLP/credit and log borrowers/capita is less tight, owing to the reasons already discussed above.

Figures 3.5. to 3.13 zoom into the scatters in Figures 3.2-3.4 further, studying the linear fit. Figures 3.5-3.7 show the predictive power of the three classic measures for log GLP/poor; Figures 3.8-3.10 show the predictive power of the three classic measures for log borrowers/per; and Figures 3.11-3.13 show the predictive power of the three classic measures for log GLP/credit. All figures show a good linear fit.

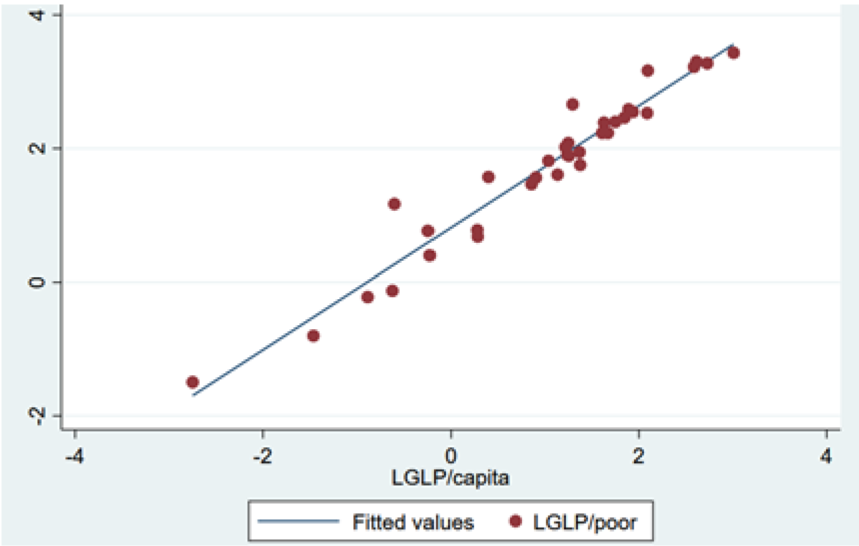

Figure 3.5. Log GLP/Poor & Log GLP/Capita

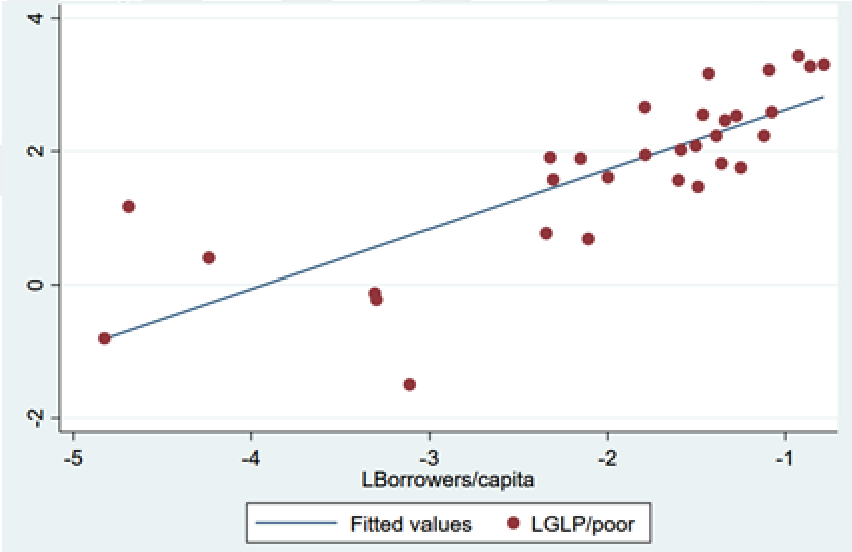

Figure 3.6. Log GLP/Poor & Log Borrowers/Capita

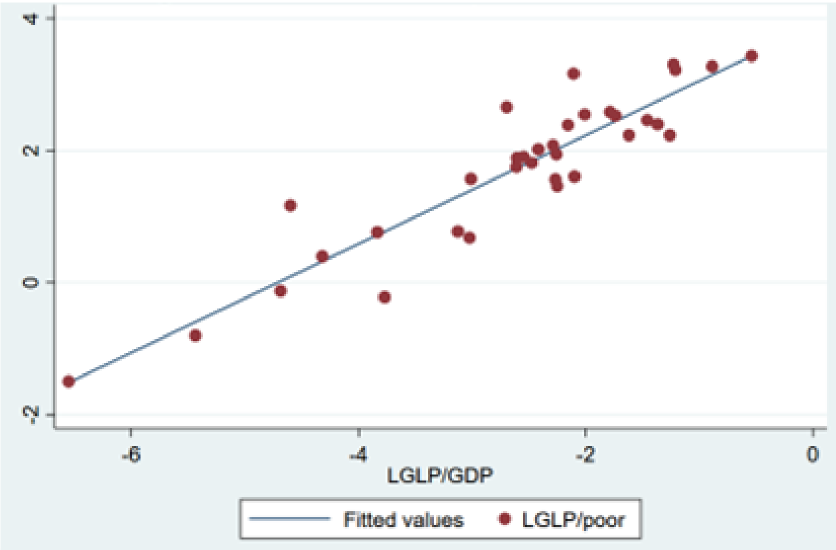

Figure 3.7. Log GLP/Poor & Log GLP/GDP

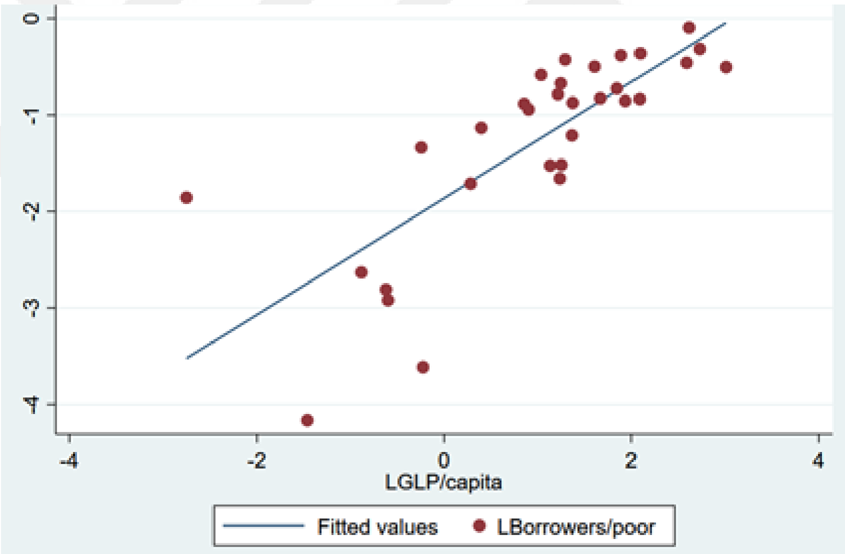

Figure 3.8. Log Borrowers/Poor & Log GLP/Capita

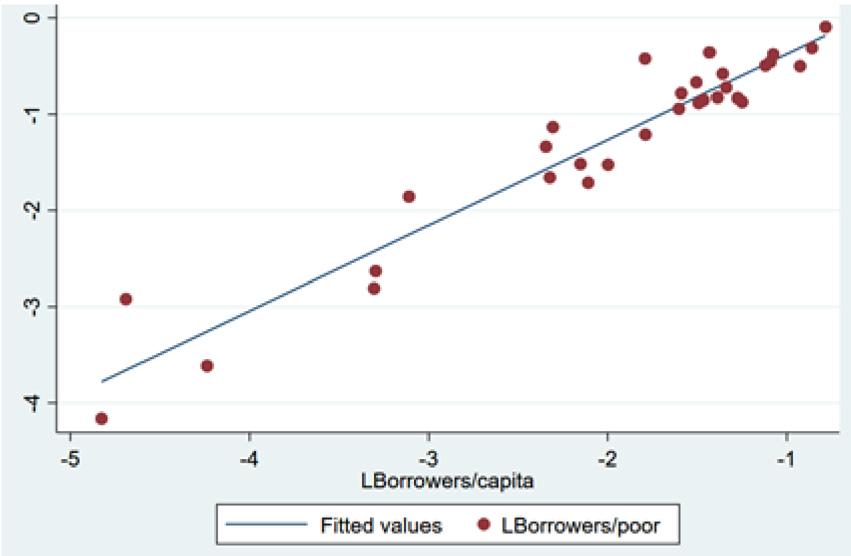

Figure 3.9. Log Borrowers/Poor & Log Borrowers/Capita

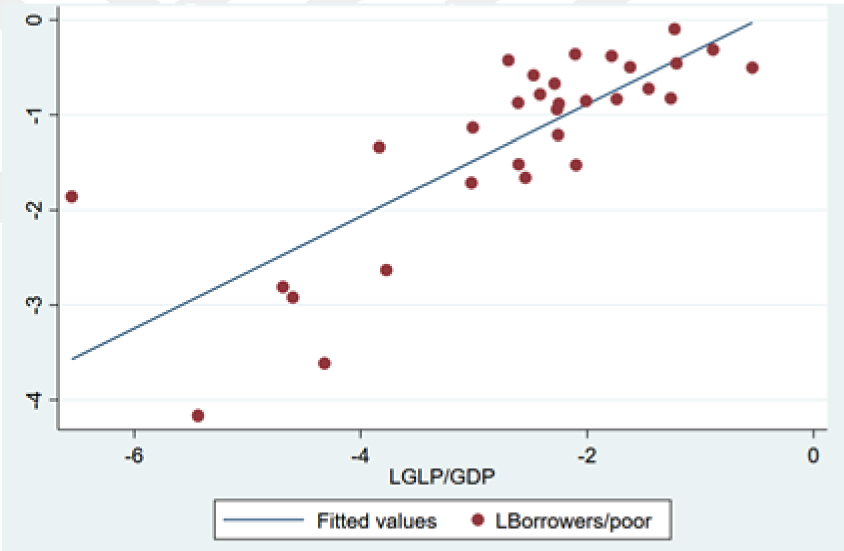

Figure 3.10. Log Borrowers/Poor & Log GLP/GDP

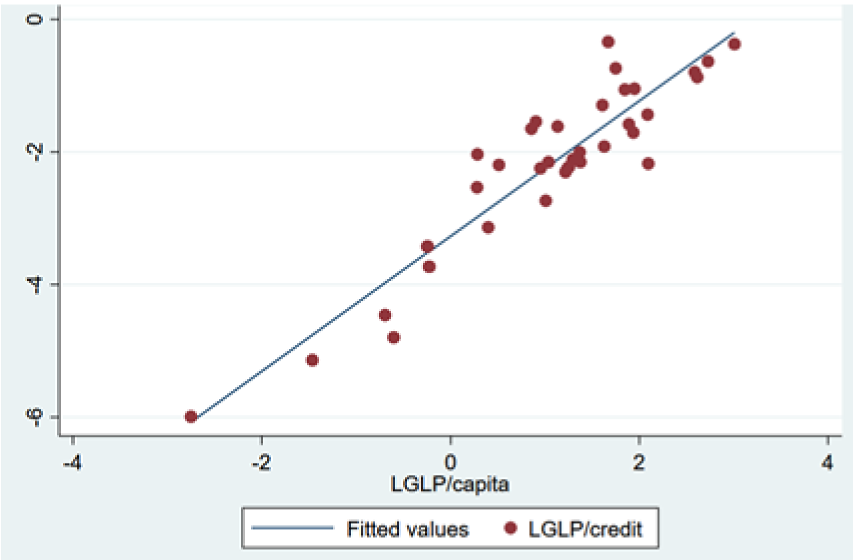

Figure 3.11. Log GLP/Credit & Log GLP/Capita

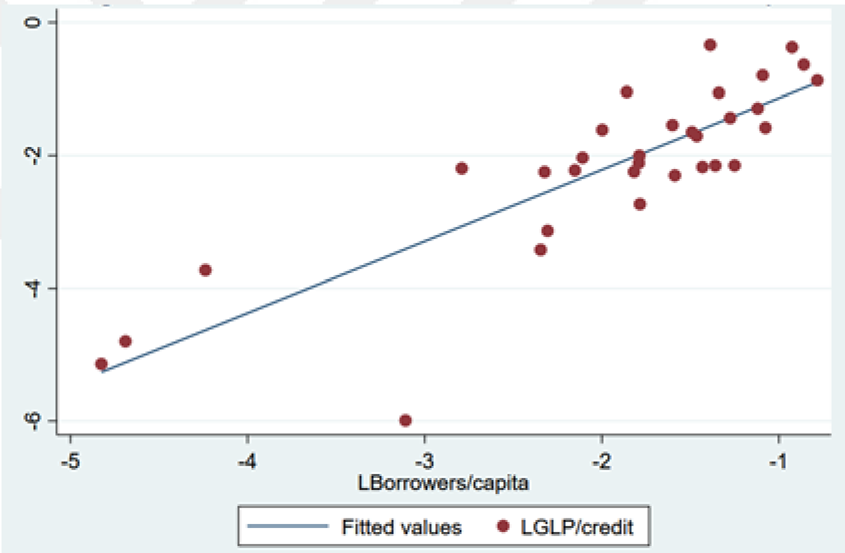

Figure 3.12. Log GLP/Credit & Log Borrowers/Capita

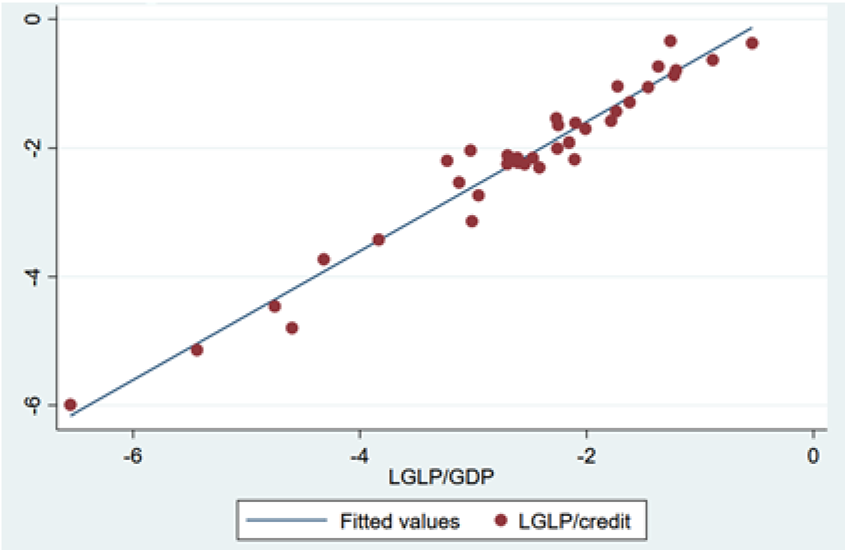

Figure 3.13. Log GLP/Credit & Log GLP/GDP

3.5. Concluding Comments on New Measures

This paper proposes three new, independent measures of microfinance intensity – GLP/poor, borrowers/poor, and GLP/credit – which are conceptually grounded and correlate neatly with classic measures of microfinance intensity used in studies generally. Employing a macro-approach to measure the effects of microfinance on country-level outcomes, such as poverty or inequality, hinges on the precision of how microfinance is measured. The three measures proposed here make measuring microfinance intensity more targeted than previous measures.

Studies in the future can use these measures to study the aggregate effects of microfinance on the poor strata of society and possibly re-study null results obtained with the classic measures previously, benefitting from the precision of these new measures. Moreover, these new microfinance measures may be constructed and tested using the overall approach taken in this study. Lastly, the two measures dependent on poverty rate – GLP/poor and borrowers/poor – presented here may be improved upon with high-quality data on poverty, as and when it becomes available.

CHAPTER IV

MODEL SPECIFICATION AND TESTS

4.1. Data

The study analyses the association between microfinance intensity and distrust levels among the poor. We use the latest available data of the year 2019 in WVS-EVS for our cross-sectional regressions. Further, we use the empirical Bayes method on a 4-period panel for years 2001, 2007, 2012, and 2019, corresponding to waves 4, 5, 6, and 7 of the World Values Survey. We use data for all countries in the four time periods for which data is available in World Values Survey and Microfinance Information Exchange datasets. The countries are listed below.

Table 4.1. List of Countries

Countries used in the analysis of Microfinance and Dist			
Albania	Egypt	Montenegro	Tunisia
Argentina	Ethiopia	Myanmar	Turkey
Armenia	Georgia	Nicaragua	Ukraine
Azerbaijan	Guatemala	Nigeria	United States
Bangladesh	Hungary	North Macedonia	Vietnam
Belarus	Indonesia	Pakistan	
Bolivia	Iraq	Peru	
Bosnia Herzegovina	Jordan	Philippines	
Brazil	Kazakhstan	Poland	
Bulgaria	Kenya	Romania	
Chile	Kyrgyzstan	Russia	
China	Lebanon	Serbia	
Colombia	Malaysia	Slovakia	
Croatia	Mexico	Tajikistan	
Ecuador	Mongolia	Thailand	

Table 4.2 provides the variables' descriptions for quick reference, while the summary statistics are reported in Table 4.3.

Table 4.2. Variables' Description

Variable	Definition	Source
Distrust Poor	Distrust levels among the poor (Income levels 1, 2, 3 out of 10)	WVS
Distrust Ultra-Poor	Distrust levels among the ultra-poor (income level 1 out of 10)	WVS
Distrust Rich	Distrust level among the rich (income level 10 out of 10)	WVS
GLP/credit*	gross loan portfolio divided by total domestic private credit	MIX; WDI
GLP/capita*	gross loan portfolio divided by the total population	MIX; WDI
GLP/GDP*	(gross loan portfolio divided by GDP)*100	MIX; WDI
Fractionalization	Ethnic fractionalization index	Alesina et. al.; Drazanova
Top decile	Pre-tax share in national income of the top10% of the economy	WID
Yield*	The average real yield on the gross loan portfolio 2011-2016 divided by its standard deviation	MIX

*These variables are log-transformed

At the outset, it is interesting to note that most people - around 80% - say that most people cannot be trusted, as reflected in the mean of distrust rows in Table 4.3. This is irrespective of the income level of the respondent or the year. Even richer respondents - who may relatively be more secure psychologically - would rather not trust strangers. The percentage of people exhibiting distrust in WVS wave 6 (corresponding to 2012) is higher for the richest stratum, with a mean of 76.9% compared to the poor at 74.8%. For the 5th wave, the distrust is almost equal, being 80.7% among the rich and 80.3% among the poor. Nevertheless, distrust among the poorest respondents is invariably the highest in all waves. The rich respondents, meanwhile, have the greatest within-group dispersion in responses, as reflected in higher standard deviation in all years, suggesting a higher heterogeneity in social behaviors among the rich respondents, compared to the poorer ones, who may be relatively similar.

Also, distrust may be growing over the years. Average distrust in the poor has risen from 73.1% in Wave 4 to 74.8% in Wave 5 to 80.3% in Wave 6 to a further higher 83.1% in Wave 7. Distrust among the poorest and the rich shows a similar pattern, which could be the effect of more countries being added to the world values survey, indicating a 'regression' to the mean as more data becomes available.

While microfinance has increased phenomenally in absolute terms over the last two decades, we don't see evidence of its salience in various countries' financial systems seeing a similar rise. Microfinance loan portfolio as a percentage of total private sector credit stood at 5.7% in 2007, and for the latest reported year, 2018, it is still at 5.8% only. As the data is highly positively skewed with a high kurtosis, indicating outliers to the right of the distribution, we log-transform the microfinance salience series.

Microfinance intensity data is again highly skewed to the right, and we use log here too. What is interesting, however, is that it does show a relatively sharp rise from 2001 to 2012. Also, the maximum and minimum values vary greatly. Particularly, countries with relatively smaller populations show higher intensity, as may be expected.

The data for controls, ethnic fractionalization index, and income share of the top decile show good properties. The probability that two random individuals in a country belonging to the same ethnic group remains relatively stable over time, on average, and is 40.8% for the most recent year, but there is a noticeable variance between countries, with the standard deviation being 0.241, with a maximum value of 0.855 (Kenya) and a minimum of 0.025 (Bangladesh).

Table 4.3. Summary Statistics

Year	Variable	No.	Mean	St. Dev.	Min	Max	Skewness	Kurtosis
2019	Distrust Poor	50	0.831	0.102	0.408	0.975	-1.756	7.242
	Distrust Ultra-Poor	50	0.85	0.13	0.333	1	-1.93	7.369
	Distrust Rich	50	0.803	0.186	0.068	1	-1.691	6.864
	GLP to private credit ratio	36	0.058	0.11	0	0.458	2.691	7.147
	GLP to population ratio	40	83.154	191.96	0.002	1020.42	3.689	15.121
	GLP as percentage of GDP	40	2.066	5.002	0	28.756	4.21	21.937
	Ethnic Fractionalisation Index*	49	0.408	0.239	0.025	0.855	0.072	2.049
	Income share of richest 10%	50	0.438	0.074	0.269	0.589	-0.055	2.673
2012	Distrust Poor	30	0.803	0.137	0.357	0.97	-1.23	4.79
	Distrust Ultra-Poor	30	0.859	0.134	0.454	1	-1.595	5.054
	Distrust Rich	30	0.807	0.182	0.418	1	-0.574	2.07
	GLP to private credit ratio	41	0.077	0.126	0	0.52	2.192	7.277
	GLP to population ratio	45	88.548	135.391	0.022	597.659	2.207	7.734
	GLP as percentage of GDP	45	2.328	3.356	0	13.959	1.873	6.168
	Ethnic Fractionalisation Index	48	0.41	0.24	0.026	0.855	0.032	2.03
	Income share of richest 10%	50	0.441	0.079	0.296	0.617	0.116	2.386
2007	Distrust Poor	26	0.748	0.146	0.456	0.947	-0.635	2.343
	Distrust Ultra-Poor	25	0.812	0.13	0.56	0.976	-0.616	1.937
	Distrust Rich	21	0.769	0.205	0.302	1	-0.49	2.371
	GLP to private credit ratio	34	0.057	0.1	0	0.483	2.734	11.098
	GLP to population ratio	45	30.296	40.024	0.004	174.274	1.715	5.859
	GLP as percentage of GDP	45	1.491	2.022	0	7.697	1.672	5.06
	Ethnic Fractionalisation Index	48	0.413	0.242	0.028	0.856	0.006	2.016
	Income share of richest 10%	50	0.451	0.078	0.306	0.593	-0.25	2.094
2001	Distrust Poor	22	0.731	0.119	0.494	0.906	-0.46	2.276
	Distrust Ultra-Poor	22	0.785	0.142	0.44	1	-1.045	3.847
	Distrust Rich	20	0.662	0.183	0.312	1	-0.541	2.616
	GLP to private credit ratio	17	0.002	0.006	0	0.025	3.21	12.053
	GLP to population ratio	30	1.928	4.753	0.001	25.626	4.336	22.068
	GLP as percentage of GDP	27	0.167	0.479	0	2.569	4.433	22.627
	Ethnic Fractionalisation Index	49	0.413	0.241	0.024	0.857	0.009	2.001
	Income share of richest 10%	50	0.452	0.09	0.293	0.63	0.001	1.961

Note: GLP data from t-1 e.g., for 2019, GLP measures used are from 2018. GLP statistics are before taking the log.
*Value of 2013, the latest available figure.

4.1.1. Measures of Microfinance Intensity

Microfinance data comes from Microfinance Information Exchange (MIX), hosted by the World Bank Data Catalogue and the World Development Indicators. MIX Market data has been reported from 1999 to 2019 and covers the financial statements, outreach, and social performance data of microfinance institutions "targeting the unbanked" in developing economies (*MIX Market | Data Catalog*, n.d.). MIX is targeted at achieving greater transparency in the microfinance industry, and while the data is self-reported, it follows predetermined formats, validation mechanisms, and standardization for ease of comparison (Imai et al., 2012).

Gross loan portfolio (GLP) - the key component of our explanatory variable, which is obtained from MIX - shows the total funds disbursed in loans by microfinance institutions (MFIs) and is adjusted for write-offs and inflation. We standardize this country-level GLP with respect to 3 alternative variables, yielding three different measures of microfinance intensity.

For the first measure, we divide GLP by the total domestic credit to the private sector (GLP/credit) obtained from the World Development Indicators (WDI) (*WDI - Home*, n.d.). This is the first study to use the ratio of GLP to credit for measuring microfinance intensity. This yields a precise estimate of the salience of microfinance in the economy, as it normalizes the GLP for the size of the financial sector rather than a general country-wide measure. This gives us confidence that the results in this study are driven by microfinance and not by overall financial development in the country.

For the second measure of microfinance intensity, we divide GLP by the population of the country, which yields microfinance loans per capita (or simply GLP/capita) (Imai et al., 2012). This measure is important in terms of indicating, potentially, the social quantum of microfinance in terms of its penetration within the life of the average person. The third measure is the same as the one used by Hermes (Hermes, 2014), in which we take the GLP as a percentage of the GDP of a country. This indicates the significance of microfinance according to the size of a country's economy.

4.1.2. Measures of Distrust

Distrust is the main outcome of interest in this study, the data for which is obtained from the WVS and EVS datasets (*WVS Database*, n.d.). WVS survey is conducted every five years, and EVS, every nine years. For the latest wave, wave 7 of WVS, the WVS-EVS integrated data for 88 countries is available. The question from the survey that is used in the current study is, "Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?"

The percentage of respondents answering “most people can be trusted” has been widely used as a measure of trust (Daskalopoulou, 2019; Knack & Keefer, 1997; Mikucka et al., 2017), and shown by Johnson and Mislin (Johnson & Mislin, 2012) to be positively correlated with experimentally measured trust. The proportion of people with the opposite response to the trust question, i.e., "need to be very careful,” is used in this study as a measure of distrust, following the approach of Aghion, Algan, Cahuc, and Shleifer (Aghion et al., 2010). We focus on distrust as it is a relatively strongly felt emotion, and in the words of McKnight and Chervany (Harrison McKnight & Chervany, 2001), "fiery and frenzied" compared to "cool and collected" trust. Social frictions should appear more quickly and conspicuously in reported “distrust” rather than “trust.”

The careful reader would note that the response "need to be very careful" indicates prudence and may simply be indicating a reluctance to immediately trust people; equating such “lack of trust” with “distrust” may be imprecise (Van De Walle & Six, 2014). While this nuance may make a difference to questions that are directly affected by the difference between “lack of trust” and “distrust,” for this paper, we think the point of the study remains irrespective of the label. We prefer the clearer and parsimonious “distrust,” but if the reader finds it more appropriate, the results can equally be interpreted using “lack of trust.”

Moreover, this study is concerned with 'social distrust', which is the absence of social/or generalized trust between strangers. This is related to, but different from, limited/particularised trust among knowns, such as that between friends and between family members, as well as civic/institutional trust, which represents trust in institutions (Danish & Nawaz, 2022), the governments, or the system (Kwon, 2019; Stone, 2001). While various forms of (dis)trust may follow similar paths, they are beyond the scope of the current work.

As the World Values Survey is conducted over 5 to 6 years, we make a simplifying assumption for running meaningful regressions and for making a comparison across waves possible: the distrust value for a given wave is assumed to represent the middle year of data collection. For the 4th Wave (1999-2004), this corresponds to the year 2001, for the 5th (2005-2009) to the year 2007, and so on. Notwithstanding, because distrust levels are unlikely to change substantially from year to year (Uslaner, 2016), the exact choice of year does not affect the overall results of the study.

Further, instead of dealing with a simple country-wide distrust measure, we distinguish distrust by income group. WVS asks respondents to rate their income on a 10-point scale, the lowest level being “1”, and the highest level being "10". We use this information to identify distrust in what we call the "ultra-poor," corresponding to the lowest level in self-reported income, that is 1; the "poor," corresponding to those on steps 1-3; and the "rich," which captures those on the 10th step. This is important as exposure to microfinance is relevant to the poor and the ultra-poor only and should not affect the rich.

4.1.3. Control Variables

Distrust in societies is correlated with ethnic heterogeneity as well as economic inequality, which we control for. All else equal, social distrust is positively related to ethnic heterogeneity as well as income inequality (Welch et al., 2005). To account for ethnic heterogeneity, we use the ethnic fractionalization index, which represents the probability that two people selected randomly in a given population will be from different groups (Alesina et al., 2003; Drazanova, 2020). The higher the index value, the greater the probability. For economic inequality, we use the pre-tax income shares of the top 10% (top decile) of the population, following the approach of Piketty and Saez (Piketty & Saez, 2003, 2006, 2014). A higher value indicates higher inequality. We obtain this data from the World Inequality Database (*World Inequality Database*, n.d.).

4.2. Econometric Tests

The general linear regression model in the panel takes the form,

$$Distrust_{\mathrm{it}} = \alpha_{\mathrm{t}} + \beta_{\mathrm{t}} MF_{\mathrm{it-1}} + \lambda_{\mathrm{t}} Z_{\mathrm{it}} + \varepsilon_{\mathrm{it}}$$

Where *MF* is a vector of 3 alternative measures of microfinance intensity; Z is a vector of covariates; epsilon is the random error term; i represents the country; and t represents the year.

Note that MF is modeled with a 1-year lag, capturing how microfinance intensity today is associated with distrust after a year. This is to be expected as the social effects of exposure to microfinance should take time to take effect, especially to be noticeable enough to show in the data. Lag is common in literature on the determinants of trust (Betkó et al., 2022; Brandt et al., 2015).

4.2.1. Cross-Sectional Regressions

For cross-sectional regression, we use the ordinary least squares (OLS), the benchmark model for analyzing associations in continuous data in a single period.

4.2.2. Empirical Bayesian Estimation

For analyzing the panel, we use the empirical Bayes method. Empirical Bayes was pioneered by Efron & Morrison (Casella, 1985; Efron & Morris, 1972a, 1972b, 1975). The method lies at the intersection of the classical Bayesian and the frequentist approach to statistics. It is frequentist in the sense that it tries to get at the underlying parameters, but it is Bayesian in the sense that it draws on the data to recreate a prior distribution, from which a posterior distribution is reached. The bias and imprecision that a small sample suffers from, the empirical Bayes method helps mitigate by generating a prior distribution from given data, from which hyperparameters are estimated to get at a posterior distribution yielding more stable results with lower standard errors, less susceptible to bias arising from erratic outliers (Carrington & Zaman, 1994; Casella, 1985; Latif & Javid, 2016; Zaman, 1996; Zwick et al., 1999). This gives us confidence that the relationship between microfinance intensity and distrust is not driven by an extremely strong association in any particular year: such extreme co-variations are allocated lower weights in proportion to their deviation from the universe of values.

We follow the general Bayesian panel approach taken by Carrington and Zaman (Carrington & Zaman, 1994) of the form,

$$Y_{it} = \beta_i X_{it} + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{(i)}$$

$$\forall\ i = 1,2,\ldots,N \quad t = 1,2\ldots,T$$

Where *Y* represents the dependent variable; *X* represents the independent variable and the covariates; *t* represents the number of time periods; *i* denotes the number of countries; β is the coefficient vector; *N* represents the total no. of countries; *T* represents the total time-periods; and ε is the random error component.

In matrix form,

$$Y_i = \begin{bmatrix} y_{i1} \\ y_{i2} \\ . \\ . \\ . \\ y_{iT} \end{bmatrix}_{T\times 1} \qquad X_i = \begin{bmatrix} x_{i1} \\ x_{i2} \\ . \\ . \\ . \\ x_{iT} \end{bmatrix}_{T\times K} \qquad \varepsilon_i = \begin{bmatrix} \varepsilon_{i1} \\ \varepsilon_{i2} \\ . \\ . \\ . \\ \varepsilon_{iT} \end{bmatrix}_{T\times 1}$$

$$Where, \quad X_{it} = [X_{it}^1 \quad X_{it}^2 \quad \ldots \quad X_{it}^k]_{\text{k-regressors}}$$

$$and,\ \varepsilon_i \sim N(0, \delta_i^2)$$

The data density is,

$$\hat{\beta}_i / \beta \sim N(\beta, \Omega_i) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{(ii)}$$

It is important to note here that this data density is as such, in contrast with the prior density, which is based on previous knowledge or belief about the data. The prior density may be given by,

$$\beta \sim N(\mu, \Lambda) \text{.......................……………………….(iii)}$$

So, the posterior density becomes (Zaman, 1996),

$$\beta / \widehat{\beta}_{\mathrm{i}} : N(m_i, V_i) \text{ …………………….....…………..(iv)}$$

Where m_i and V_i are,

$$m_i = V_i \left(\hat{\Omega}_i^{\ -1} \widehat{\beta}_{\mathrm{i}} + \Lambda^{-1} \mu \right) \quad and \quad V_i = \left(\hat{\Omega}_i^{\ -1} + \Lambda^{-1} \right)^{-1} \text{ ……..……(v)}$$

As the Classical Bayes estimator is the mean of posterior, equation (v) may be written as,

$$\widehat{\beta}_{\mathrm{i}(CB)} = V_i \left(\hat{\Omega}_i^{\ -1} \widehat{\beta}_{\mathrm{i}} + \Lambda^{-1} \mu \right)$$

and its variance-covariance matrix is,

$$V_i = \left(\hat{\Omega}_i^{\ -1} + \Lambda^{-1} \right)^{-1}$$

But the two hyperparameters, i.e., μ and Λ, are unknown. The empirical Bayes method uses the available data to estimate these hyperparameters and construct prior distribution from the data instead of previous knowledge or belief. Thus, the empirical Bayes estimator may be written as,

$$\widehat{\beta}_{\mathrm{i}(EB)} = \widehat{V}_i \left(\hat{\Omega}_i^{\ -1} \widehat{\beta}_{\mathrm{i}} + \widehat{\Lambda}^{-1} \hat{\mu} \right) \text{……………………(vi)}$$

Where the estimated hyperparameters are,

$$\widehat{\Lambda} = \left(\sum_{i=1}^{N} \hat{\Omega}_i^{\ -1} \right)^{-1}$$

and,

$$\hat{\mu} = \widehat{\Lambda} \left(\sum_{i=1}^{N} \widehat{\Omega}_i^{\ -1} \widehat{\beta}_{\mathrm{i}} \right)$$

It is important to understand the idea behind empirical Bayesian priors. Frequentist statistics is based on the idea that parameters θ are fixed quantities (with probability 1. Bayesian statistics, on the other hand, tries to make a less authoritative but perhaps more robust claim, trying to get at the underlying probabilities of the parameters rather than treating them as fixed quantities, i.e., it begins by trying to get at probability distributions of parameters.

The probability distribution of the parameter at the start is called the prior distribution. This prior distribution is based on initial belief or previous knowledge.

Bayesian estimates are based on these prior distributions and thus tend to shrink towards the priors. With good priors, this is an advantage. One can reach sound estimates even with relatively fewer data. But with imprecise priors, a good posterior will need much more data to get away from the gravity of priors and arrive at the right results.

One effect of priors is that the estimates are predicted with lower standard errors. With inaccurate priors, this comes out as a weakness of Bayesian analysis, but with relatively accurate priors, this becomes a strength.

The posterior distribution is a function of data as well as the prior distribution. Posterior distribution arrived at from a previous study may be used as prior distribution for a subsequent study. With more research, the prior distribution should become more representative of the underlying population data. Perhaps, this would mean that with more and more data, an OLS regression based on a frequentist approach will lead to results that are closer and closer to the Bayesian estimates. As data approaches infinity, the two estimates should be the same.

Naturally, the question of determining priors lies at the heart of Bayesian analysis and has attracted much attention. Priors can be informative - with hard information about the data - or non-informative - vague priors such as Jeffreys prior.

Strong priors can affect the posterior distribution significantly, while weak priors have less influence on the posterior distribution. According to Gelman (2020), when faced with sparse data, weakly informative priors can help.

Empirical Bayes uses the available data to estimate the "hyperparameters," and to construct a prior distribution. The prefix 'hyper' indicates that these priors are estimated from the data, as opposed to simple priors, which are based on some rule based on previous data or belief.

If data is a constraint, empirical Bayes allows one to reach better estimates that have been disciplined according to the very own structure of underlying distribution. Thus, empirical Bayes can help avoid the subjectivity that springs from having to define priors, as in purely Bayesian analysis.

4.2.3. Two-Stage Least Squares

While the empirical Bayesian analysis minimizes the problem posed by extreme values, it does not address the issue of potential endogeneity. Microfinance intensity and distrust among the poor may be correlated with a third omitted variable, for instance, which affects both. Similarly, microfinance intensity may be higher in environments with higher levels of distrust. The association observed could be affected by any such unobserved relationships.

The 2-Stage Least Squares (2SLS) allows us to account for these concerns, but a novel instrument is needed, associated with microfinance intensity 2018 but not distrust. We use the real inflation-adjusted yield on the gross loan portfolio, which measures the interest revenues of microfinance institutions, as an instrument. Specifically, because an MFI's decision to expand the loan portfolio in a particular year is affected by past interest earnings - and their stability (Conning, 1999; Meyer, 2019) - we divide the average real yield of gross loans over the 2011-2016 period by the standard deviation of this yield over the same period. We see no reason to expect distrust to be correlated with the past microfinance yield in a country. Any association between distrust and the standard deviation of the yields is even less plausible. Thus, yield, adjusted for its volatility, makes for a good instrument correlated with microfinance intensity but not distrust.

CHAPTER V

RESULTS

5.1. Cross-Sectional Regressions

Table 5.1 shows the estimates from cross-section OLS regressions for the year 2019, where the main columns indicate distrust level by income group and sub-columns (1), (2), and (3) denote independent regressions using GLP/credit, GLP/capita, and GLP/GDP as the explanatory variable, respectively. Microfinance intensity is positively associated with distrust levels among the poor at a 1% level. The higher the intensity of microfinance in an economy, the higher the distrust levels among the poor, which suggests an effect of microfinance on relatively poor communities that are generally the target population of MFIs.

The effects of microfinance intensity on the ultra-poor are significant only with the first measure of intensity and at the 5% level. This indicates a weaker relationship of microfinance intensity with the ultra-poor, which could be due to the ultra-poor being 'left behind' even by financial inclusion initiatives (Kusum Mukherjee, 2014). Because of this, they may be less exposed to the immediate effects on trust levels, though still exposed to spill-over effects (Banerjee et al., n.d.) from other people's exposure and the generalized rise in distrust in neighborhoods. Together, the results suggest an effect of microfinance on the low-income population, generally, i.e., the target population of MFIs. These aggregate effects may be read in line with earlier studies, which point to the negative externalities in social network effects of microfinance that go beyond the immediate borrowers (Banerjee et al., n.d.). If microfinance affects distrust levels, it should impact only low-income people, not affecting the rich. Indeed, we don't find a statistically significant relationship between microfinance and distrust in regressions of any of the three measures of microfinance intensity. As expected, both control variables - fractionalization and top decile income - are positively associated with distrust.

Table 5.1. Results of 2019 OLS

	Distrust Poor			Distrust Ultra-poor			Distrust Rich		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
GLP/credit	0.033***			0.033**			0.042		
	[0.011]			[0.013]			[.025]		
GLP/capita		0.032***			0.028			0.032	
		[0.013]			[.018]			[.026]	
GLP/GDP			0.031***			0.028			0.028
			[.011]			[.0172]			[.025]
Fractionalisation	0.119*	0.117**	0.107**	0.098	0.161*	0.152*	0.192	0.142	0.134
	[0.063]	[0.054]	[0.054]	[0.075]	[.088]	[0.089]	[.141]	[.126]	[.128]
Top Decile	0.625***	0.609***	0.633***	0.601**	0.188	0.207	0.572	0.496	0.530
	[.219]	[0.208]	[.204]	[0.258]	[.337]	[.334]	[.487]	[.483]	[.481]
Constant	0.575***	0.481***	0.526***	0.612***	.662***	0.703***	0.551**	0.501**	0.539**
	[0.107]	[0.094]	[0.096]	[0.127]	[0.152]	[.156]	[.239]	[.218]	[.225]
F-statistic	9.43***	9.48***	9.48***	6.05***	2.42*	2.53*	2.84*	1.680	1.590
P > F	0.000	0.000	0.000	0.002	0.082	0.073	0.054	0.189	0.209

Standard errors in brackets. *p < 0.1; **p < 0.05; ***p < 0.01. (Dependent Variable: Distrust, by income group)

Table 5.2. Empirical Bayes Regressing Distrust on GLP/Credit

	Distrust Poor					Distrust Ultra-poor					Distrust Rich				
	Priors	2019	2012	2007	2001	Priors	2019	2012	2007	2001	Priors	2019	2012	2007	2001
GLP/credit	0.042***	0.040***	0.042***	0.040***	0.046***	0.027***	0.029***	0.028***	0.025**	0.026***	-0.008	0.006	-0.012	-0.024	-0.004
	[0.008]	[.007]	[.008]	[.008]	[.008]	[0.010]	[0.008]	[0.009]	[0.009]	[0.009]	[0.016]	[0.013]	[0.014]	[0.014]	[0.015]
Fractionalisation	0.108**	0.112***	0.112***	0.102**	0.108**	0.093*	0.093**	0.089*	0.086*	0.105**	-0.002	0.042	-0.051	0.022	-0.016
	[0.044]	[.025]	[.040]	[.042]	[.039]	[0.052]	[.043]	[0.048]	[0.049]	[0.048]	[0.083]	[0.072]	[0.072]	[0.076]	[0.080]
Top decile	0.396	0.455***	0.397***	0.365**	0.362**	0.277	0.376**	0.264	0.198	0.251	0.274	0.348	0.390	0.089	0.270
	[.150]	[.123]	[.136]	[.139]	[.139]	[0.173]	[0.143]	[0.156]	[0.158]	[0.164]	[0.271]	[0.235]	[0.233]	[0.240]	[0.269]
Constant	0.690	0.657***	0.684***	0.693***	0.707***	0.748***	0.708***	0.759***	0.779***	0.753***	0.658***	0.641***	0.621***	0.692***	0.671***
	[.074]	[.060]	[.004]	[.070]	[.070]	[.086]	[0.070]	[0.077]	[0.079]	[0.082]	[0.135]	[0.117]	[0.114]	[0.122]	[0.133]

Standard errors in brackets. *p < 0.1; **p < 0.05; ***p < 0.01. Dependent variable: distrust, by income group.

Table 5.3. Empirical Bayes Regressing Distrust on GLP/Capita

	Distrust Poor					Distrust Ultra-poor					Distrust Rich				
	Priors	2019	2012	2007	2001	Priors	2019	2012	2007	2001	Priors	2019	2012	2007	2001
GLP/capita	0.041***	0.039***	0.043***	0.042***	0.043***	0.030***	.030***	0.033***	0.03***	0.028***	0.016	0.021	0.015	0.007	0.019
	[0.008]	[0.007]	[0.008]	[0.008]	[0.008]	[0.011]	[0.009]	[0.010]	[0.070]	[0.010]	[0.016]	[0.014]	[0.015]	[0.014]	[0.015]
Fractionalisation	.0945**	0.103***	.010***	0.082**	0.086**	0.087	0.106**	0.082*	0.066	0.089	-0.049	0.005	-0.096	-0.049	-0.058
	[0.041]	[0.033]	[0.038]	[0.040]	[0.039]	[0.054]	[0.046]	[0.048]	[0.200]	[1.806]	[0.079]	[0.067]	[0.069]	[0.073]	[0.074]
Top decile	0.444***	0.487***	0.428***	0.420***	0.438***	0.077	0.099	0.091	0.037	0.086	0.410	0.425	0.526	0.250	0.432
	[0.144]	[0.118]	[0.130]	[0.134]	[0.135]	[0.181]	[0.159]	[0.161]	[0.163]	[0.610]	[0.271]	[0.236]	[0.233]	[0.245]	[0.261]
Constant	0.536***	0.522***	0.537***	0.547***	0.539***	0.748***	0.729	.744***	0.773	0.745	0.620***	0.591***	0.589***	0.697***	0.606***
	[0.066]	[0.054]	[0.060]	[0.061]	[0.062]	[0.083]	[0.073]	[0.000]	[0.000]	[0.000]	[0.126]	[0.109]	[0.110]	[0.114]	[0.121]

Standard errors in brackets. *p < 0.1; **p < 0.05; ***p < 0.01. Dependent variable: distrust, by income group.

Table 5.4. Empirical Bayes Regressing Distrust on GLP/GDP

	Distrust Poor					Distrust Ultra-poor					Distrust Rich				
	Priors	2019	2012	2007	2001	Priors	2019	2012	2007	2001	Priors	2019	2012	2007	2001
GLP/GDP	0.044***	0.039***	0.045***	0.048***	0.046***	0.036***	0.033***	0.034***	0.038***	0.040***	0.020	0.023	0.015	0.019	0.020
	[0.008]	[0.033]	[0.008]	[0.008]	[0.008]	[0.011]	[0.010]	[0.010]	[0.011]	[0.011]	[0.018]	[0.014]	[0.015]	[0.017]	[0.017]
Fractionalisation	0.082*	0.092***	0.081**	0.692*	0.080**	0.081	0.102**	0.066	0.065	0.090*	-0.014	0.029	-0.068	-0.009	-0.012
	[0.041]	[0.033]	[0.038]	[0.039]	[0.038]	[.055]	[0.047]	[0.050]	[0.052]	[0.050]	[0.081]	[0.069]	[0.072]	[0.076]	[0.075]
Top decile	0.383**	0.456***	0.395***	0.353**	0.316	0.095	0.121	0.137	0.075	0.046	0.517	0.497**	0.622**	0.432	0.527*
	[0.0146]	[0.119]	[0.135]	[0.138]	[0.136]	[0.194]	[0.167]	[0.174]	[0.180]	[0.175]	[0.298]	[0.252]	[0.262]	[0.278]	[0.279]
Constant	0.630***	0.599***	0.627***	0.646***	0.653***	0.782***	0.761***	0.776***	0.797***	0.795***	0.567***	0.571***	0.540***	0.600***	0.548***
	[0.071]	[0.057]	[0.065]	[0.068]	[0.066]	[0.096]	[0.081]	[0.085]	[0.090]	[0.087]	[0.147]	[0.122]	[0.129]	[0.138]	[0.138]

Standard errors in brackets. *p < 0.1; **p < 0.05; ***p < 0.01. Dependent variable: distrust, by income group.

5.2. Empirical Bayes

Tables 5.2, 5.3, and 5.4 report the estimates for the empirical Bayes panel with GLP/credit, GLP/capita, and GLP/GDP, respectively, as the main explanatory variable. For each income group, the first column indicates empirical Bayesian priors (henceforth, Bayesian prior). Bayesian prior is a precision-weighted average of OLS estimates for 2001, 2007, 2012, and 2019. Estimates from the Bayesian prior may be conceptualized in how they differ from the pooled OLS: Bayesian prior assumes heteroscedasticity across different cross-sections in contrast to the pooled OLS, which assumes homoscedasticity. In the WVS data, likely, the variation of distrust across different time periods will not be the same. This may be due to several factors: for example, the variance of the incremental sample for every new wave may be correlated with some 'type' of countries added, which may affect overall variance. Another potential channel affecting variance across cross-sections may be the shocks, such as Covid (Abbass et al., 2022; Begum et al., 2022; Abbass et al., 2021; Abbass et al., 2022; Begum et al., 2022; Fu et al., 2022) in Wave 7, in which a tighter distribution of distrust is likely. The priors show microfinance intensity to be associated with distrust in the poor as well as the ultra-poor according to all three measures of microfinance intensity.

The priors and the year-wise posterior estimates are statistically significant at the 1% level for the poor as well as the ultra-poor for all three measures of microfinance intensity. This is in sharp contrast to distrust among the rich, which shows no significant association with any measure of microfinance. Furthermore, in contrast to the OLS estimates, distrust in the ultra-poor is also significant in empirical Bayes results. This may be due to greater precision achieved in the panel due to more data and greater efficiency of empirical Bayes. In other words, while the effects of microfinance intensity on distrust among the ultra-poor are smaller than the poor, empirical Bayes estimates can capture these effects. This may be seen in relatively smaller coefficients of microfinance intensity in Tables 5.2, 5.3, and 5.4, for distrust in the ultra-poor, compared to those for distrust among the poor, as well as slightly weak significance (but still having $p<0.01$). As discussed earlier, this is to be expected as microfinance loans often fail to reach the ultra-poor (Hulme, 2000).

5.3. Two-Stage Least Squares (2SLS)

In the first stage, all three measures of microfinance intensity show a statistically significant relationship with the instrumental variable (IV) yield (Table 5.5).

Table 5.5. First Stage of 2SLS

	GLP/credit	GLP/capita	GLP/GDP
Yield	1.127*	1.442***	1.346**
	[0.562]	[0.462]	[0.506]
Fractionalisation	0.911	-0.148	0.574
	[0.883]	[0.668]	[0.731]
Top decile	-0.861	1.506	0.360
	[3.232]	[2.633]	[2.881]
Constant	-3.017	-0.854	-2.074
	[1.493]	[1.239]	[1.356]
F statistic	4.023	9.741	7.090

Standard errors in brackets. *p < 0.1; **p < 0.05; ***p < 0.01. Instrument: Yield.

In the second stage estimates (Table 5.6), GLP/credit, GLP/capita, and GLP/GDP show a statistically significant association with distrust in the poor as well as the ultra-poor. Distrust in the rich remains insignificant, as in earlier regressions. Also, again in 2SLS, the results for the ultra-poor are slightly weaker than the relatively larger category of the poor.

Table 5.6. Results of 2nd Stage of 2SLS

	Distrust Poor			Distrust Ultra-poor			Distrust Rich		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
GLP/credit	0.101**			0.091*			0.107		
	[0.049]			[0.053]			[0.084]		
GLP/capita		0.078**			0.092*			0.073	
		[0.031]			[0.049]			[0.064]	
GLP/GDP			0.083**			0.099*			0.079
			[0.035]			[0.056]			[0.070]
Fractionalisation	0.092	0.142**	0.106	0.077	0.201*	0.158	0.182	0.167	0.133
	[0.096]	[0.064]	[0.069]	[0.103]	[0.103]	[0.110]	[0.163]	[0.132]	[0.138]
Top decile	0.618*	0.480*	0.567**	0.544	-0.712	-0.020	0.793	0.545	0.627
	[0.318]	[0.261]	[.269]	[0.341]	[0.419]	[0.428]	[0.540]	[0.539]	[0.540]
Constant	0.724***	0.475***	0.581***	0.761***	0.712***	0.838***	0.568*	0.410*	0.510**
	[0.183]	[0.115]	[0.128]	[0.196]	[0.185]	[0.204]	[0.311]	[0.238]	[0.257]
F stat (first stage)	4.022	9.741	7.090	4.022	9.741	7.090	4.022	9.741	7.090
Prob > F (first stage)	0.055	0.004	0.012	0.055	0.004	0.012	0.055	0.004	0.012

Standard errors in brackets. *p < 0.1; **p < 0.05; ***p < 0.01. Dependent variable: distrust, by income group.

It may be noted that second-stage estimates are subject to the strength of the instrument, indicated in F-statistic. The F-statistic of 9.7 for GLP/capita almost meets the rule of thumb value of 10, suggested by Staiger, Stock, and Watson (Staiger et al., 1996) for unbiased estimates. The value for GLP/credit and GLP/GDP, although significantly related to the instrumental variable (Table 5.5), falls short of meeting the F-statistic of 10.

5.4. Weak Instruments-Robust Conditional IV Tests

To ensure that the results are not an artifact of a potentially weak instrument, we estimate weak instruments-robust (D. Andrews et al., 2007; Moreira, 2003) Conditional Likelihood Ratio, Lagrange Multiplier Score, and Anderson-Rubin Statistic, and report coefficient, p-values, and coverage-corrected confidence sets, as suggested by Andrews, Stock, and Sun (I. Andrews et al., 2019). The results reported in Tables 5.7 and 5.8 show all three measures of microfinance have a significant effect on distrust among the poor and the ultra-poor, respectively.

To summarise, the findings from OLS, empirical Bayes, as well as instrument variable estimation show microfinance to be associated with a worsening of trust levels, in line with earlier studies which find a negative effect of microfinance on various constituents of social capital, including trust (Karlan, 2007; Le, 2021; Rahman, 1999).

(Dependent Variable: Distrust among poor)

Table 5.7. Weak Instrument-Robust 2SLS for Distrust in Poor

LIML estimate of beta (GLP/credit) = 0.100798			
Test	Confidence Set		P-value
Conditional LR	[0.0288419,	23.62876]	0.0087
Anderson-Rubin	[0.0288419,	23.62832]	0.0087
Score (LM)	[0.0288419,	23.62832]	0.0087

LIML estimate of beta (GLP/capita) = 0.077772			
Test	Confidence Set		P-value
Conditional LR	[0.0251332	.214914]	0.0043
Anderson-Rubin	[0.0251332	.214914]	0.0043
Score (LM)	[0.0251332	.214914]	0.0043

LIML estimate of beta (GLP/GDP) = 0.0833191			
Test	Confidence Set		P-value
Conditional LR	[0.0272524,	0.3064244]	0.0087
Anderson-Rubin	[0.0272524,	0.3064244]	0.0087
Score (LM)	[0.0272524,	0.3064244]	0.0087

Table 5.8. Weak Instrument-Robust 2SLS for Distrust in Ultra-Poor

LIML estimate of beta (GLP/credit) = 0.0911413			
Test	Confidence Set		P-value
Conditional LR	[0.0072805,	23.42728]	0.0350
Anderson-Rubin	[0.0072805,	23.42753]	0.0087
Score (LM)	[0.0072805,	23.42753]	0.0087

LIML estimate of beta (GLP/capita) = 0.0920796			
Test	Confidence Set		P-value
Conditional LR	[0.0075603	0.3124471]	0.0320
Anderson-Rubin	[0.0075603	0.3124471]	0.0320
Score (LM)	[0.0075603	0.3124471]	0.0320

LIML estimate of beta (GLP/GDP) = 0.0833191			
Test	Confidence Set		P-value
Conditional LR	[0.0075603,	0.3124471]	0.0320
Anderson-Rubin	[0.0075603,	0.3124471]	0.0320
Score (LM)	[0.0075603,	0.3124471]	0.0320

(Dependent Variable: Distrust among the ultra-poor)

CHAPTER VI

CONCLUSION

While the social effects of microfinance are extensively documented in qualitative studies, there are still few empirical studies on the subject. This has resulted in a crucial gap in our understanding of the social effects of microfinance, where the differing results in qualitative vis-à-vis quantitative studies may often be attributed to methodological choices. The review of literature, presented in the 2^{nd} chapter, tries to map the roots of this chasm in the body of knowledge. This thesis contributes to bridging the gap between the qualitative and the quantitative approaches, taking a primarily quantitative approach. Chapter 3, methodology, proposes novel empirical measures for measuring microfinance intensity across countries with greater precision. We analyze the correlation of these measures with previous measures used in the literature. We show that the measures proposed are not only more precise but also provide greater variation across countries, allowing us to better capture the effect of microfinance intensity in cross-country analyses.

Lastly, this thesis contributes to the empirical literature on the relationship between microfinance and social capital, bringing forth new evidence on the association between microfinance intensity and social distrust. The results, based on OLS and empirical Bayes, show an association between microfinance intensity—measured using three alternative, independent measures—and distrust among the low-income strata in a country. Moreover, using an instrumental variable for microfinance intensity, we find evidence in favor of the hypothesis that microfinance affects distrust. We don't find any association between microfinance and distrust levels among the rich in our sample, potentially because the rich are not exposed to microfinance.

The findings of this study are in line with earlier studies, which report economic interventions can have social consequences. In particular, the results presented in this thesis are closely related to the findings of Banerjee et al. (2021a), who report the overall weakening of social networks in communities upon greater exposure to microfinance. According to the analysis presented in this study, one explanation for social network shrinkage found by Banerjee et al. (2021b) may be higher levels of distrust in people. The relationship between microfinance intensity and distrust in the low-income strata found in our study shows in country-level data, perhaps solely because it has effects not only on the borrower-to-borrower social links but also effects borrower-to-non-borrower and the non-borrower-to-non-borrower links (Banerjee et al., 2021b). This suggests general equilibrium effects within the low-income communities in countries with a high prevalence of microfinance, strong enough to show in aggregate data, as found in this thesis.

But why does microfinance have social effects? One possible mechanism presented in earlier research (Banerjee et al., 2021b) is that the availability of microfinance in an area reduces the dependence on informal credit institutions within a community on which people would previously rely. Thus, microfinance acts as a substitute for pre-existing informal credit opportunities. People socialize less because they are less financially dependent on each other. Therefore, social networks can shrink (Banerjee et al., 2021b). In the same vein, it may be argued that if trusting behavior is an outcome of socialization rather than vice versa, distrust can arise from comparatively less socialization in communities with higher microfinance exposure. In short, formal credit options reduce the need to socialize, people interact less resultantly, and this affects their ability or inclination to trust strangers over time. The relationship between social interaction and social trust is already established in the literature, and many studies show that increased social interaction can result in more trusting behavior (Hansen et al., 2003; Migheli, 2012). Less interaction can, therefore, result in lesser levels of trust or higher levels of distrust.

While the above explanation is plausible and must not be discounted, we propose another crucial channel by which microfinance may lead to distrust: the use of social as opposed to physical collateral. Traditionally, microfinance institutions have used some variation of the group-lending model in which peers come together to form a borrowing group. While defaults/delinquencies may not show up on the balance sheets of microfinance institutions as other members are obliged to pay on behalf of the defaulting member owing to joint liability (Kiiru, 2007; Rathore, 2017), such instances may be common within groups. This can happen explicitly, for example, when the group must dig into the collective pre-emptive savings account being maintained alongside the loan account to compensate for a member's default (note that even this default doesn't appear in MFI's balance sheets) (Marr, 2015), or implicitly, when another member pays an installment on someone's behalf, hoping it as being a temporary arrangement. The *incidence* of repayment, thus, may not be equal across members across time (Nandhi, 2012). Worse, a group member who is not eyeing future loans may – or may be deemed to have – default(ed) strategically. Whether explicit or implicit, delinquency or default, under genuine financial distress or strategic, such incidents result in peer pressure, social sanctions, and/or social exclusion, sometimes with the backing of MFI staff, trying to recover a loan (Ito, 2003). Such problems can fracture social ties, leading to distrust (Marr, 2006).

With the sheer rise in the outreach of microfinance and the strict discipline, borrowers are required to show—sometimes with a repayment schedule requiring even weekly payments— such incidents are all the more likely. Most of the borrowers, as may be expected of any random sample of the human population, are not 'natural' entrepreneurs, are usually inexperienced (Bashir et al., 2021), and their incomes are unlikely to grow significantly - even less, as fast as the interest rates in the commercially oriented micro-loans project. They are liquidity-constrained, which tempts them into borrowing, but financially unsophisticated, which makes repayment difficult. Thus, delinquencies and default are common, even if they don’t appear in MFIs’ books, and can have social consequences.

More recently, there has been a rise in individual, alongside group lending in microfinance. But the mechanisms these models follow for unsecured credit again rely on the social capital of the borrower, where a guarantor partially substitutes for physical collateral. This, again, leverages social capital, specifically trust, sometimes possibly beyond what may be socially desirable.

From a regulator's point of view, it is important to cap interest rates within reasonable limits and to promote responsible lending and recovery practices. For their part, microfinance institutions need to be conservative rather than liberal in lending (even though most literature pushes liberal lending for faster 'financial inclusion'). This is important to decrease the rate of default and its social repercussions. Meanwhile, scholars of joint liability need to solve the paradox of social sanctions having to drive exclusion rather than inclusion if the threat of punishment is at all to be credible and group loans are to work. If the cost of financial inclusion is social exclusion, in other words, we need to know what the numbers are—and when and where the trade-off may be worth it.

In this study, we (i) identified the dearth of evidence on the social and psychological consequences of microfinance (ii) introduced three new measures of country-level microfinance intensity; (iii) used volatility-adjusted past portfolio yield as an instrument for microfinance intensity for the first time; (iv) investigated the effect of microfinance on distrust across countries using three different measures of microfinance intensity, and used distrust data for three income groups, using a battery of tests; (v) employed empirical Bayes for the first time for cross-country analysis of microfinance intensity; and (vi) presented novel evidence on the potential causal association between an economic variable—microfinance intensity—and a social psychological indicator—generalized distrust— using empirical data from open-access datasets.

6.1. Limitations and Future Research

The findings presented here can benefit from more data, especially from using alternative measures of trust, in the same way as we used alternative measures of microfinance intensity in this thesis. Moreover, the relationship between microfinance loans and distrust should ideally be corroborated with micro-level—preferably experimental—evidence. Future research can also explore the effects of microfinance on other social and psychological indicators of well-being.

While there is a thick strand of the theoretical and empirical literature on incentive structures in microfinance from the lender's point of view, there is a need to understand the social mechanisms which make these incentive structures work for the lender – perhaps, the incentive structure beneath the incentive structure. Do unethical coercive practices for recovery, forced liquidation of assets, deterioration of relationships, and extreme distress – as reported in sociology studies (Jain & Moore, 2003; Le, 2021; Rahman, 1999) – lie behind the decent repayment rates, low default risk, and the magic of joint liability that we see in many empirical studies? Research at the intersection of economics, psychology, and sociology can help break down these issues into workable hypotheses providing much-needed insight into what works for the debtor as well as the creditor.

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APPENDIXES

APPENDIX A

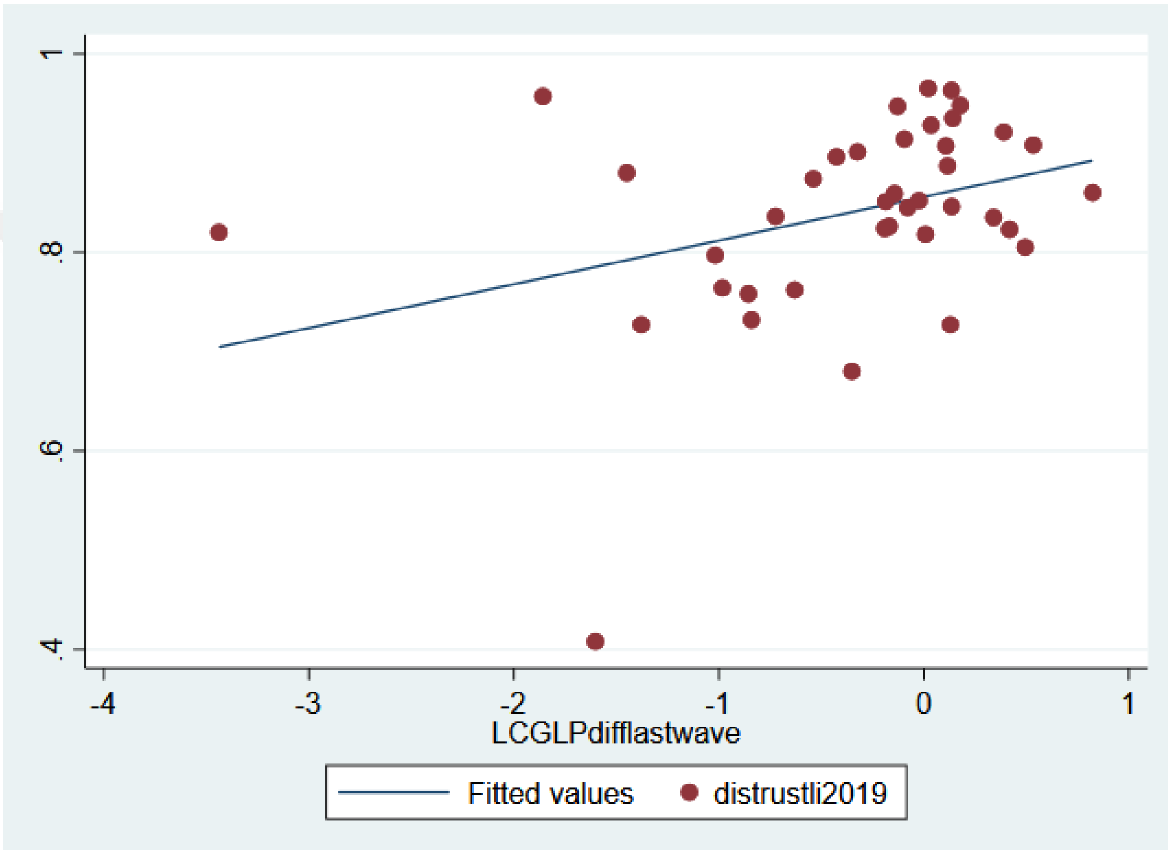

Figure A.1. Growth in GLP/Capita between WVS Wave 6 and 7 and Distrust (Poor)

APPENDİX B

Table B.1. Pooled OLS and Random Effects Model (Dependent Variable: Distrust)

Explanatory Variables	*Pooled OLS*						*Random Effects*					
	Poor		Ultra-poor		Rich		Poor		Ultra-poor		Rich	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Log GLP to private credit ratio	0.040***		0.026***		0.008		0.029***		0.018*		0.008	
	[.009]		[.010]		[.017]		[.009]		[.010]		[.017]	
Log GLP per capita		0.043***		0.031**		0.019		.036***		.026**		0.019
		[0.009]		[.011]		[.016]		[.009]		[.011]		[.016]
Ethnic Fractionalisation	0.107**	0.083*	0.089*	0.086	-0.013	-0.041	.118**	0.08	0.069	0.079	-0.013	-0.041
	[.047]	[0.044]	[.052]	[.052]	[.088]	[.079]	[.060]	[.052]	[.068]	[.061]	[.088]	[.079]
Income share of richest 10%	0.374**	0.400***	0.218**	0.068	0.367	0.397	.325**	0.408**	0.259	0.1	0.367	0.397
	[.153]	[.148]	[.168]	[.174]	[.303]	[.274]	[.176]	[.164]	[.204]	[.195]	[.303]	[.274]
Constant	0.687***	0.551***	.774***	0.751***	0.653***	.617***	0.679***	.555***	0.744***	0.743***	.653***	0.617***
	[.076]	[.068]	[.084]	[.080]	[.151]	[.127]	[.084]	[.075]	[.097]	[.089]	[0.151]	[.127]

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