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A HELPING HAND: THE RELATIONSHIP OF MICROFINANCE AND POVERTY, A MACRO PERSPECTIVE

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A helping hand: The relationship of microfinance and poverty, a macro perspective

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Abstract

Access to the financial sector and infrastructure is a significant issue in many developing countries, leading to slow development of entrepreneurship and slow economic growth. One of the most notable private sector attempts to solve these issues has been the rise of microfinance, which gives out loans to marginalised groups and encourages development of new businesses. While the intention of these institutions is admirable, their efficacy with respect to poverty reduction is not easy to measure. We build on previous research on the topic of poverty alleviation through microfinance by proposing new instrumental variables that look at the geographically neighbouring countries to tackle reverse causality issues. These instruments together with some other from previous studies are used in a fixed effects panel regression model to potentially establish a causal relationship between microfinance intensity and poverty indicators in a country. We find a negative and statistically significant relationship between microfinance intensity and poverty. These results are robust against most tests, except for when looking at the depth of poverty, indicating that microfinance does not help the most impoverished. We also find reason to believe that the effect of microfinance on poverty has diminished or even reversed in the years following the global financial crisis.

Our findings have implications on policy makers tackling issues of poverty and motivating economic activity as well as researchers further developing the research on this subject matter.

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1. Introduction

Access to the financial sector is crucial in the establishment of businesses and creation of revenue generating activities. From gaining the initial capital to start a business, to ensuring income or gaining additional funds for necessary investments for additional profitability, it is hard to imagine how much slower the growth of such businesses is without it. However, for many people in developing regions of the world, the access to this financial infrastructure is limited at best. Furthermore, governmental support in these regions is often similarly underdeveloped, creating a vicious cycle that leads to slow economic growth through a lack of infrastructure (United Nations, 2018).

What we have seen as a direct result of these circumstances is the rapid development of the microfinance field within these developing regions to provide a private sector solution to this problem. Microfinancing is typically provided in the form of small-sized loans by Microfinance institutions or MFIs. MFIs are often non-governmental organisations with a social agenda to help marginalised groups of people. These institutions give out loans that are relatively small in size and have comparatively smaller interest rates than payday lenders which microfinance institutions are often compared to (Credit Summit, n.d.). In theory, these institutions being around should significantly help in increasing the growth of the economy and decreasing poverty within marginalised communities, as is in line with the agenda of these institutions, however, the total effect of microfinance on poverty is difficult to measure.

In this paper we use a methodology largely inspired by Bangoura et al. (2016) to calculate two variables that measure microfinance activity intensity within a country for a particular year. We then propose a novel instrumental variable (IV) to adjust for reverse causality issues when looking at the effects of microfinance on poverty. This instrument is the microfinance intensity in geographically neighbouring countries. A set of existing and newly proposed instruments as well as data on microfinance intensity and poverty indicators in each country is used to create a 2SLS regression model with fixed effects to determine the potentially causal relationship between poverty and microfinance. Additionally, we perform a number of robustness tests for our regression model and methods used to ensure the validity of our results. Our research design and methods are all tailored to address our research question which we have phrased as:

RQ: How does the intensity of microfinance activity affect the poverty indicators in a country?

Our findings suggest that there is indeed an effect between microfinance activity and poverty. This effect being that more microfinance activity leads to lower levels of poverty. Our findings are robust to most checks, including most poverty indicators and different microfinance activity measures. We see that the effect of microfinance activity on poverty has decreased over time as, when splitting the dataset into 2 periods, we saw that the effect became smaller in the second period as well as the statistical significance of our results did not remain. Furthermore, we found that microfinance likely has a smaller effect on the poorest segments of the population as using the poverty gap at \$1.90 lead to statistically insignificant results, whereas poverty gaps at \$3.20 and \$5.50 a day showed significant results. Overall, we believe our findings suggest that microfinance activity can definitely influence the level of poverty in a country, even if that effect has diminished over time and may not help the most impoverished.

The thesis will be structured as follows: Section 2 will consist of the Literature Review on the general topic of microfinance and previous attempts of looking at how it affects poverty, Section 3 will have an outline of the data we use to answer our research question, mainly where it is obtained from, some summary statistics and variables included in our models, Section 4 will consist of the methodology we use to answer our research question, Section 5 consists of our Results, in Section 6 we discuss our findings from the previous section, Section 7 is for the limitations of our thesis and potential improvements for further research, Section 8 will summarize the conclusions of our thesis.

2. Literature review

2.1. What is microfinance?

Microfinance Institutions (Later on shortened to MFIs) is a term that has seen a significant growth in popularity since its inception, used to describe a type of financial institution, especially in countries with lower incomes, increased poverty rates and underdeveloped infrastructure (Finca international, 2020). What the term refers to are financial institutions that typically provide loans (in rarer cases, financial products such as savings insurance or transfers) to primarily businesses owned by marginalised groups of people in society i.e., the poor, people in rural areas with a lack of infrastructure and women, who in many cases have been excluded from participation in the traditional banking sector. The aim of MFIs is to provide help and liquidity to these people and give them an opportunity to create an improved and self-sufficient lifestyle (Finca international, 2020). While the funds given out are loans and definitely require to be repaid in-full, including interest, what MFIs provide are loans that can be more easily repaid and introduce systems to incentivize repayment and avoid interest traps. They also often focus on giving out loans for developing businesses, once again promoting self-sufficiency and avoiding trapping these people in debt forever. Still, these institutions cannot fully replace the traditional banking system and typically provide much smaller sized loans which are meant for creating small businesses or funding some everyday expenses or living situation improvements (Finca international, 2020).

Initially operating under the term microcredit which started being used in 1970 microfinance represents a private sector attempt to provide better futures for the poor segments of the population. Since then, this movement to fight poverty has outgrown the microcredit label and is now typically referred to under the umbrella term of microfinance which includes loans as well as services such as savings insurance and other similar services, all being united by the factor of the main audience being the poorer segments of society. Around the early 2000s research activity and the number of case studies targeted at the impact of microfinance started quickly growing, even resulting in the United Nations proclaiming 2005 as the international year of Microcredit (United Nations, 2004). Following the growing interest in this field and availability of world-wide data on MFIs, the 2010s showed research on microfinance from a new perspective. Microfinance started gaining enough relevance to be seen in the same picture with the existing public sector attempts of decreasing poverty so more large-scale and macroeconomic research began being done. Technological developments that give more access to country level data also enable more macroeconomic research to be done to find what the exact effects of microfinance activity are. Global trends of microfinance intensity in terms of portfolio size as a share of GDP and number of active borrowers per capita can be seen in Appendix A.

Since its initial start in 1970, the popularity of microfinance has been rising not only in terms of research interest but also in practical application, with a reported 916 of the world's largest MFIs reporting to the microfinance information exchange (MIX) in 2018 and around 140 million borrowers benefiting from the services of these MFIs in 2018 alone (Convergences, 2019). What is important to distinguish, however, is that development in microfinance is not uniform across the world. Fittingly, far more MFIs are created in countries where more people live under the poverty line and are in need of these services. Currently, countries such as Bangladesh and others in the southern Asian region are leading the development of microfinance while countries with higher standards of living tend to have much less interest in developing this sector. The contrast of microfinance development can be explained by the lesser need for this service in developed countries, yet it is still an important detail to keep in mind when conducting this kind of research.

We would also like to draw a distinction between what we classify as MFIs and what are the differences between them and the so called "payday lending" institutions around the world, which is a question that might arise to any reader. This is most likely due to the fact that payday lending institutions also specialise in lending very small loans on short terms, however, they are typically associated with predatory lending with high interest rates to people who have no other possible source of funding. This type of predatory lending can be viewed not as an attempt to genuinely help impoverished communities, but rather to earn profits by exploiting the situation they are in. To avoid any ambiguity between these types of institutions, our approach is to use institutions listed in the World Bank MIX market database as institutions that are to be considered MFIs rather than payday lenders. Limiting the scope of our research to only include MFIs from the MIX database limits how much data we have, but it gives us a very constant level of reporting quality as well as ensures the fit of all included institutions into the microfinance term. The reason for choosing this specific database will be explained in detail in the Data section of this paper.

2.2. Microeconomic approach

Up until the mid 2010s, the approach of looking at MFI intensity and how it could affect the living conditions of societies had mostly been written in a case-study format, i.e., looking at specific countries or sometimes even smaller subdivisions like towns or communities to observe the direct effects of microfinance on those receiving it.

This format has a distinct advantage over wider macroeconomic approaches in terms of establishing causal effects and proving them. Factors can be isolated using, for example, a difference in difference approach as suggested by Armendariz & Morduch (2005), where a control group is found that is nearly identical to the one being researched, with the main difference being the element the effects of which are being researched. In our case that would mean finding a group where microfinance is introduced and another where it is not available and seeing how poverty indicators develop due to this one difference. The advantage of this approach is that the number of other affecting factors is minimal and the effect can be measured more precisely. Furthermore, looking at more specific cases also lets researchers observe the channels through which poverty is affected by having access to these funds. This can make significant differences in research and the outcomes from it, such as observing effects that might be counter-intuitive or not obvious, yet still significant. A unique set of circumstances where this difference in difference approach was used is a unique implementation of microfinance institutions in northern Thailand in the late 1990s, researched by Coleman (2006). In this case, he used data on households who participated in microfinance from a town where microfinance services were available and compared how poverty indicators in this group differed from those in a town where microfinance services were not yet available. The crucial circumstance in this case is that for households from the second group to eventually have access to MFIs, they had to declare their interest to participate ahead of time, thus revealing which households microfinance would have a possibility to make an impact on. These unique circumstances were able to eliminate the people who weren't interested in microfinance participation from their research as they would likely show very little change since gaining access to it. The findings of this research were that while participation in microfinance did have a positive impact on various measures of poverty, the effect was a lot more noticeable for the wealthier members of communities as they became parts of committees in these MFIs at a much larger rate and were able to borrow larger sized loans. Unfortunately, such unique circumstances as for this research rarely present themselves and it has now been more than 20 years since the data Coleman used for his research was gathered in 1996. Thus, we feel that further research is required to see the broader effects of microfinance that we can observe today.

Another significant piece of research using the case study format was done by Chowdhury et al. (2005) and used surveys and interviews from 954 households in Bangladesh. Their research was focused on the long-term effects of microfinance participation on poverty, seeing as a loan is more or less guaranteed to directly affect poverty and income inequality in the short term, but a longer-term effect that increases the earning ability of households is the greater goal. Using a logit regression method, it was found that microfinance has a significant impact on alleviating both objective and subjective poverty for the first 6 years after receiving a loan from one of these institutions with the effect tending to level out after this period.

2.3. Macroeconomic approach

While the microeconomic perspective can have some advantages in a clearer way to conclusions, to see if microfinance can be scaled to fight poverty on a larger scale, a more macroeconomic approach is necessary. Some macroeconomic research on microfinance that is relevant to our research is that of Kai & Hamori (2009) who are some of the first ones and they find that MFIs can reduce income inequality, although they do not look at the possibility that poverty and MFI intensity could have reverse causality issues; Imai et al. (2012) who look at a panel of country data (from 2003 and 2007) using an IV approach to account for endogeneity issues find that MFI intensity is an effective tool for poverty reduction overall. Although an IV approach is used to account for endogeneity, we believe that the instrumental variables used could be improved, specifically as it pertains to the usage of the cost of contract enforcement. The authors of this work argue that this instrument is exogenous as poverty and the cost of contract enforcement are not related. This is because the cost of contract enforcement is related to the quality of institutions and people from impoverished communities typically do not hold seats in these institutions, therefore there should be no effect of one on the other. We find that this explanation is underdeveloped and lacks reference. At the very least, we believe that countries with high levels of poverty could also suffer from issues such as corruption in their governmental institutions, thus reducing the quality of these institutions and therefore increasing the cost of contract enforcement. In addition to this, the usage of 2 years worth of observations without tackling the missing poverty data problems, as we will see later, could be improved upon.

Hermes (2014), who also examines the effect that MFIs have on the gap between the rich and poor in a country, finds a negative relationship between the 2 but argues that the economic effect is very small. Hermes' argument is that, while microfinance undeniably has some effect on measures of poverty, the effect is likely to be unnoticeable overall due to the small size of the sector. Despite this, Hermes argues that the effect does have importance in helping the underprivileged, even if the effect on the country as a whole is rather small. This research is a great development of research regarding income inequality reduction; however, we cannot fully relate the methods and results of this paper to ours as income inequality is not necessarily correlated with poverty as a whole. Furthermore, the research of Hermes (2014) uses a cross-sectional regression model without fixed effects. This means that, while we believe that the instrumental variables used, those being a country's legal origin and the absolute latitude coordinate of a country's capital, could be exogenous, we cannot apply them to our model. If we were to use these categorical variables (time invariant) as our instruments, we would be likely to run into perfect multicollinearity. A very similar approach to the work of Hermes (2014) was used by Lacalle-Calderon et al. (2018). This paper uses the same instruments as Hermes (2014) and comes to the conclusion that microfinance activity is negatively associated with income inequality. Given the similarity of this paper to that of Hermes (2014) and very little novelty in findings or method, we apply the same critiques to the methodology of this paper and will be mainly referring to the work of Hermes (2014), when constructing our methodology.

Miled & Rejeb (2016) is one of the more recent papers on the effects of microfinance activity on poverty. They use IVs to account for reverse causality effects, similarly to Imai et al. (2012) and find that the microfinance loans per capita are negatively associated with the poverty headcount ratio. The instruments used in this paper are the cost of enforcement of contracts as well as the 6-year lagged average of the gross loan portfolio of MFIs. As mentioned, when discussing the work of Imai et al. (2012), we believe that the cost of contract enforcement is not the best instrument to use in this case as it is difficult to argue for the endogeneity of this instrument. Another issue that makes this paper more complicated to apply for our case is that data for only 2005 and 2011 is used in this paper.

Bangoura et al. (2016) is the most recent paper we could find on the macroeconomic effects of microfinance on poverty. They introduce a model that accounts for country heterogeneity and find that MFIs intensity is negatively associated with income inequality but similarly to a lot of previous research the findings were weak in indicating specific causal effects. The findings were broadly that the causal effects vary depending on the country and the targeting strategy of the MFIs themselves as it pertains to the size of the loans given out. Another element that was a significant improvement in this research was the introduction of an interpolation method to fill out missing poverty gap observations in the dataset and gain meaningful findings. However, we believe that the interpolation method used by Bangoura et.al. (2016) is susceptible to inaccuracies when estimating values for periods containing black swan events. The authors of this paper did not perform checks to verify the accuracy of their interpolations as it relates to these events and only performed a robustness check relating to the amount of interpolated data which is something we can improve upon in our research.

2.4. Transmissions channels

The sets of empirical research on the impact of microfinance suggest that there should be an expected relationship between microfinance and poverty, moreover, the increased popularity and number of MFIs with the aim of reducing poverty point towards this relationship being negative. However, a more thorough theoretical analysis of how microfinance activity might influence the underprivileged segments of the population can help us in finding how this effect can be researched further empirically as well by pointing out important factors.

According to literature on the matter, there are 2 channels through which microfinance can affect poverty. The first of which is that development of microfinance as a part of developing the entire financial services sector in general can improve economic growth for the country where these MFIs are located (for example, King & Levine (1993), De Gregorio & Guidotti (1995)). It can be argued that, depending on what the proportions of income distribution are, the benefits of this growth could disproportionately help the richer segments of society and increase income inequality. However, looking at purely poverty as in our metric, any growth should only have a positive impact on poverty if any at all.

The second channel creates an impact through a distributional effect that impacts inequality of income. Argued by (Beck et al. (2007) or McKenzie & Woodruff (2008), for example) is the reasoning that if financial services were to be better targeted at helping the poorer segments of the population, they would reduce the income inequalities between this and other segments of the population and increase the income for this segment. Moreover, more access to the financial sector among the impoverished communities can grant them access to revenue generating activities such as entrepreneurship or safeguards against volatility of their income in the form of insurance which is also sometimes offered by MFIs. Considering that MFIs are by definition targeted at helping this specific segment of people, there is a precedent to expect a negative relationship between microfinance activities and poverty from a theoretical point of view.

2.5. Room for improvement

To further build on the research conducted by the aforementioned academics on the topic of MFI loan intensity on the indicators of poverty in developing nations on a macroeconomic scale, we propose to amend the model used by Imai et al. (2012). Our proposed amendment is to change the list of control variables that are likely to affect poverty indicators and should be separated from the effects of microfinance. The list of our amended control variables includes government transfers, arable land, domestic credit, GDP per capita, inflation, youth, imports and exports of a country, rural population, the Polity2 score and fixed effects to avoid omitted variable bias. The specific reasoning for the inclusion of each of these variables will be explained later in the paper. Furthermore, we believe that previous research is lacking in establishing valid instruments that could test causality in this question. We set out to develop this field of research by outlining possible instruments to be used from a theoretical perspective and testing their adequacy. It is also important to note that the dataset we will be using for our research will include the newest data that has yet been used for this kind of research and this data will include a longer period of time than what has been available for any prior research.

Microfinance is a quickly growing private sector attempt to reduce poverty by giving out loans to individuals who would likely have no other way to access them. From a theoretical perspective there is reason to believe that this could be the case and case study research also points to the same conclusions. However, research from a macroeconomic perspective could still be significantly improved to see if microfinance does in fact lead to the desired effects that we suspect.

In developing a hypothesis to test in our paper, we look at the results of other research, and we find that the work of Imai et al. (2012) and Bangoura et al. (2016) find statistically and economically significant results indicating that MFI intensity is associated with smaller levels of poverty in a country. Hermes (2014), although talking about the effects of MFIs on inequality, concluded the effect of MFIs to be statistically significant but economically negligible, indicating that the literature so far has been slightly inconclusive in its findings. Nonetheless, we will state our hypothesis as the following:

H1: An increase in MFI intensity decreases the level of poverty in a country.

3. Data

Similarly to the previous attempts in looking at the effects of MFI intensity on poverty from a macroeconomic perspective, such as Imai et al. (2012) and many others, we will be getting our MFI data from the world bank MIX database (The World Bank, n.d.-a). The MIX database aggregates data on microfinance institutions that willingly submit their data to this database. This includes financial and operational data from 2961 MFIs that cover 118 countries. The database has been in place since 2002, however, only in 2019 the MIX database became publicly available. A heatmap of the Microfinance institutions listed on the MIX market database across the globe can be seen in Appendix B.

While a concrete definition of what can and cannot be considered microfinance remains elusive, certain criteria have to be outlined to retain the legitimacy of this database. The World Bank (2007, p. 4) lists a set of 9 key characteristics of MFIs used to classify financial service providers:

1. "Small transactions and minimal balances (whether loans, savings or insurance)
2. Loans for entrepreneurial activity
3. Collateral-free loans
4. Group lending
5. Target poor clients
6. Target female clients
7. Simple application processes
8. Provision of services in underserved communities
9. Market-level interest rates".

It should be noted that while these are the main characteristics associated with MFIs, there are some that are more important than others and some that are not uniformly present in all MFIs. The size of the loans provided is among the more important features that separate MFIs from other types of financial institutions. At the same time, while most MFIs provide loans for entrepreneurial activities, it is certainly not all of them. Thus, a certain level of professional judgement is applied when classifying MFIs while no uniformly used definition of the term exists (The World Bank, 2007, p. 4).

Most important variables for us that are available on this database would be the average size of the gross loan portfolio and average number of active borrowers for each MFI. These are the primary indicators of MFI activity as an increase in both of these metrics would mean that an MFI is being more active and if it were to have any effect on poverty indicators, this effect should also become bigger. Apart from these variables, the MIX database also accumulates some basic information such as the country where each MFI is located which is important for our research and some more non-performance-related data such as the gender balance of MFIs which is interesting to see but has a significantly lower quality of data as well as mostly missing values. The other major database we will be using is the world bank world development indicators database (The World Bank, n.d.-b). This database provides data on poverty indicators such as the poverty gap at $3.20 a day (2011 PPP) which will be our main measure of poverty and other factors which could affect this measure such as access to clean water, electricity and others. The world development indicators database contains data on 217 countries from the year 1960 all the way to 2020.

The data will be retrieved for the years 1999-2018. This is the whole extent of the MIX dataset for the MIX database so we will be using the according data from the world development indicators database. We would have liked to also use data that includes the beginning of the Covid-19 pandemic, but the data for this time frame has not yet been uploaded on the MIX database for public use. The usage of panel data in comparison to a cross-sectional approach, as, for example, done by Hermes (2014), who experienced data availability issues, is chosen to account for various fixed effects and look at the time dynamics of MFI intensity in a country.

The world bank MIX database is the largest single database that stores data on MFIs. Although some MFIs might not report their performance to the MIX, most of the large MFIs from regions where microfinance activity is more popular do and thus provide an overview of the most impactful players in the microfinance space. It is also important to mention that there are significant benefits to using this database as it uses predetermined formats for reporting and unified reporting standards as well as cross-checking of information received to ensure the validity of it. Regarding the world development indicators database, it is one of the most comprehensive databases on poverty and includes the variables necessary for our research such as a wide array of data on poverty headcount ratio statistics and measurements of population living under different poverty lines.

3.1. Missing data

A problem that should be addressed on the poverty data is that for many of the countries in the dataset, there are multiple missing values. This is a problem as a lack of observations leaves us with little to no room to observe correlations and effects. To tackle this problem we, similarly to (Bangoura et al., 2016), use an interpolation method of applying constant growth rates between 2 existing poverty observations to fill in the gaps of data within our sample of countries. We start with the entire dataset of countries that we could find data on in the world development indicators database for the years 1999-2018. We then filter this list to only include the data on countries that also have data on the MIX database to ensure that we can use these countries for analysis. This still leaves us with many countries which have many missing observations, potentially leaving us with a varying quality of findings. To fill out the gaps that are still missing in these countries we will be using interpolation assuming constant geometric growth rates. The interpolation method we use assumes a constant growth rate between any 2 existing data points, if the ones between them are missing observations. If the missing data is at the beginning or at the end of our observed period, we take the 2 closest existing data points, and use the same constant growth rate between these 2 points to assign a value to this missing data point based on the known information and assuming that the closest observed growth rate could be extrapolated to fill the missing gap. This approach can be problematic as linear interpolation might not represent the underlying missing data accordingly. The more missing data we assume, the less accurate our results are presumed to be. However, to deal with this issue we will be running a robustness check to test the sensitivity of our data to interpolation. To do this we will be filtering out a subset of our poverty data called sample B (Appendix C) that only includes countries with at least 5 observations for the poverty gap at $3.20 a day. We will be comparing the results of the regression between these two samples to see to what extent our results change from us improving the overall accuracy of results. We also check and filter impossible values created by this interpolation method in this specific case, for instance, when the poverty gap might be larger than 100% which is impossible, or when the poverty gap for a smaller denomination is larger than the poverty gap for a larger denomination. Finally, we also create a visualisation of our dataset where we highlight years for which countries have missing poverty data. We visually inspect this dataset to observe countries for which there are large gaps in data that have to be interpolated. The observations for each country and year can be seen in Appendix D, where a red highlighted cell means a missing value. For this imputation method we use the MS Excel Fill/Series/Growth/Trend function combination.

3.2. Drawbacks of the interpolation method

Although on average one could expect that this interpolation method of missing poverty gap data would perform reasonably well, black swan events such as the Global Financial crisis (GFC) might not be captured with this linear interpolation method. The GFC is loosely defined as going from 2007 till 2009 (Habib & Venditti,2018), however, we will extend the period under consideration till 2010, to take into account the time it would take for members of impoverished communities to recover from the effects. As an additional robustness check against these black swan events, we propose splitting the dataset into 3 parts, which results in having data before the GFC, during it, and after the GFC. When this is done, we would run the necessary regressions on the pre-GFC and post-GFC periods and cross-check whether our conclusions differ from our main regressions using all of the interpolated data.

3.3. Choice of variables

We will be largely basing our choice of variables from the MIX database on the methodology of previous research such as the research done by Imai et al. (2012) and Bangoura et al. (2016) and selecting variables needed to calculate the microfinance activity intensity which are the average size of the gross loan portfolio and the average number of active borrowers for these microfinance institutions. As mentioned before, these measures both indicate the activity of these institutions, being that their main activity is to give out loans to borrowers, so increases in these metrics would indicate more activity on the part of an MFI. The averages are chosen to better reflect the actual intensity on an annual basis and filter out any year-end spikes. These variables will then be divided by the GDP of that respective country in the case of the gross loan portfolio and the total population of the country in the case of the total number of active borrowers to get to an indicator of microfinance activity intensity variables. The control variables we pick from the previous research on the topic will be noted as a vector X, which will consist of the GDP per capita (current USD), domestic credit (to the private sector by banks as % of GDP), arable land (% of total land mass), inflation (annual % of consumer prices), youth (people 0-14 years old as % of total population), imports and exports (both as % of GDP) rural population (as a % of total population), government transfers and subsidies (% of government expenses) and the Polity2 score of a country, which is a categorical variable ranging from -10 to 10 that looks at country's political regime and determines whether it is more democratic (higher value), or on the other side of the spectrum, dictatorial (lower value).

Regarding one of our most important control variables, the governmental social transfers. We will be including this measurement as it is often seen as a standard measure for tackling poverty reduction by giving funds to the less fortunate. Attempts to quantify the effect of this measure on poverty reduction and statistics shown on the matter such as (Inchauste & Lustig, 2017) point towards a need to control for the effects of this variable to isolate the pure effect of microfinance activity on poverty reduction. On top of this, the very mechanism by which social transfers work also bears a striking similarity to that of microfinance in that it provides funds to primarily impoverished or otherwise marginalised communities with the aim of providing help to those who need it and increase the quality of life and wellbeing for the members of these communities. Since these basic mechanisms work in a similar fashion, they are also likely to have similar effects on poverty reduction, if there are any so we would expect there to be a negative relationship between this variable and our poverty indicators. Any differences such as MFI versus governmental provision, which may or may not have an effect, are subject to our research and would provide meaningful insights to us if we are to find any. A similar approach was used by Bangoura et al (2016) where they used the percentage of a country's GDP spent on healthcare and education when looking at the impact of MFIs on income inequality. The point of including these variables is that these investments of the government are supposed to improve the income and thus quality of living of communities by increasing their qualifications through education and improving their health through healthcare. Our approach is different, since we look at not only these types of in-kind transfers, but the total in-kind and in-cash transfers made by the government of a country in that specific year. This way we capture not only the governmental investments in infrastructure which would presumably improve the quality of living in the long term, but also more direct help of the government such as subsidies or benefits that are paid out and can help members of impoverished communities to start their own businesses or improve living conditions in very direct ways.

The GDP per capita is then used as a general measure of economic development which has an expected negative relationship with poverty.

Domestic credit controls for the lending activity of the traditional financial sector which is significant if we want to isolate the effect of specifically microfinance institutions (Beck et al., 2007). Furthermore, domestic credit presents a potential effect that could be very similar to microfinance. Despite the target audiences of the traditional financial sector and microfinance being different, the main mechanism by how these two activities could influence poverty could be largely the same. Especially as it concerns the first transmission channel, we discussed which should decrease poverty through boosting overall GDP growth by giving out loans. Therefore, the domestic credit is a significant control variable we use not only for isolating the effect of microfinance but one that we can actually use later on to compare the effects on poverty between microfinance and the traditional financial sector. For this measure, the expected relationship with poverty is negative, similarly to microfinance activity.

Arable land is expected to have a negative relationship with poverty as it provides a much-needed resource for food production and production of agricultural products for trade so access to more of it should reduce poverty and is a control often included in this type of literature.

Inflation is used as a measure of economic instability and as higher inflation and rapid changes in price is more likely to negatively affect segments of society with less income overall, we expect this to have a positive relationship with poverty (Beck et al., 2007).

Next, we also use the level of a country's rural population as a share of total population which we expect to have a positive relationship with poverty as people living in rural areas have less access to infrastructure and job opportunities, thus driving their income down compared to people living in more urban areas.

Youth is used as a variable to measure the potential growth of GDP in the future as a higher share of people in this age range indicates more future workers. If the opposite is true and there is a low share of the population within this age range that means that it will be difficult to increase the share of working-age people who are driving up the GDP, thus the expected relationship is negative.

The imports and exports of each country are included to represent the effect international trade has on economic growth and thus poverty. Typically, such as in (Bangoura et al., 2016) the openness which is defined as the sum of exports and imports as a proportion of GDP is used, but we split the variable up into 2 parts to better argue for the exogeneity of the instruments we will be using later on in the paper. If we were to use the openness as in works before, there could be the case where the exports of our domestic country could go up as a result of the neighbouring country's decreased poverty, but that could be mitigated by a decrease in the country's exports, and by splitting up the openness in these 2 components, we try to avoid the situation. Here we expect exports to have a negative relationship with poverty whereas imports are expected to have the opposite effect.

The inclusion of government transfers we have explained already above, however, we expect it to have a negative relationship with poverty as that is the main aim of in-kind and direct transfers by the government.

Finally, the Polity2 score is included as according to (Acemoglu et al.,2019) democracy is shown to have a positive impact on GDP growth and thus our expected relationship with poverty would be negative. This data is obtained from the GovData360 database (The World Bank, n.d.-c).

The end dataset we are going to use for our first regressions will consist of 2 samples, one with 950 country-year observations (these are the countries that had at least 3 poverty observations), the other is with 641 country-year observations (these are countries that had at least 5 poverty observations) to check for the robustness of our results. The summary statistics of each variable used can be seen in Appendix E.

In addition to the variables mentioned before, for our 2SLS regressions we will also be including 4 instrumental variables. The first two instruments we include are the 1 year lagged values of the MFI intensity variables we outlined before (average gross loan portfolio and average number of active borrowers). The other 2 instruments we use in our paper are averages of the 2 MFI intensity variables among neighbouring countries. The data for these countries is already available in the MIX database so we assign the neighbouring countries for each country in our dataset (Appendix F) and calculate the averages among each country's neighbours.

It is important to emphasise that the data on MFIs is self-reported and only MFIs that choose themselves to submit data on their performance to the MIX database are included so it is not a complete representation of the entire microfinance activity of a region, however, it should still be proportional to the overall view and show aggregates of growth or decline of the industry in this sample. As mentioned previously, there are also significant benefits to using this particular database due to the unified reporting standards and cross checking to ensure data validity.

4. Methodology

To answer our research question and potentially establish a causal relationship between the MFI intensity and the poverty within a country, we will begin by using a multivariate OLS regression. We will be basing our model off of the work done by Imai et al. (2012) and Bangoura et al. (2016). As our dependent variable we will be using the poverty gap at $3.20 a day in each of the countries, and we will be regressing this on a vector of control variables listed above and also the gross loan portfolio of MFIs within each country. As our data set will consist of panel data, we will also control for fixed effects to further attempt to isolate the MFI intensity impact on a country's poverty indicators.

To measure MFI intensity, we will be calculating the average gross loan portfolio variable ourselves using the methodology used by Imai et al. (2012) and Bangoura et al. (2016). Using the data from the MIX database on MFIs, we will be aggregating data on the average gross loan portfolio of MFIs on a country level by summing data from all the available MFIs based on the country where they are located. This aggregated average gross loan portfolio is then divided by the total GDP of a respective country when looking at the average gross loan portfolio variable. We will also be using the average number of active borrowers as a variable to complete a robustness check on our MFI intensity variable. This variable will be calculated in a similar manner where we use the country level data on average number of borrowers and divide it by the total population of each country.

As the dependent variables in our research, we will be using a country's level of poverty. Our main measure of poverty will be the poverty gap at $3.20 (at 2011 prices, PPP). The poverty gap is measured as the mean shortfall between incomes and the poverty line which is then divided by the poverty line itself. For example, if a country has a mean shortfall of $1.60 to the $3.20 a day poverty line, the poverty gap would be 1.60/3.20=0.5. The poverty gap is used instead of measures such as the headcount ratio because it reflects the severity of poverty for a country, so improvements can be monitored even if very few people are actually brought above the poverty line. Additionally, we will be also using the poverty gaps at $1.90 and $5.50 to cross-check the regression results for multiple proxies of the general poverty level. This way we can avoid making misleading generalising conclusions based on just one measure.

Also, as our data consists of a panel, similarly to Bangoura et al. (2016) we will be using the fixed effects model in which the mean of each variable is subtracted from the observation and therefore we will be controlling for specific macroeconomic and institutional contexts that have been shown to affect an MFI's effectiveness (Ahlin et al., 2011).

To summarise, the first regression we will be using to answer our research question will be the following fixed effect model:

$$(1)\quad Pov_{it} - \overline{Pov}_{i} = \beta_1\,(GLP_{it} - \overline{GLP}_{i}) + \beta_2\,(X_{it} - \bar{X}_{i}) + (u_{it} - \bar{u}_{i})$$

where Pov is the poverty gap at $ 3.20 (2011 prices, PPP) of a country i at time t, GLP is the gross loan portfolio of all of the MFIs in a country i at time t divided by the GDP of a country, X is a vector consisting of the following controls: GDP per capita, domestic credit (to the private sector by banks as % of GDP), arable land (% of total land mass), inflation (annual % of consumer prices), youth (people 0-14 years old as % of total population), import and export (both as % of total GDP), rural population (as a % of total population), government transfers (% of expenses),the Polity2 score, and u which is the error term of the OLS regression. The components with bars over them indicate the mean of each of the variables for country i. To answer our research question, we will mainly be interested in the regression coefficient of 1.

4.1. IV approach

Naturally, and as noted in previous work by Imai et al. (2012) and Bangoura et al. (2016), the OLS regression will not be enough to establish a causal relationship between the factors due to reverse causality issues. This is because not only might the intensity of MFI loans in a country impact the poverty within it, but also impoverished nations might attract various organisations to set up MFI institutions, as noted by Tarozzi et al. (2013). Additionally, poverty could also induce people to take up more loans, further complicating the situation. To avoid such reverse causality issues and further develop our regression beyond correlation analysis, we will be using an instrumental variable (IV) approach, similarly to Bangoura et al. (2016) and Imai et al. (2012). This works by finding a replacement to the independent variable that is highly correlated with the endogenous independent variable and uncorrelated with the error term.

The previous literature also consists of various attempts in using an IV approach, with the past instruments being: the past level of the independent variables (number of active borrowers, and gross loan portfolio), domestic credit provided by the financial sector, the number of MFIs, improved water source and sanitation facilities, the government effectiveness index (Bangoura et al., 2016) the cost of contract enforcement, and the average lagged 5 year value of the gross loan portfolio in a country (Imai et al., 2012).

4.2. Proposed instruments

Although finding good instruments is not the easiest of tasks, we propose using the following ones: the mean value of the average gross portfolio variable among the neighbouring countries for every single observation and the 1-year lagged values of MFI intensity variables. We define a neighbouring country as having a land border with the country we are interested in (the domestic country), as done by Caselli & Reinaud (2020). We argue that MFI intensity might come in regional waves, similarly to other research done in different spheres of economics where similar instrumental variables are used by Acemoglu et al. (2019), Caselli & Reinaud (2020), Persson & Tabellini (2009). Therefore, the average gross loan portfolio variable for any country should be highly correlated with the average in their surrounding area. This correlation can come from various sources, e.g., from the fact that private companies and NGOs can open new institutions after witnessing that the financing activities in a neighbouring country are successful, or, for instance, through information flows from people across the border concerning various crediting possibilities. We also believe that these regional waves should not in any direct way affect the level of poverty in the domestic country, except for by uniformly increasing the level of microfinance activity which could lead to a similarly uniform effect on the poverty level within this region.

A potential way for this instrument to not be valid might come through the existence of strong trade relations between neighbouring countries, i.e., if a neighbouring country has a decrease in the level of poverty, our domestic country of interest would be expected to see an increase in the levels of export to this neighbouring country, thus potentially affecting the level of poverty in our domestic country. In our case, and as addressed, for instance, by Caselli & Reinaud (2020), this can be mitigated by including the domestic country's trade openness (the sum of exports and imports as a fraction of GDP) in the regression model. We split up the openness variable into its components, i.e., exports and imports (both in % of GDP) as previously mentioned, since we want to better control for the effect of exports as a result of decreased poverty in neighbouring countries. Otherwise, this effect might be overshadowed in the aggregate openness variable by an opposite change in imports.

Another issue with using this type of instrument as averages between neighbouring countries is the fact that some countries might have massive neighbours that might bias the instrument, as mentioned by (Cherif et al.,2018) but in our case we already weigh the MFI intensity variables by GDP and population before taking the averages between multiple countries, so in our case we believe that we do not face this kind of problem.

The last potential issue we see in this case is that the number of neighbours for each country can vary a lot (Appendix F). This means that the quality of our instrument may vary similarly, however, this may not be a particularly significant issue as countries which have very few neighbouring countries may be more largely influenced by each neighbour than those which have many. To account for this, we will also include a check in which instead of using the neighbouring countries, we will use the MFI intensities of the broader geographical region of a domestic country (Sub-Saharan Africa, Southeast Asia, etc.) which will mean that the MFI intensity is taken from a larger sample of close countries, thus limiting the effect of the mentioned problem.

The second set of instrumental variables we use are the 1 year lagged values of our MFI intensity variables which is an Instrument also used in previous literature by Bangoura et. al. (2016). This instrument should be correlated with our independent variables as it may show longer period changes, potentially spanning multiple years. Furthermore, it should also provide some exogeneity as it should not affect poverty in the current period directly, apart from contributing to the change in our MFI intensity variables. Also, the poverty level in one year cannot anymore affect the level of MFI intensity in a previous year, limiting the possibility of a reverse causality.

The IV regressions therefore can be summarised as:

$$(2)\ (GLP_{it}-\overline{GLP}_i)' = \beta_1 (GLP_{it-1} - \overline{GLP}_i) + \beta_2 (NOAB_{it-1} - \overline{NOAB}_i) + \beta_3 (IV\_GLP_{it} - \overline{IV\_GLP}_i) + \beta_4 (IV\_NOAB_{it} - \overline{IV\_NOAB}_i) + \beta_5 (X_{it} - \bar{X}_i) + (\varepsilon_{it} - \bar{\varepsilon}_i)$$

where $(GLP_{it}-GLP_i)'$ indicates the exogenous part of the previously endogenous MFI intensity variable for country i at time t, which is regressed on the 1 year lagged value of the GLP over GDP and NOAB is the 1 year lagged value of the average number of active borrowers over total population, and IV represents whether we are looking at the neighbouring countries' average gross loan portfolio over GDP or the average number of active borrowers over the total population. X is a vector of controls and ε is the error term.

Afterwards this exogenous MFI intensity is placed into the equation (1) to obtain:

(3) $(Pov_{it}-\overline{Pov}_i) = \beta_1 (GLP_{it} - \overline{GLP}_i)' + \beta_2 (X_{it}-\bar{X}_i) + (u_{it} - \bar{u}_i)$

This, however, is not done manually in practice, since this would provide incorrect standard errors of regression coefficients (Wooldridge, 2012), instead we use built-in functions in R.

The set of tests required for endogeneity, strength and validity of our proposed instruments can be seen in the Results and discussion section.

5. Results

5.1. OLS FE regressions

To start gathering results and make progress towards testing our hypothesis, we first begin with analysing a univariate fixed effect (FE) panel regression by regressing the poverty gap at $3.20 a day on the gross loan portfolio divided by the GDP of each state (see Table 1). This is a preliminary look at the result we expect to see, it is by no means a finished version, but it could indicate if our hypothesis is completely wrong as in this case even the univariate regression would show results conflicting with our hypothesis. As expected from our literature review, the results of this very preliminary test show a negative relationship between the level of poverty in a country and the size of the gross loan portfolio, and it also shows that this coefficient is statistically significant at any conventional level of confidence.

Table 1. Univariate regression

	Dependent variable: Poverty gap at $3.20 a day (2011 prices, PPP)	
	Coefficient	Standard error
Average gross loan portfolio (% of GDP)	-0.95835***	(7.8770)
Observations	1,663	
R2	0.086	
Adjusted R2	0.035	
F Statistic	148.039*** (df = 1; 1575)	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 1 - This table presents the OLS results for the correlation between the poverty gap at $3.20 a day and the average gross loan portfolio as % of the GDP. The data used in this OLS regression is gathered from the World Bank's MIX market database as well as the World Bank's World Development Indicators database.

After the univariate regression, we proceed to introduce all of the previously mentioned control variables into the regression, as an attempt to improve the exogeneity of our results by accounting for other effects that could influence them. The results can be seen below in Table 2. These 2 regressions (OLS and IV in Table 2) will be referred to as the main regressions later in our work.

More specifically, we introduce Domestic credit provided to banks as % of GDP; Annual inflation of consumer prices; Import of a country and the export of a country, population ages 0-14 as a % of total population, arable land as a % of total land area within a given country, rural population of a country, governmental subsidies and the Polity2 score of a country for each of the years. Regarding some of the main findings of it, we see that the MFI intensity variable is still negatively associated with the level of poverty, which we hypothesised would be the case. The MFI intensity variable now is significant at the 1% level of significance and has a negative sign, as predicted. The results of the F test indicate that the model we use is not jointly insignificant. Regarding the goodness of fit, our model explains around 48.1% of the variance of the dependent variable. While this is obviously an out of context observation and is by no means a trusted result, it can be looked at as a preliminary indicator of this relationship and doesn't discourage further research into the topic.

Regarding other control variables and how they are associated with the poverty variable, we can see that the domestic credit to the private sector is also negatively associated with poverty and this relationship is statistically significant. This is expected from our literature review. The relationship between inflation and poverty also follows what we saw in the literature review, since it is positively correlated with the levels of poverty. Subsidies and transfers are negatively correlated with poverty, although the relationship is not statistically significant.

Table 2 - Main OLS and IV regression results

	Dependent variable: Poverty gap at $3.20 a day (2011 PPP) (%)	
	OLS	IV
Average gross loan portfolio (% of GDP)	-0.19702**	-0.14925*
	(0.07958)	(0.888000)
GDP per capita (constant 2010 US$)	0.0003**	0.0001
	(0.0001)	(0.00010)
Domestic credit to private sector by banks (% of GDP)	-0.051***	-0.033**
	(0.014)	(0.01300)
Inflation, consumer prices (annual %)	0.006	-0.005
	(0.007)	(0.00800)
Import (as % of GDP)	-0.036*	-0.024
	(0.02)	(0.01800)
Export (as % of GDP)	0.025	0.001
	(0.02)	(0.01900)
Population ages 0-14 (% of total population)	0.620***	0.546***
	(0.093)	(0.08500)

Arable land (% of land area)	7.790**	12.116***
	(3.16)	(3.10700)
Rural population (as % of total population)	-0.35048***	-0.27128***
	(5.946)	(5.54700)
Subsidies and other transfers (% of expense)	0.021	0.039**
	(0.019)	(0.01700)
Observations	950	899
R2	0.481	0.22
Adjusted R2	0.425	0.112
F Statistic	29.390*** (df = 27; 857)	219.448***
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 2 - This table presents our main OLS and IV results for the relationship between MFI intensity and poverty. We control for country and time fixed effects and also a list of covariates mentioned previously in the text. The Polity 2 scores are included in the regression as factors, but they are excluded from the output table due to readability issues, please see other tables in the Appendix to see how the regression tables look like with included Polity 2 scores. The standard errors of the regression coefficients are placed in parentheses below each respective coefficient. The data used in these regressions is obtained from the World Bank's MIX market database as well as the World Bank's World Development Indicators database and the World Bank's GovData 360 database.

5.2. Instrumental Variable approach

To further develop our regression model, we will next be introducing Instrumental variables to determine the possible causal relationship between MFI intensity and poverty in a country. Previously we only focused on a multiple linear regression, thus it at most establishes how these 2 variables are correlated/associated with one another, but still not solving the reverse causality problem.

The instruments we propose, as already mentioned in the methodology section, are the average MFI intensity variables (both in terms of gross loan portfolio and number of active borrowers) of neighbouring countries and the 1 year lagged values of both MFI intensity variables.

We start by constructing the regressions (2) and (3) from our data set and computing various tests for endogeneity, instrument weakness and validity. The first-stage regression can be seen in Appendix G Similarly to the previously mentioned work (Imai et al., 2012 and Hermes, 2014), we run the Wu-Hausman test for endogeneity by adding the residuals from regression (2) and adding them to regression (1) (as shown in

Wooldridge, 2012), then testing whether the coefficient before this added residual is different from zero. Our results reject the hypothesis that our OLS model with the MFI intensity variable is exogenous. This is consistent with general intuition and previous literature, so we conclude that using the IV approach is preferred over using the regular OLS.

Next, when we have concluded that an IV approach should be used, a formal test for the strength of our chosen instruments should be made. We run the Stock & Yogo (2005) test for weak instruments, in which we regress the endogenous variable (MFI intensity) on the set of instruments and exogenous controls (equation (2)) and then test whether the regression coefficients for the proposed instruments are jointly different from 0. If the F value on this joint hypothesis is larger than 10, the general rule of thumb would indicate that the proposed instruments are strong. After running the test ourselves, we find that the F value for us is 400.72. Although the results should be treated with caution, we conclude that our instruments are likely not to be weak.

As we have 4 instruments and only 1 endogenous MFI intensity variable, our IV model is overidentified. This lets us perform an overidentification test such as the Sargan (1988) J test for overidentifying restrictions. This can be done by taking the residuals from regression (3) and regressing them on the instruments and set of exogenous control variables. The test performed is a Chi-square test with the null hypothesis being that the errors are uncorrelated with the instrumental variables. We obtain a Chi-square value of 6.456, so we cannot reject the null. From this it can be concluded that at least some of the instrumental variables are exogenous (Wooldridge, 2012).

It should be noted that the results of these tests do not guarantee the exogeneity of the model and the strength of instruments. Rather they are a set of formal checks to at least have some idea of the validity and strength of the methods we are working with.

The results from Table 2 indicate that the MFI intensity variable still has a negative relationship with the poverty indicator and the relationship is significant at the 10% level of confidence. The coefficient itself has gotten smaller for the IV regression compared to the OLS, going from -0.19702 to -0.14925. Furthermore, the significance of this coefficient has gone from being significant at the 5% confidence level for OLS to being significant at the 10% confidence level for the IV regression. In further chapters we will test whether this finding is robust against the choice of dataset, independent variable and the MFI intensity variable. Regarding other findings, the domestic credit to the private sector by banks is still negatively associated with the poverty indicator, whilst, for instance, subsidies are positively and significantly associated with poverty. The relationship between the youth, extent of urbanisation, and arable land with poverty are consistent with the findings of our main OLS model.

5.3. Robustness checks for regressions

5.3.1. Checks for interpolation

Our series of robustness checks can be divided into multiple groups. First is the robustness check running regression (1) but this time using a subset of countries where each country has at least 5 observations for their poverty indicators, previously referred to as sample B (Appendix C). This way we would be limiting the amount of interpolation needed to fill out the dataset so there is a possibility this would improve the accuracy of our results, however, if it turns out that our sample is not very sensitive to interpolation, we could still use our larger sample to analyse a larger number of countries.

In Appendix H we see from this robustness check that our main variable of interest, which is the MFI intensity in a country, does not change that much apart from increasing in absolute value in both the OLS and IV regression, since it is still negatively associated with the poverty gap and is still statistically significant at 1% and 5% levels of significance, respectively. This is an indication that our main findings are not too sensitive to the extent of interpolation used, since using a more precise set of data yielded essentially the same results. Regarding other findings of this check, we see that the domestic credit to the private sector by banks is still negatively associated with poverty, and is statistically significant both for OLS and IV regressions. Inflation still has a positive correlation with poverty, whereas government subsidies are significant both for OLS and IV but are positive in both cases. Regarding the model together, they both can explain approximately 30% of the variance of the dependent variable. Furthermore, both models are not jointly insignificant, as indicated by the F test.

Similarly to the previous regression, the second check also concerns sensitivity to interpolation, however, this time we would be splitting our sample A into two sections. One that covers a period before the financial crisis (data until the year 2007) and the other would cover data for the post-financial crisis period (data after the year 2009). This way we would be excluding the time period for our data that includes a significant black swan event as this event would likely lead to inaccurate interpolation results. In our result of this robustness check, we see an important issue in approaching the interpolation issue in this way. The regression results can be seen in Appendix I. Our results show that in both before and after this crisis period, the relationship between the gross loan portfolio of MFIs and our measure of poverty becomes statistically insignificant. Furthermore, for the post-GFC period in the IV regression, the coefficient has even become positive, although still statistically insignificant. We believe that there are multiple possible explanations for why this is the case. First and foremost, the number of observations has significantly decreased as we now analyse 8-year long periods instead of a 20-year period, thus it could be that we can draw no conclusion from this regression at this stage. Alternatively, if we assume that there is no issue with the regression results, this could indicate that the effect of microfinance activity on poverty is not clear and has decreased or even reversed after the global financial crisis. Either way, the fact that the results of this robustness check are statistically insignificant is a shortcoming of the paper which could be improved upon in the future. Since we have no way of knowing the exact reason for our statistically insignificant results, only the fact that they are indeed insignificant, we do not know if having more observations would lead to significant results or if our results are simply indicative of no conclusive relationship between microfinance and poverty.

An additional robustness check we include in this section is the exclusion of certain countries who have a potentially problematic distribution of missing poverty data based on visual inspection of the missing data (see appendix D). From the list of countries we choose to exclude the following: Venezuela; Uzbekistan; Croatia; Serbia; Romania; Zimbabwe; North Macedonia and Montenegro. These countries are excluded since they have many missing observations in a row, which could potentially undermine the validity of our interpolation method. The OLS and IV results of the regression when excluding this list of countries can be seen in appendix J and we can see that the results for the MFI variable have not changed in terms of sign and statistical significance.

The last check we implement with regards to the validity of the interpolation method we use is, instead of splitting the data set into pre-financial crisis and post-financial crisis periods, to calculate the 5-year averages of our variables and run our FE regressions on these average values. This is done to average out various interpolation inaccuracies that might occur during the financial crisis by “placing” this period into multiple 5-year periods (there are 4 of them). This way we also do not filter out a specific period and run the regression across the whole period of time. Similarly to the results seen when splitting up the data, we find that using 5-year averages shows inconclusive results for the relationship between MFI and poverty (Appendix K), since the coefficients are negative both for OLS and IV results, but they are statistically insignificant.

5.3.2. Checks for sensitivity towards selected variables

The third check concerns our proxy of microfinance activity intensity. We have been previously using the size of the gross loan portfolio of MFIs as our main indicator or microfinance activity, however, this is not the only way that microfinance activity can be measured. The number of borrowers that have benefitted from MFIs might be a better indicator of microfinance activity and show more clearly the effects of this activity on poverty indicators, thus we test our regression model with this variable as well.

We use the same regressions as before, but now we replace the average gross loan portfolio over GDP variable with NOAB which is the average number of active borrowers over total country population for country i at time t. We also perform 3 tests for our new IV regression (endogeneity, weak instrument test, and test for overidentifying restrictions) and come to the same conclusions as before. We reject the null of the model being exogenous and we also find that the instruments we choose seem to be strong predictors of the average number of active borrowers (F=634.96), and finally, we also find that at least some of our instruments are not endogenous (Chi-square = 4.77) through the overidentification test, since we still have more proposed instruments than our 1 MFI intensity variable. The results we obtain can be seen in Appendix L**.**

We find that our main conclusions regarding the direction and statistical significance of the MFI intensity variable are similar to before. Now the regression coefficient is negative for both regressions and statistically significant at the 5% level both for the OLS regression and IV regressions. This leads us to believe that our findings are robust against the proxy we pick for being the MFI intensity. In other words, not much is different in our main findings depending on how we measure microfinance activity.

Next, we check our model using the poverty gap at different poverty lines. As there are three different poverty gap measures available to us (at $1.90, $3.20 and $5.50

a day), we believe that we should test whether our results differ based on which measure of poverty we use as the dependent variable. So, we run the OLS and IV regressions with controls twice more by using the poverty gaps at $1.90 and $5.50 a day respectively, and report the results in Appendix M. The conclusions based on these regressions can be summarised as follows: the main findings remain consistent with previous iterations, however, when using $1.90 a day as the poverty gap, the relationship with our MFI intensity variable becomes insignificant for both the OLS and IV regressions. Furthermore, for the IV regression, the correlation we observe for our main independent variable is positive, although highly statistically insignificant (P-value around 0.91). This is an interesting finding since it shows that for both regressions the average gross loan portfolio is not a significant predictor of the poverty gap at $1.90 a day. This is not the case for the poverty gap at $5.50 a day, as here our results retain significance as well for both regressions.

5.3.3. Other robustness checks

In addition to the previous checks, we also compute the main OLS regression but with robust standard errors. This is done to account for potential heteroscedasticity, autocorrelation and cross-sectional dependence in the error terms of our model. For this we use the Driscoll & Kraay (1998) which is an extension of the Newey West HAC estimator for panel data in which spatial dependence is taken into account (Vogelsang 2012). The results can be seen in Appendix N, where we see that the newly calculated standard errors do not change our main conclusions regarding the direction and statistical significance of the MFI intensity variable in relation to the poverty variable. The values of the regression coefficients are identical to Table 2 since these types of robustness tests regarding standard errors will only re-calculate the standard errors by trying to make them more appropriate by accounting for heteroscedasticity, autocorrelation and spatial correlation.

To tackle the potential problem of a country having very few neighbours, which would then undermine the validity of our proposed instruments regarding neighbouring country MFI intensity, we follow the methodology used by Acemoglu et al. (2019) and compute the MFI intensity values for countries based on broader geographic regions (see Appendix F for the classifications, which we obtain from The World Bank, n.d.-a). This way, each country has a broad set of “neighbours” that would tackle the problem. We run the IV regression as done for our main results in Table 2 but now replacing the neighbouring countries with the region, the results can be seen in Appendix O. The results show similar conclusions, since the relationship between MFI intensity and poverty is still negative and statistically significant.

5.4. Depth of poverty

The consistent finding that the poverty gap at $1.90 a day has no statistically significant relationship with the microfinance intensity variable could potentially mean that microfinance does not reach and help the extremely poor, since consistent findings of a negative and statistically significant relationship exist when increasing the threshold of poverty to $3.20 and $5.50 a day.

To test this, we run regression (1) but we substitute the dependent variable of the poverty gap at $3.20 a day (2011 prices, PPP) with its squared value, as done by (Imai et al., 2012). This is done because this squared term emphasises the people who are furthest from the $3.20 line in terms of the shortfall of income. The results of this test can be seen in Appendix P. We find that the microfinance intensity is highly insignificant in determining the squared poverty gap with a p-value of 0.777. This seems to potentially confirm our suspicions that microfinance does not even reach the most impoverished parts of a country. This, however, is not the same as saying that microfinance intensity does not help reduce poverty, but rather that the effects of microfinance are different depending on the magnitude of poverty.

6. Discussion

To discuss the findings of the previous sections, we will start by summarising the main overall findings. We start with an OLS regression to monitor basic correlations and see if the data is in line with our general assumptions. To tackle reverse causality issues, we introduce instrumental variables into our regression. The main results for the OLS and IV regressions can be seen in Table 2 and we see that we find a statistically significant negative relationship between the average gross loan portfolio variable and poverty, which is consistent for both regressions.

Our findings remain consistent when using a smaller and more precise sample (Appendix C). Moreover, a change of the proxy we use for microfinance intensity also returned results that are consistent with previous findings for both regressions (Appendix L). When testing the robustness of our model with regards to our dependant variable which measures poverty, we found that our findings were consistent when using the poverty line of $5.50 a day (Appendix M), however, when using the poverty line of $1.90 a day, our results were statistically insignificant in both regressions (Appendix M). This is an interesting result as it could have implications on how microfinance activity affects people based on the depth of poverty. We test for this by using a squared measure of the poverty indicator which would emphasise the poorest countries as done previously by (Imai et al., 2012). The results of this test can be seen in Appendix P and returned a statistically insignificant relationship between the squared poverty indicator and the average gross loan portfolio variable, leading us to believe that the effect of microfinance is inconclusive for the most poor. We theorise that this might be related to people living in extreme poverty not being able to use microfinance to start businesses as some level of income would likely be needed even if microfinance is available. Thus, people would need to be above a certain threshold of income to harness the benefits of microfinance to their advantage. This is, however, just a theory, which we cannot test within this paper.

The robustness check concerning the periods used in interpolation which splits our sample into three time periods and excludes the period of the global financial crisis returned insignificant results, although the relationship between microfinance intensity and poverty was negative in all cases except for the post financial crisis period in the IV regression, where the relationship was insignificant and very slightly positive (Appendix I). We believe that this is likely due to the fact that splitting our regression in this way significantly reduced the available number of observations we could use, meaning no significant conclusions can be drawn. It should, however, be noted that this could mean the effect of MFI intensity on poverty has either reduced or even reversed after the GFC. We then proceeded to test our results to address interpolation issues, now employing a division of our data into 5-year average data, rather than annual data. When looking at the result of this modification, we find that the coefficients for the MFI variables are negative both for OLS and IV, although insignificant in both cases. Finally, when testing whether our proposed instruments for neighbouring countries are sensitive towards the number of neighbours a country has by including broader geographical regions, we find that the coefficients are still negative and statistically significant for both the OLS and IV regressions (Appendix O).

While a negative and statistically significant relationship bodes well for the confirmation of our hypothesis, for these findings to be relevant and applicable for policy making, the effect should also have some economic significance. It is difficult to interpret our results in absolute terms as coefficients cannot be interpreted as direct results, thus, we must find ways of gauging the significance of our findings in the context of the real world. One such way could be to compare the economic effects of microfinance to alternate methods of targeting poverty alleviation, that being the domestic credit or the governmental subsidies. The impact of domestic credit on reducing poverty has been more researched (Beck et al., 2007 and Jeanneney & Kpodar, 2011) and can thus be used to compare effects with microfinance activity. One of the main measures of financial development used in these papers is the domestic credit to the private sector and the findings are that more credit to the private sector significantly decreases poverty. Seeing as we also use domestic credit in our research as one of the control variables, we can take a look at what sort of effect this variable has in our regressions and very broadly compare it with the effects of microfinance intensity as it relates to reducing poverty. It is important to emphasise that no concrete findings about how these two effects compare can be drawn from this surface-level analysis, however, we can see that these effects are at the very least comparable, as the coefficient for microfinance intensity is quite consistently higher than the one associated with the effect of domestic credit. It can be assumed that there might still be some interference between these two variables and some effect might be allocated to one or the other by mistake, but we can still say that the marginal economic effects are comparable.

A way of determining the absolute size of the impact of microfinance on the poverty levels would be to multiply the coefficient before the main independent variable (in our case the average gross loan portfolio divided by the GDP of a country) by the standard deviation of its distribution. This is a variation of the standardised regression coefficient analysis and is used to evaluate the relative sizes of multiple regression coefficients in situations like ours (Siegel, 2016). This way we can see the effect of an expansion by 1 standard deviation on our dependent variable. We prefer this interpretation instead of strictly linearly interpreting the coefficient itself because the independent variable could not even be possible to increase by 1 unit in some cases, which would mean that this simple interpretation is fundamentally illogical. The results we obtain from doing this are that an increase by 1 standard deviation in the average gross loan portfolio over GDP for a country would result in a decrease of 0.3433 standard deviations of the poverty gap (results obtained from Table 2 and appendix D)**.** We do the same with the Domestic credit to the private sector by banks to compare the size of these 2 effects on poverty. We find that the same change in the domestic credit to the private sector would result in a decrease of 0.8264 standard deviations in poverty. We again repeat the process for Government subsidies, and find that the effect for Government subsidies is 0.6758 and is to be interpreted the same way as previously. While the size of the impact of the MFI variable in this comparison is smaller than that of the domestic credit and subsidies, we find that these impacts are still comparable and that the effect of MFI activity does have a non-negligible effect on poverty.

7. Limitations and further improvements

Our work addresses the effects of microfinance on poverty. This section will consist of the limitations we face and room for further improvements in research for this topic.

To start, a lot of the novelty of our work comes from new proposed instruments to address the reverse causality issues typically found in this type of research. While we believe our instruments to be an improvement over the current available literature on the matter, we cannot deny the possibility of new, more exogenous instruments being proposed in future research, since there might be other ways of the exogeneity assumption to not hold for our instruments, that we did not account for. Therefore, our proposal cannot be treated as a perfect approach to addressing reverse causality when looking at the impact of microfinance on poverty.

Next, the data for our work comes from the largest database in the world on Microfinance institutions, which is the MIX database from the World Bank. Although the largest, it can be by no means considered an all-encompassing source of data, since maybe smaller institutions or institutions in countries not included in the dataset might exist. An improvement here would be to combine other sources of data into a larger dataset to then use to answer the question on how microfinance affects poverty. However, we believe that this was outside the scope of our paper.

As discussed extensively in our work, interpolation was a necessary yet problematic part of our research. Without using some sort of an interpolation method, we risk not being able to analyse our data sufficiently due to missing observations (as seen in Appendix D). However, the interpolation method we used was quite simple and as shown by some of our robustness checks, our results did not hold up when excluding the global financial crisis periods or when using 5-year average data. If the research on the subject matter is to be developed, finding more complete data or more precise methods of interpolation, could remove the uncertainty we faced in our research due to these limitations.

Finally, an element that could restrict our research is the choice of poverty measures. In our research we use the poverty gap at 3 different poverty lines - $1.90, $3.30 and $5.50 a day. From the data that we collected, this measure of poverty had the most complete data, however, if the previously addressed problem of data completeness and interpolation could be tackled, other measures of poverty could also be used.

8. Conclusions

The purpose of this research was to examine the relationship between microfinance intensity in a country and the levels of poverty. To research this topic, we outlined a research question stated as **"How does the intensity of microfinance activity affect the poverty indicators in a country?".** We find a fairly consistent negative and statistically significant effect of microfinance on poverty levels across the 20 years worth of observations we look at. Additionally, we find that the effect microfinance has on poverty can vary significantly depending on the depth of poverty. More precisely, we find that microfinance has an inconclusive effect on the poorest segments of the population compared to others, where the effect is significant. Finally, we find that the effect of microfinance has potentially diminished following the global financial crisis.

Our findings are relevant to researchers since we further develop the currently existing literature on microfinance and poverty alleviation by proposing new instruments and new tests for the robustness of results. Further research could be based on our work, to analyse if or why the effect of microfinance on poverty has decreased over time as this was one of our key results which we could not find a definitive answer to.

In addition to this, our findings are significant to policy makers, especially in regions where a lack of access to credit and infrastructure can cause entrepreneurship and economic development to suffer. Testing the economic impact of MFI intensity, we find effects of similar magnitude to domestic credit and governmental subsidies, meaning that these effects are significant enough to be considered when developing policy with the aim of affecting poverty levels.

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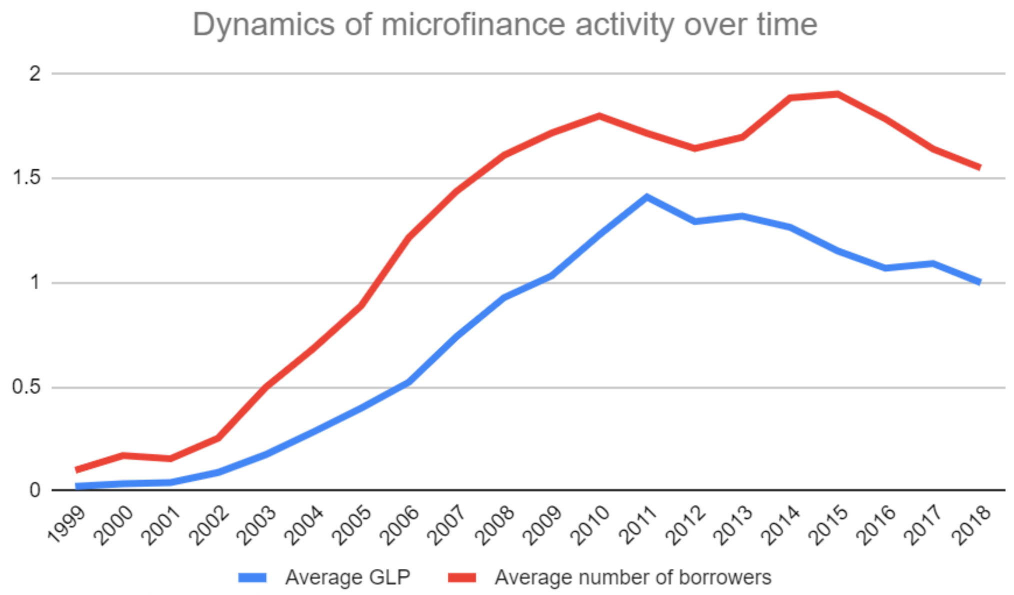
10. Appendices

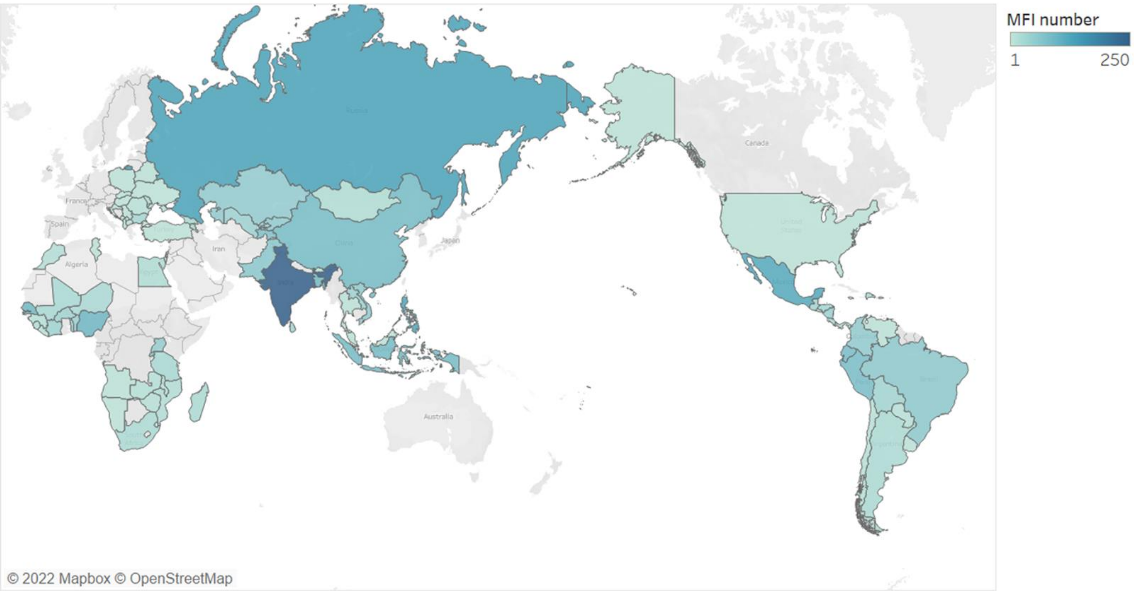
Appendix A - aggregates of Average GLP and Average number of active borrowers variables over time



Appendix A - This appendix presents the aggregates of our variables - Average gross loan portfolio divided by GDP and Average number of active borrowers divided by the population - over time. The data used in this graph is obtained from the World Bank's MIX market database as well as the World Bank's World Development Indicators database and it is generated by the authors.

Appendix B - Number of MFIs by country

Sheet 1



Map based on Longitude (generated) and Latitude (generated). Color shows details about MFI number. Details are shown for Country name.

Appendix B - This appendix presents the distribution of microfinance institutions around the world in 2018. The data used in this graph is obtained from the World Bank's MIX market database. The heatmap is generated by the authors using Tableau software.

Appendix C - Number of available poverty gap observations for each country

	Country	Number of available poverty gap observations	% of missing observations
Excluded from sample B	Angola	3	85%
	Azerbaijan	3	85%
	Benin	3	85%
	Burkina Faso	3	85%
	Cote d'Ivoire	3	85%
	Eswatini	3	85%
	Gambia, The	3	85%
	Guatemala	3	85%
	Guinea	3	85%
	India	3	85%
	Jamaica	3	85%
	Liberia	3	85%
	Malawi	3	85%
	Mali	3	85%
	Morocco	3	85%
	Mozambique	3	85%
	Namibia	3	85%
	Nigeria	3	85%
	Samoa	3	85%
	Senegal	3	85%
	Sierra Leone	3	85%
	Timor-Leste	3	85%
	Togo	3	85%
	Tonga	3	85%
	Uzbekistan	3	85%
	Bangladesh	4	80%
	Bhutan	4	80%
	Bosnia and Herzegovina	4	80%
	Jordan	4	80%
	Lao PDR	4	80%
	Nicaragua	4	80%
	Niger	4	80%
	Tanzania	4	80%
	Tunisia	4	80%
Sample B	Madagascar	5	75%
	Malaysia	5	75%
	Montenegro	5	75%
	Rwanda	5	75%

South Africa	5	75%
Sri Lanka	5	75%
Zambia	5	75%
Serbia	6	70%
Tajikistan	6	70%
Uganda	6	70%
Egypt, Arab Rep.	7	65%
Israel	7	65%
Philippines	7	65%
Venezuela, RB	7	65%
Albania	8	60%
Chile	8	60%
Mongolia	8	60%
West Bank and Gaza	8	60%
Pakistan	9	55%
Vietnam	9	55%
Croatia	10	50%
North Macedonia	10	50%
Ukraine	10	50%
Belarus	11	45%
China	11	45%
Mexico	11	45%
Kosovo	12	40%
Bulgaria	13	35%
Romania	13	35%
Hungary	14	30%
Kazakhstan	14	30%
Slovak Republic	14	30%
Poland	15	25%
Thailand	17	15%
Turkey	17	15%
Bolivia	18	10%
Brazil	18	10%
Colombia	18	10%
Ecuador	18	10%
Argentina	19	5%
Armenia	19	5%
Dominican Republic	19	5%
Honduras	19	5%
Kyrgyz Republic	19	5%
Paraguay	19	5%
Uruguay	19	5%

Costa Rica	20	0%
El Salvador	20	0%
Georgia	20	0%
Indonesia	20	0%
Moldova	20	0%
Panama	20	0%
Peru	20	0%
Russian Federation	20	0%
United States	20	0%

Appendix C - This appendix presents which countries are included in each of the samples A and B and the number of poverty gap at $3.20 a day (2011 PPP) observations for each country. The data used for creating this table is obtained from the World Bank's World Development Indicators database.

Appendix D - Overview of missing observations by country and year for the poverty gap at $3.20 a day

Country Name	99	00	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18
Albania				2.9			1.8			0.8				1.3		2.5	1.7	2	1.8	
Angola		30								27										39
Argentina	5.4	6.4	9.5	14	6.7	5	4	3.1	2.5	2.4	2.1	1.5	1.1	1.2	1	1.1		1.1	1	1.3
Armenia	14		14	12	9.8	7.1	4.3	3.3	2.8	1.7	2.5	2.6	2.5	2.2	2.4	2.3	2.1	1.9	1.6	2.1
Bangladesh		27					22					19						15		
Belarus	1.8	7.8	3.9	2.7	2.2	0.9	0.5	0.2	0.2	0.1	0.1									
Benin					38								39				40			
Bhutan					15				8.8					3.4					2.6	
Bolivia	22	25	19	2.7		12	16	14	11	9.2	8.7		6	6.9	5.7	5.1	5.2	6.2	5.5	4.3
Brazil	11		9.8	8.9	9.5	8.4	7.5	6.3	6.1	5	4.8		4.1	3.4	2.8	2.4	2.8	3.4	3.7	3.7
Bulgaria								5	1.6	1.1	1	1.6	2.1	1.9	1.9	1.5	2.8	1.8	1.2	0.8
Burkina Faso					43						4.7					32				
Chile		4.3			4			1.6			1.3		0.8		0.4		0.3		0.3	
China	3.5			25			16			12		9.7	7.4	6.2	2.8	2.1	1.4	1		
Colombia	18	16	18	11	1.8	9.8	8.8			9.1	8	6.9	5.9	5.8	5.3	4.8	4.3	4.3	3.9	4
Costa Rica	5.8	6.1	4.5	4.1	4.1	3.8	2.9	2.9	1.8	2	2.2	1.5	1.6	1.5	1.5	1.4	1.5	1.3	1	1.3
Cote d'Ivoire				22						25							24			
Croatia											0.9	1.2	0.7	0.8	0.9	0.9	0.6	0.6	0.5	0.4

Dominican Republic		**4.7**	**3.8**	**5.1**	**6.1**	**7.9**	**5.4**	**4.4**	**4.2**	**3.9**	**3.4**	**3.1**	**3.1**	**3.1**	**2.6**	**2.3**	**1.9**	**1.7**	**1**	**0.6**
Ecuador	**19**	**23**			**13**	**13**	**1.2**	**7.3**	**7.4**	**6.8**	**6.4**	**5.2**	**4.4**	**4.1**	**3.2**	**2.6**	**3.3**	**3.3**	**2.9**	**3.1**
Egypt, Arab Rep.	**5.3**					**8.2**				**7.4**		**4.7**		**3.5**			**3.4**		**6.3**	
El Salvador	**15**	**1.6**	**12**	**12**	**13**	**9.7**	**9.2**	**6.4**	**4.6**	**6.4**	**6.2**	**5.6**	**4.9**	**4.2**	**3.5**	**3.4**	**2.5**	**2.8**	**2.2**	**2**
Eswatini		**36**									**33**							**23**		
Gambia, The					**35**							**21**					**11**			
Georgia	**16**	**17**	**17**	**9.8**	**1**	**9.3**	**1**	**9.9**	**1.7**	**9.5**	**9.4**	**1.7**	**1.1**	**8.2**	**6.3**	**5.1**	**4.3**	**4.3**	**4.8**	**4.6**
Guatemala		**8.3**						**9.5**								**8.3**				
Guinea				**47**					**43**					**29**						
Honduras	**22**		**17**	**19**	**23**	**22**	**22**	**19**	**14**	**14**	**12**	**13**	**13**	**16**	**13**	**13**	**12**	**13**	**13**	**13**
Hungary						**0.1**	**0.6**	**0.1**	**0.1**		**0.1**	**0.1**	**0.1**	**0.3**	**0.1**	**0.6**	**0.5**	**1.1**	**0.6**	**0.2**
India						**3.7**					**27**		**2.6**							
Indonesia	**30**	**29**	**27**	**19**	**19**	**20**	**18**	**21**	**18**	**17**	**16**	**14**	**12**	**11**	**9.9**	**8.9**	**7.8**	**7.2**	**6.1**	**5.1**
Israel			**0.2**				**0.5**		**0.3**			**0.3**		**0.5**		**0.3**		**0.2**		
Jamaica	**2.9**			**3.1**		**2.2**														
Kazakhstan			**9**	**6.7**	**5**	**3**	**6.3**	**0.9**	**0.4**	**0.3**	**0.3**	**0.2**	**0.1**	**0.1**				**0.1**	**0.1**	
Kosovo					**3.7**		**4.9**	**4.5**			**3.6**	**3.4**	**2.3**	**1.2**	**0.7**	**1.2**	**0.8**	**0.8**	**0.7**	
Kyrgyz Republic		**29**	**26**	**25**	**21**	**12**	**13**	**8.9**	**8.5**	**4.6**	**3**	**4.5**	**2.9**	**3.5**	**4.2**	**2.4**	**3.5**	**2.4**	**2.5**	**1.8**
Lao PDR				**26**					**23**					**14**						**1.8**

Liberia									52							33		34		
Madagascar	48		52				52					58		59						
Malawi						52						53						5.1		
Malaysia					1.7			0.9		0.9			0.2		0.1					
Mali			43					38			37									
Mexico		7.7		6.3		5.4	5.7	4		4.9		4.3		3.7		3.7		2.2		1.8
Moldova	30	28	23	15	8.4	9.2	13	3	1.7	1.9	1.6	1	0.7	0.6	0.3	0.1	0.2	0.2	0.1	0.1
Mongolia				9.6					2.3			1.8	1.2	0.7		0.5		1.1		0.9
Montenegro														3.5	2.9	2.3	2.1	2.6		
Morocco		7.1						3.9							1.5					
Mozambique				60						52						47				
Namibia					25						19						12			
Nicaragua			14				8.5				7.2					3.5				
Niger							56		51				37			34				
Nigeria					42						42									3.5
North Macedonia											8.2	9.4	7.4	6	4.6	4.1	4.5	3.8	3.8	2.7
Pakistan			27			20	19		17			12	12		9.6		7.8			7.9
Panama	12	1.4	13	9.3	9.2	8.4	8	8.8	6.6	4.3	3	3.8	2.9	3.6	2.7	3.1	2.1	2.1	2.2	1.7
Paraguay	8.2		7.2	1.6	6.9	5.2	5.1	6.8	6.1	4	4.6	4.6	4.4	2.9	1.9	2.1	1.9	1.8	1.1	1.4
Peru	14	13	14	12	1.5	11	13	1.9	9.2	7.5	6.3	5	4.6	4.3	3.9	3.5	3.5	3.3	3.2	2.6

Philippines		12			12			13			1.5			1.2			7			3.9
Poland						1.8	0.8	0.6	0.4	0.2	0.3	0.3	0.3	0.2	0.4	0.4	0.3	0.2	0.3	0.2
Romania								6.1	4.4	3.4	2.8	3.6	4.4	4.8	5.2	5.3	4.2	2.8	2.7	2
Russian Federation	4.8	3.5	2.3	1.5	1.6	1.3	1	0.7	0.4	0.2	0.1	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Rwanda		58					51					46			42			41		
Samoa				2.9						1.7					2					
Senegal			36				30						3.1							
Serbia														4.9	5.4	6.3	6	5.9	4.8	
Sierra Leone					53								39							32
Slovak Republic						0.1	0.2	0.2	0.3	0.3	0.3	0.4	0.3	0.3	0.3	0.6	0.5	1.3		0.2
South Africa		26					2.4			14		14				15				
Sri Lanka				1.3				6.1			4.3			3.4				2.1		
Tajikistan	38				23	14			9.6		5.2						4.5			
Tanzania		65							44				37						36	
Thailand	4	4		2.3		1.6		1.2	0.7	0.5	0.5	0.4	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1
Timor-Leste			30						30							21				
Togo								41					41				38			
Tonga		2.4									1.9						1.5			
Tunisia		6.5					4					2.3					0.6			

Turkey				**2.9**	**4**	**2.5**	**2.6**	**1.9**	**1.5**	**1.2**	**1.1**	**1**	**0.8**	**0.6**	**0.5**	**0.4**	**0.5**	**0.3**	**0.3**	**0.2**
Uganda	**49**			**47**			**42**				**34**			**28**				**31**		
Ukraine				**2.2**	**1.1**	**0.9**	**0.4**	**0.2**	**0.2**		**0.1**						**0.1**	**0.1**		**0.1**
United States	**0.6**	**0.6**	**0.8**	**0.7**	**0.9**	**0.9**	**0.9**	**0.9**	**0.9**	**1**	**0.8**	**1**	**0.9**	**1**	**0.9**	**1.1**	**1**	**1**	**1.1**	**1**
Uruguay		**0.6**	**0.6**	**0.7**	**1**	**1.3**	**1.1**	**0.8**	**0.6**	**0.4**	**0.4**	**0.3**	**0.2**	**0.2**	**0.2**	**0.2**	**0.2**	**0.1**	**0.1**	**0.1**
Uzbekistan		**45**		**41**	**44**															
Venezuela, RB	**1.2**		**8.9**	**14**	**17**	**14**	**13**	**6.4**												
Vietnam				**29**		**22**		**17**		**14**		**4.6**		**3.2**		**2.9**		**2.1**		**1.8**
West Bank and Gaza						**1.2**	**1**	**0.6**	**1.9**		**0.5**	**0.6**	**0.5**					**1**		
Zambia				**39**		**45**		**48**				**50**					**46**			
Zimbabwe													**17**						**25**	

Appendix D - This appendix presents for which countries in which years there are missing observations for the poverty gap at $3.20 a day variable (highlighted in red). Countries which are highlighted as yellow are deemed by the authors to be problematic for the interpolation method used and are excluded in a robustness check testing for the robustness of the interpolation method used. The data used for this table is obtained from the World Bank's World Development Indicators database.

Appendix E - Summary statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Arable land (% of land area)	1,632	0.269	0.260	0.011	0.113	0.317	2.147
Domestic credit to private sector by banks (% of GDP).	1,626	33.442	25.042	0.916	14.346	46.857	157.809
GDP per capita (constant 2010 USD)	1,657	4,863.217	6,693.299	272.991	1,090.868	6,028.871	54,953.620
Inflation, consumer prices (annual %)	1,573	7.876	17.920	-18.109	2.379	8.400	324.997
Poverty gap at $1.90 a day (2011 prices, PPP)	1,663	6.959	9.541	0.000	0.400	10.562	44.188
Poverty gap at $3.20 a day (2011 prices, PPP)	1,663	15.150	16.313	0.002	2.100	26.727	61.584
Poverty gap at $5.50 a day (2011 prices, PPP)	1,663	27.506	22.283	0.038	8.362	48.232	75.726
Population ages 0-14 (% of total population)	1,663	31.829	10.702	0.000	24.050	41.909	50.264
Average gross loan portfolio in neighbouring countries (% of GDP)	1,605	0.007	0.018	0.000	0.0002	0.008	0.414
Average number of active borrowers in neighbouring countries (% of total population)	1,605	0.010	0.015	0.000	0.0005	0.013	0.106
Average gross loan portfolio (% of GDP)	1,663	0.9	2.3	0	0.000	1	29.45
Average number of active borrowers (% of total population)	1,663	1.5	2.7	0	0.000	2	16.5
Import (% of GDP)	1,663	40.500	21.245	0.000	25.639	52.773	172.570
Export (% of GDP)	1,663	31.624	18.281	0.000	19.815	40.183	121.311
Rural population (% of total population)	1,663	48.4	20.7	0.000	34.0	65.4	85.9
Subsidies and other transfers (as % of total expenses)	974	37.839	17.328	0.450	24.257	50.782	72.575

Appendix E - This appendix presents summary statistics of each of the variables used in our regression models. The data used for this table is obtained from the World Bank's World Development Indicators database and the World Bank's MIX market database.

Appendix F - Summary of allocated region and number of neighbouring countries for each country.

Country	Region	Number of neighbouring countries
Albania	Europe & Central Asia	4
Angola	Sub-Saharan Africa	4
Argentina	Latin America & Caribbean	5
Armenia	Europe & Central Asia	4
Bangladesh	South Asia	2
Belarus	Europe & Central Asia	5
Benin	Sub-Saharan Africa	4
Bhutan	South Asia	2
Bolivia	Latin America & Caribbean	5
Brazil	Latin America & Caribbean	10
Bulgaria	Europe & Central Asia	5
Burkina Faso	Sub-Saharan Africa	6
Chile	Latin America & Caribbean	3
China	East Asia & Pacific	16
Colombia	Latin America & Caribbean	5
Costa Rica	Latin America & Caribbean	2
Cote d'Ivoire	Sub-Saharan Africa	5
Croatia	Europe & Central Asia	5
Dominican Republic	Latin America & Caribbean	1
Ecuador	Latin America & Caribbean	2
Egypt, Arab Rep.	Middle East & North Africa	4
El Salvador	Latin America & Caribbean	2
Eswatini	Sub-Saharan Africa	2
Gambia, The	Sub-Saharan Africa	1
Georgia	Europe & Central Asia	4
Guatemala	Latin America & Caribbean	4
Guinea	Sub-Saharan Africa	6
Honduras	Latin America & Caribbean	3
Hungary	Europe & Central Asia	7
India	South Asia	6
Indonesia	East Asia & Pacific	3
Israel	Middle East & North Africa	5
Jamaica	Latin America & Caribbean	1
Kazakhstan	Europe & Central Asia	5
Kyrgyz Republic	Europe & Central Asia	4
Lao PDR	East Asia & Pacific	5
Liberia	Sub-Saharan Africa	3

Madagascar	Sub-Saharan Africa	1
Malawi	Sub-Saharan Africa	3
Malaysia	East Asia & Pacific	3
Mali	Sub-Saharan Africa	7
Mexico	Latin America & Caribbean	3
Moldova	Europe & Central Asia	2
Mongolia	East Asia & Pacific	2
Montenegro	Europe & Central Asia	4
Morocco	Middle East & North Africa	3
Mozambique	Sub-Saharan Africa	6
Namibia	Sub-Saharan Africa	4
Nicaragua	Latin America & Caribbean	2
Niger	Sub-Saharan Africa	7
Nigeria	Sub-Saharan Africa	4
North Macedonia	Europe & Central Asia	4
Pakistan	South Asia	4
Panama	Latin America & Caribbean	2
Paraguay	Latin America & Caribbean	3
Peru	Latin America & Caribbean	5
Philippines	East Asia & Pacific	1
Poland	Europe & Central Asia	7
Romania	Europe & Central Asia	5
Russian Federation	Europe & Central Asia	14
Rwanda	Sub-Saharan Africa	4
Samoa	East Asia & Pacific	1
Senegal	Sub-Saharan Africa	5
Serbia	Europe & Central Asia	8
Sierra Leone	Sub-Saharan Africa	2
Slovak republic	Europe & Central Asia	5
South Africa	Sub-Saharan Africa	6
Sri Lanka	South Asia	1
Tajikistan	Europe & Central Asia	4
Tanzania	Sub-Saharan Africa	8
Thailand	East Asia & Pacific	4
Timor-Leste	East Asia & Pacific	1
Togo	Sub-Saharan Africa	3
Tonga	East Asia & Pacific	1
Tunisia	Middle East & North Africa	2
Turkey	Europe & Central Asia	8
Uganda	Sub-Saharan Africa	5
Ukraine	Europe & Central Asia	7
Uruguay	Latin America & Caribbean	2

Uzbekistan	Europe & Central Asia	5
Venezuela, RB	Latin America & Caribbean	3
Vietnam	East Asia & Pacific	3
Zambia	Sub-Saharan Africa	8

Appendix F - This appendix presents a summary of the number of neighbouring countries as well as the region for each country used in the dataset. The data used for this table is obtained from the World Bank's World Development Indicators database.

Appendix G - Regression results for first stage regression

	Dependent variable: Average gross loan portfolio
lag(Average gross loan portfolio)	0.683***
	(0.02700)
lag(Average number of active borrowers)	0.144***
	(0.02500)
Average gross loan portfolio in neighbouring countries (% of GDP)	0.111**
	(0.04700)
Average number of active borrowers in neighbouring countries (% of total population)	-0.128**
	(0.06400)
GDP per capita (constant 2010 US$)	0
	0.00000
Domestic credit to private sector by banks (% of GDP)	0.00004
	(0.00004)
Inflation, consumer prices (annual %)	0.00004*
	(0.00002)
Import (as % of GDP)	0.00004
	(0.00010)
Export (as % of GDP)	-0.0001*
	(0.00010)
Population ages 0-14 (% of total population)	0.0001
	(0.00030)
Arable land (% of land area)	0.003
	(0.00900)
Rural population (as % of total population)	-0.014
	(0.01600)
Polity 2 score of -1	0.007
	(0.00800)
Polity 2 score of -10	-0.001
	(0.00900)
Polity 2 score of -2	0.003
	(0.00900)
Polity 2 score of -3	0.001
	(0.00800)
Polity 2 score of -4	0.004
	(0.00800)
Polity 2 score of -5	-0.0002
	(0.00900)
Polity 2 score of -6	0.001
	(0.00800)
Polity 2 score of 0	0.005
	(0.00800)

Polity 2 score of 1	0.006
	(0.00800)
Polity 2 score of 10	-0.002
	(0.00800)
Polity 2 score of 3	0.007
	(0.00800)
Polity 2 score of 4	0.006
	(0.00800)
Polity 2 score of 5	0.003
	(0.00800)
Polity 2 score of 6	0.007
	(0.00800)
Polity 2 score of 7	0.002
	(0.00800)
Polity 2 score of 8	0.005
	(0.00800)
Polity 2 score of 9	0.002
	(0.00800)
Subsidies and other transfers (% of expense)	0.00001
	(0.00005)
Observations	899
R2	0.693
Adjusted R2	0.649
F Statistic	59.046*** (df = 30; 786)
Note:	*p<0.1; **p<0.05; ***p<0.01

Appendix G - This appendix presents the regression results of our first stage regression used for constructing our 2SLS IV regression. The data used in these regressions is obtained from the World Bank's MIX market database as well as the World Bank's World Development Indicators database and the World Bank's GovData 360 database.

Appendix H - Regression results for robustness check using countries with at least 5 observations.

	Dependent variable:	
	Poverty gap at $3.20 a day (2011 PPP) (%)	
	OLS	IV
Average gross loan portfolio (% of GDP)	-0.22873***	-0.18533**
	(0.0824800)	(0.0824000)
GDP per capita (constant 2010 US$)	0.001***	0.0004***
	(0.00020)	(0.00020)
Domestic credit to private sector by banks (% of GDP)	-0.048***	-0.033**
	(0.01600)	(0.01400)
Inflation, consumer prices (annual %)	0.023***	0.025**
	(0.00900)	(0.01200)
Import (as % of GDP)	-0.080***	-0.068***
	(0.03100)	(0.02500)
Export (as % of GDP)	0.074**	0.080***
	(0.02900)	(0.02400)
Population ages 0-14 (% of total population)	0.594***	0.489***
	(0.11500)	(0.09700)
Arable land (% of land area)	6.268*	9.926***
	(3.49100)	(3.12100)
Rural population (as % of total population)	-0.44741***	-0.38036***
	(0.0610600)	(0.0516900)
Polity2-2	-4.297	-4.175
	(3.56700)	(2.85200)
Polity2-3	-2.613	-2.776
	(2.19500)	(1.75900)
Polity2-4	-3.279	-3.570*
	(2.48100)	(1.98700)
Polity2-5	-1.121	-1.511
	(3.44100)	(2.75200)
Polity2-6	-5.161*	-4.705**
	(2.72100)	(2.21200)
Polity20	-0.05	0.813
	(2.68500)	(2.16300)
Polity21	-16.459***	
	(3.09900)	
Polity210	-1.666	0.883
	(2.46700)	(2.04300)
Polity23	-3.063	-3.675*
	(2.58600)	(2.07600)
Polity24	0.15	-0.608
	(2.43400)	(1.95000)
Polity25	-4.360*	-5.368***

	(2.45500)	(1.98500)
Polity26	-0.844	-2.228
	(2.38600)	(1.92300)
Polity27	-2.697	-3.433*
	(2.32200)	(1.86500)
Polity28	-0.752	-1.239
	(2.34200)	(1.89900)
Polity29	-3.738	-3.464*
	(2.28300)	(1.84000)
Subsidies and other transfers (% of expense)	0.039*	0.053***
	(0.02300)	(0.01900)
Observations	641	596
R2	0.311	0.296
Adjusted R2	0.202	0.181
F Statistic	9.964*** (df = 25; 553)	213.243***
Note:	*p<0.1; **p<0.05; ***p<0.01	

Appendix H - This appendix presents the OLS and IV regression results for a robustness check testing the sensitivity of our results to the extent of interpolation used. Countries with less than 5 observations are excluded from the dataset which is used for this regression. The data used in these regressions is obtained from the World Bank's MIX market database as well as the World Bank's World Development Indicators database and the World Bank's GovData 360 database.

Appendix I - Regression results for robustness check splitting the dataset into pre and post GFC periods.

	Dependent variable:			
	Poverty gap at $3.20 a day (2011 PPP) (%)			
	Before GFC		After GFC	
	OLS	IV	OLS	IV
Average gross loan portfolio (% of GDP)	-1.18195*	-0.93173	-0.03924	0.21705
	(0.61375)	(0.65728)	(0.067380)	(0.150310)
GDP per capita (constant 2010 US$)	-0.0003	-0.001	0.0002	-0.0001
	(0.0005)	(0.0010)	(0.0002)	(0.0002)
Domestic credit to private sector by banks (% of GDP)	-0.054*	-0.025	-0.057***	-0.061***
	(0.0320)	(0.0310)	(0.0150)	(0.0160)
Inflation, consumer prices (annual %)	0.027***	0.027***	0.033**	0.027*
	(0.0080)	(0.0110)	(0.0160)	(0.0150)
Import (as % of GDP)	-0.085*	-0.075*	0.025*	0.035***
	(0.0490)	(0.0450)	(0.0130)	(0.0130)
Export (as % of GDP)	0.054	0.015	-0.057***	-0.041**
	(0.0470)	(0.0530)	(0.0190)	(0.0190)
Population ages 0-14 (% of total population)	2.293***	2.365***	0.393***	0.393***
	(0.3540)	(0.4310)	(0.1040)	(0.1130)
Arable land (% of land area)	-25.560**	-18.083	9.747**	5.709
	(10.6630)	(11.4780)	(4.8710)	(4.9050)
Rural population (as % of total population)	-0.78365***	- 0.78826***	0.12621	0.03638
	(0.215420)	(0.204880)	(0.10049)	(0.11393)
Polity 2 score of 4			0.557	-0.308
			(1.5850)	(1.5340)
Polity 2 score of 3			-0.235	-1.033
			(1.5560)	(1.4570)
Polity 2 score of -1			-1.159	-1.853
			(1.8080)	(1.6920)
Polity 2 score of -10	1.372	0.847		
	(3.8130)	(3.2370)		
Polity 2 score of -2	-2.298	-4.951	2.425	2.328
	(4.1240)	(3.8540)	(2.2180)	(2.1300)
Polity 2 score of -3	-4.451	-4.838*	2.382	1.993
	(3.4080)	(2.7870)	(1.7050)	(1.6360)
Polity 2 score of -4	-0.994	-6.189*	1.27	1.106
	(3.9920)	(3.7520)	(1.6660)	(1.6380)
Polity 2 score of -5	-0.606	-0.216		
	(2.9860)	(2.3970)		
Polity 2 score of -6	-6.216	-8.248**	0.95	

	(4.0430)	(3.4260)	(2.2100)	
Polity 2 score of 0	0.168	-0.192	0.889	1.325
	(3.0280)	(2.4270)	(1.5530)	(1.4490)
Polity 2 score of 1	-5.693**		-3.500**	-3.844**
	(2.4920)		(1.7090)	(1.6380)
Polity 2 score of 10	-5.565**	2.677	0.583	1.659
	(2.1560)	(2.4400)	(1.6690)	(1.6290)
Polity 2 score of 5	1.73	-1.359	-0.35	-0.788
	(2.1020)	(1.9030)	(1.4620)	(1.3350)
Polity 2 score of 6	1.331	-1.136	0.461	-0.058
	(2.2360)	(1.9590)	(1.5310)	(1.4220)
Polity 2 score of 7	1.762	-3.113	0.571	0.687
	(2.4500)	(2.1580)	(1.5000)	(1.4080)
Polity 2 score of 8	2.263*	1.143	0.717	0.925
	(1.2910)	(1.1380)	(1.5720)	(1.4820)
Polity 2 score of 9			-0.496	-0.527
			(1.5700)	(1.4630)
Subsidies and other transfers (% of expense)	-0.024	-0.015	0.022	0.022
	(0.0390)	(0.0340)	(0.0150)	(0.0140)
Observations	290	253	514	448
R2	0.469	0.451	0.238	0.223
Adjusted R2	0.265	0.21	0.062	0.019
F Statistic	8.016*** (df = 23; 209)	144.257***	5.198*** (df = 25; 417)	113.139***
Note:	*p<0.1; **p<0.05; ***p<0.01		*p<0.1; **p<0.05; ***p<0.01	

Appendix I - This appendix presents OLS and IV regression results when splitting the data into a pre-global financial crisis and post-global financial crisis periods. The data used in these regressions is obtained from the World Bank's MIX market database as well as the World Bank's World Development Indicators database and the World Bank's GovData 360 database.

Appendix J - Regression results for robustness check excluding countries with large interpolated periods

	Dependent variable:	
	Poverty gap at $3.20 a day (2011 PPP) (%)	
	OLS	IV
Average gross loan portfolio (% of GDP)	-0.29316***	-0.20121**
	(0.0818500)	(0.0853800)
GDP per capita (constant 2010 US$)	-0.00002	0.0004***
	(0.00003)	(0.00010)
Domestic credit to private sector by banks (% of GDP)	-0.077***	-0.021*
	(0.01300)	(0.01300)
Inflation, consumer prices (annual %)	0.014*	-0.008
	(0.00800)	(0.00800)
Import (as % of GDP)	-0.041**	-0.023
	(0.01800)	(0.01700)
Export (as % of GDP)	-0.027	0.002
	(0.01900)	(0.01900)
Population ages 0-14 (% of total population)	0.972***	0.601***
	(0.04200)	(0.08200)
Arable land (% of land area)	3.425**	13.264***
	(1.56600)	(2.97900)
Rural population (as % of total population)	0.06642***	-0.26029***
	(0.0211200)	(0.0532600)
Polity 2 score of -1	2.288	3.959
	(4.04300)	(2.81300)
Polity 2 score of -10	4.422	6.133**
	(4.21900)	(2.86500)
Polity 2 score of -2	9.895**	2.967
	(4.24900)	(2.84000)
Polity 2 score of -3	5.12	2.898
	(3.99100)	(2.69300)
Polity 2 score of -4	5.496	3.098
	(3.91000)	(2.67100)
Polity 2 score of -5	2.469	2.087
	(4.28300)	(2.85700)
Polity 2 score of -6	3.881	1.853
	(3.99500)	(2.72700)
Polity 2 score of 0	5.475	4.196
	(3.85500)	(2.60000)
Polity 2 score of 1	2.143	1.438
	(4.14700)	(2.96900)
Polity 2 score of 10	2.655	4.723*

	(3.83700)	(2.72700)
Polity 2 score of 3	1.969	2.539
	(3.85100)	(2.57700)
Polity 2 score of 4	3.94	4.248*
	(3.88100)	(2.57800)
Polity 2 score of 5	6.598*	0.83
	(3.81800)	(2.52300)
Polity 2 score of 6	2.846	3.294
	(3.78000)	(2.53200)
Polity 2 score of 7	3.096	1.614
	(3.74500)	(2.50200)
Polity 2 score of 8	-3.557	1.386
	(3.80100)	(2.58400)
Polity 2 score of 9	3.186	2.059
	(3.80000)	(2.56500)
Subsidies and other transfers (% of expense)	0.085***	0.031*
	(0.01900)	(0.01700)
Observations	896	847
R2	0.71000	0.23000
Adjusted R2	0.666	0.12
F Statistic	70.358*** (df = 27; 777)	217.700***
Note:	*p<0.1; **p<0.05; ***p<0.01	

Appendix J - This appendix presents OLS and IV results when excluding countries with potentially problematic distributions of missing poverty gap data. The data used in these regressions is obtained from the World Bank's MIX market database as well as the World Bank's World Development Indicators database and the World Bank's GovData 360 database.

Appendix K - Regression results for robustness check using 5-year average values instead of yearly values

	Dependent variable:	
	Poverty gap at $3.20 a day (2011 PPP) (%)	
	OLS	IV
Average gross loan portfolio (% of GDP)	-0.23782	-0.2167
	(0.22015)	(0.91208)
GDP per capita (constant 2010 US$)	0.0003	0.0003
	(0.00040)	(0.00100)
Domestic credit to private sector by banks (% of GDP)	-0.075**	0.002
	(0.03600)	(0.05100)
Inflation, consumer prices (annual %)	-0.007	-0.008
	(0.01800)	(0.09300)
Import (as % of GDP)	-0.047	0.00004
	(0.08300)	(0.07900)
Export (as % of GDP)	-0.03	-0.06
	(0.07400)	(0.07100)
Population ages 0-14 (% of total population)	0.656**	0.723***
	(0.25700)	(0.25200)
Arable land (% of land area)	9.574	14.466
	(7.77400)	(11.64000)
Rural population (as % of total population)	-0.2321	-0.01343
	(0.1575200)	(0.1808900)
Polity2 score	-0.137	-0.034
	(0.12200)	(0.12600)
Subsidies and other transfers (% of expense)	-0.018	-0.048
	(0.06400)	(0.06200)
Observations	163	137
R2	0.277	0.217
Adjusted R2	-0.332	-0.638
F Statistic	3.060*** (df = 11; 88)	18.055*
Note:	*p<0.1; **p<0.05; ***p<0.01	

Appendix K - This appendix presents OLS and IV results when turning the data set into 5-year averages. The data used in these regressions is obtained from the World Bank's MIX market database as well as the World Bank's World Development Indicators database and the World Bank's GovData 360 database.

Appendix L - Regression results for robustness check using the average number of active borrowers as the main independent variable

	Dependent variable:	
	Poverty gap at $3.20 a day (2011 PPP) (%)	
	OLS	IV
Average number of active borrowers (% of total population)	-0.16205**	-0.17110**
	(0.069310)	(0.072930)
GDP per capita (constant 2010 US$)	0.0003**	0.0001
	(0.0001)	(0.0001)
Domestic credit to private sector by banks (% of GDP)	-0.053***	-0.032**
	(0.0140)	(0.0130)
Inflation, consumer prices (annual %)	0.006	-0.004
	(0.0070)	(0.0080)
Import (as % of GDP)	-0.037*	-0.025
	(0.0200)	(0.0180)
Export (as % of GDP)	0.028	0.003
	(0.0200)	(0.0190)
Population ages 0-14 (% of total population)	0.591***	0.514***
	(0.0950)	(0.0860)
Arable land (% of land area)	7.694**	11.967***
	(3.1620)	(3.1050)
Rural population (as % of total population)	-0.34312***	-0.26559***
	(0.059390)	(0.055350)
Polity 2 score of -1	3.335	4.036
	(3.3690)	(2.9500)
Polity 2 score of -10	7.002**	6.452**
	(3.4000)	(3.0120)
Polity 2 score of -2	3.849	3.084
	(3.3740)	(2.9770)
Polity 2 score of -3	1.415	2.754
	(3.2070)	(2.8230)
Polity 2 score of -4	3.104	3.066
	(3.1940)	(2.7990)
Polity 2 score of -5	2.063	2.456
	(3.4220)	(2.9960)
Polity 2 score of -6	1.584	2.338
	(3.2580)	(2.8610)
Polity 2 score of 0	3.642	4.443
	(3.1080)	(2.7230)
Polity 2 score of 1	-4.164	-0.66
	(3.2470)	(2.9430)
Polity 2 score of 10	1.809	5.233*
	(3.1810)	(2.8560)
Polity 2 score of 3	2.073	2.4

	(3.0860)	(2.7000)
Polity 2 score of 4	3.636	4.386
	(3.0810)	(2.6980)
Polity 2 score of 5	0.68	0.593
	(3.0220)	(2.6440)
Polity 2 score of 6	2.639	2.924
	(3.0290)	(2.6510)
Polity 2 score of 7	2.179	1.932
	(2.9990)	(2.6240)
Polity 2 score of 8	2.684	2.52
	(3.0820)	(2.7030)
Polity 2 score of 9	0.879	1.451
	(3.0660)	(2.6870)
Subsidies and other transfers (% of expense)	0.019	0.037**
	(0.0190)	(0.0170)
Observations	950	899
R2	0.232	0.221
Adjusted R2	0.13	0.113
F Statistic	9.376*** (df = 27; 838)	222.457***
Note:	*p<0.1; **p<0.05; ***p<0.01	

Appendix L - This appendix presents OLS and IV results when substituting the independent variable of the average gross loan portfolio with the average number of active borrowers. The data used in these regressions is obtained from the World Bank's MIX market database as well as the World Bank's World Development Indicators database and the World Bank's GovData 360 database.

Appendix M - Regression results for robustness check substituting the main dependent variable

	Dependent variable:			
	Poverty gap at $1.90 a day (2011 PPP) (%)		Poverty gap at $5.50 a day (2011 PPP) (%)	
	OLS	IV	OLS	IV
Average gross loan portfolio (% of GDP)	-0.0353	0.00705	-0.43504***	-0.40199***
	(0.0567100)	(0.0635000)	(0.1084100)	(0.1215900)
GDP per capita (constant 2010 US$)	0.0001	0.0001	0.00004	-0.0005**
	(0.00010)	(0.00010)	(0.00020)	(0.00020)
Domestic credit to private sector by banks (% of GDP)	-0.028***	-0.020**	-0.115***	-0.086***
	(0.01000)	(0.00900)	(0.01900)	(0.01800)
Inflation, consumer prices (annual %)	0.001	-0.002	0.028***	0.001
	(0.00500)	(0.00600)	(0.00900)	(0.01100)
Import (as % of GDP)	-0.030**	-0.023*	-0.021	-0.003
	(0.01400)	(0.01300)	(0.02700)	(0.02400)
Export (as % of GDP)	-0.018	-0.031**	0.084***	0.053**
	(0.01400)	(0.01400)	(0.02800)	(0.02600)
Population ages 0-14 (% of total population)	0.257***	0.196***	0.804***	0.690***
	(0.06600)	(0.06100)	(0.12700)	(0.11600)
Arable land (% of land area)	3.563	5.890***	9.656**	17.347***
	(2.25200)	(2.22100)	(4.30500)	(4.25400)
Rural population (as % of total population)	-0.11945***	-0.07120*	-0.61887***	-0.52422***
	(0.0423700)	(0.0396600)	(0.0810000)	(0.0759500)
Polity 2 score of -1	4.412*	4.707**	0.803	1.943
	(2.40000)	(2.11100)	(4.58800)	(4.04200)
Polity 2 score of -10	1.458	1.329	9.204**	8.796**
	(2.41600)	(2.14900)	(4.61900)	(4.11600)
Polity 2 score of -2	3.757	3.548*	5.427	3.978
	(2.40400)	(2.13100)	(4.59500)	(4.08000)
Polity 2 score of -3	3.215	3.956*	-1.716	0.264
	(2.28500)	(2.02000)	(4.36800)	(3.86900)
Polity 2 score of -4	3.68	3.623*	1.453	1.653
	(2.27500)	(2.00300)	(4.34900)	(3.83600)
Polity 2 score of -5	2.26	2.427	1.557	2.269
	(2.43700)	(2.14300)	(4.66000)	(4.10400)
Polity 2 score of -6	2.481	2.926	0.281	1.744
	(2.31900)	(2.04500)	(4.43400)	(3.91600)
Polity 2 score of 0	5.220**	5.782***	0.871	2.094
	(2.21400)	(1.94900)	(4.23300)	(3.73200)
Polity 2 score of 1	-0.671	2.462	-6.162	-2.377

	(2.31300)	(2.10600)	(4.42300)	(4.03300)
Polity 2 score of 10	2.939	5.178**	1.226	5.724
	(2.26600)	(2.04500)	(4.33300)	(3.91600)
Polity 2 score of 3	3.544	3.707*	0.756	1.175
	(2.19900)	(1.93400)	(4.20400)	(3.70300)
Polity 2 score of 4	4.115*	4.643**	1.799	2.981
	(2.19500)	(1.93200)	(4.19700)	(3.69900)
Polity 2 score of 5	1.167	0.997	-0.038	-0.012
	(2.15300)	(1.89300)	(4.11500)	(3.62400)
Polity 2 score of 6	3.473	3.667*	1.462	1.922
	(2.15900)	(1.90000)	(4.12800)	(3.63700)
Polity 2 score of 7	3.444	3.229*	0.083	-0.255
	(2.13600)	(1.87800)	(4.08400)	(3.59500)
Polity 2 score of 8	3.362	3.143	3.302	2.77
	(2.19500)	(1.93500)	(4.19700)	(3.70500)
Polity 2 score of 9	2.596	2.909	0.002	0.538
	(2.18400)	(1.92300)	(4.17600)	(3.68300)
Subsidies and other transfers (% of expense)	0.018	0.037***	0.005	0.032
	(0.01300)	(0.01200)	(0.02600)	(0.02300)
Observations	950	899	950	899
R2	0.151	0.158	0.281	0.265
Adjusted R2	0.038	0.041	0.186	0.163
F Statistic	5.510*** (df = 27; 838)	147.954***	12.116*** (df = 27; 838)	280.658***
Note:	*p<0.1; **p<0.05; ***p<0.01		*p<0.1; **p<0.05; ***p<0.01	

Appendix M - This appendix presents OLS and IV results when substituting the dependent variable of the poverty gap at $3.20 a day with poverty gaps at $1.90 and $5.50 a day. The data used in these regressions is obtained from the World Bank's MIX market database as well as the World Bank's World Development Indicators database and the World Bank's GovData 360 database.

Appendix N - Regression results for robustness check using robust standard errors

	Dependent variable:	
	OLS	IV
Average gross loan portfolio (% of GDP)	-0.23305***	-0.14925**
	(0.059630)	(0.059430)
GDP per capita (constant 2010 US$)	-0.0004***	0.0001
	(0.0001)	(0.0002)
Domestic credit to private sector by banks (% of GDP)	-0.047***	-0.033**
	(0.0140)	(0.0140)
Inflation, consumer prices (annual %)	0.020***	-0.005
	(0.0060)	(0.0060)
Import (as % of GDP)	-0.042	-0.024
	(0.0330)	(0.0260)
Export (as % of GDP)	0.011	0.001
	(0.0340)	(0.0240)
Population ages 0-14 (% of total population)	1.064***	0.546***
	(0.2010)	(0.0660)
Arable land (% of land area)	13.165***	12.116***
	(3.5260)	(1.5900)
Rural population (as % of total population)	-0.1291	-0.27128***
	(0.120500)	(0.102240)
Polity 2 score of -1	4.262	4.014**
	(2.5900)	(1.8530)
Polity 2 score of -10	5.323***	6.032***
	(1.5550)	(1.3320)
Polity 2 score of -2	4.314**	3.017**
	(1.9780)	(1.2060)
Polity 2 score of -3	2.723**	2.793***
	(1.2560)	(0.7970)
Polity 2 score of -4	3.973**	3.069***
	(1.8440)	(1.0850)
Polity 2 score of -5	0.669	2.362***
	(1.6960)	(0.7880)
Polity 2 score of -6	2.171	2.133**
	(1.4730)	(0.8770)
Polity 2 score of 0	4.346**	4.539**
	(2.1100)	(1.8810)
Polity 2 score of 1	-1.585	-0.707
	(2.1500)	(1.8870)
Polity 2 score of 10	1.607	5.263***
	(1.6310)	(1.9480)

Polity 2 score of 3	2.436	2.454**
	(1.5970)	(1.0050)
Polity 2 score of 4	3.479*	4.473***
	(2.1060)	(1.5580)
Polity 2 score of 5	2.35	0.602
	(1.5940)	(0.6690)
Polity 2 score of 6	3.715**	3.127***
	(1.8690)	(1.1960)
Polity 2 score of 7	2.443	1.884*
	(1.5620)	(1.0420)
Polity 2 score of 8	2.945	2.606**
	(1.9650)	(1.1670)
Polity 2 score of 9	1.272	1.45
	(1.8520)	(1.0490)
Subsidies and other transfers (% of expense)	-0.007	0.039**
	(0.0140)	(0.0160)
Note:	*p<0.1; **p<0.05; ***p<0.01	

Appendix N - This appendix presents our main OLS and IV regression results with Driscoll & Kraay (1998) robust standard errors. The data used in these regressions is obtained from the World Bank's MIX market database as well as the World Bank's World Development Indicators database and the World Bank's GovData 360 database.

Appendix O - Regression results for robustness checks using the broader geographic region instead of neighbouring countries for our instrumental variables

	Dependent variable:
	Poverty gap at \$3.20 a day (2011 PPP) (%)
Average gross loan portfolio (% of GDP)	-0.16828*
	(0.088560)
GDP per capita (constant 2010 US\$)	0.0004***
	(0.0001)
Domestic credit to private sector by banks (% of GDP)	-0.039***
	(0.0130)
Inflation, consumer prices (annual %)	-0.003
	(0.0080)
Import (as % of GDP)	-0.02
	(0.0180)
Export (as % of GDP)	0.001
	(0.0190)
Population ages 0-14 (% of total population)	0.543***
	(0.0850)
Polity 2 score of -1	3.856
	(2.9580)
Polity 2 score of -10	6.110**
	(3.0130)
Polity 2 score of -2	3.089
	(2.9860)
Polity 2 score of -3	2.651
	(2.8300)
Polity 2 score of -4	2.953
	(2.8070)
Polity 2 score of -5	2.427
	(3.0040)
Polity 2 score of -6	1.757
	(2.8640)
Polity 2 score of 0	4.176
	(2.7280)
Polity 2 score of 1	-0.789
	(2.9510)
Polity 2 score of 10	3.563
	(2.8040)
Polity 2 score of 3	2.427
	(2.7100)
Polity 2 score of 4	4.326

	(2.7060)
Polity 2 score of 5	0.623
	(2.6520)
Polity 2 score of 6	3.058
	(2.6620)
Polity 2 score of 7	1.864
	(2.6310)
Polity 2 score of 8	2.992
	(2.7090)
Polity 2 score of 9	1.459
	(2.6950)
Arable land (% of land area)	8.751***
	(3.0210)
Rural population (as % of total population)	-0.26143***
	(0.055430)
Subsidies and other transfers (% of expense)	0.036**
	(0.0170)
Observations	918
R2	0.216
Adjusted R2	0.109
F Statistic	219.953***
Note:	*p<0.1; **p<0.05; ***p<0.01

Appendix O - This appendix presents OLS and IV results when modifying our instrumental variables regarding regional waves from using average data on neighbouring countries to using average data for the broader geographic region in which a country is located. The data used in these regressions is obtained from the World Bank's MIX market database as well as the World Bank's World Development Indicators database and the World Bank's GovData 360 database.

Appendix P - Regression results for robustness check using the squared poverty gap at $3.20 a day variable

	Dependent variable:	
	Poverty gap at $3.20 a day (2011 PPP) (%) squared	
	OLS	IV
Average gross loan portfolio (% of GDP)	-1.10589	2.78828
	(3.9193)	(4.4662)
GDP per capita (constant 2010 US$)	-0.003	0.018**
	(0.0050)	(0.0070)
Domestic credit to private sector by banks (% of GDP)	-1.097	-0.804
	(0.6690)	(0.6580)
Inflation, consumer prices (annual %)	0.149	-0.629
	(0.3370)	(0.4120)
Import (as % of GDP)	-2.444**	-1.908**
	(0.9470)	(0.8920)
Export (as % of GDP)	-0.434	-1.111
	(1.0000)	(0.9540)
Population ages 0-14 (% of total population)	26.638***	9.782**
	(4.111)	(4.276)
Arable land (% of land area)	423.480***	414.718***
	(156.56)	(156.25)
Rural population (as % of total population)	-1.86205	-4,96068*
	(2,5496)	(2,7900)
Polity 2 score of -1	328.609*	315.812**
	(168.75)	(148.49)
Polity 2 score of -10	211.861	198.416
	(169.84)	(151.19)
Polity 2 score of -2	130.24	87.682
	(168.95)	(149.86)
Polity 2 score of -3	147.652	165.501
	(160.19)	(142.11)
Polity 2 score of -4	218.634	195.833
	(159.71)	(140.92)
Polity 2 score of -5	88.433	135.36
	(171.06)	(150.77)
Polity 2 score of -6	146.12	142.177
	(162.50)	(143.86)
Polity 2 score of 0	344.926**	345.952**
	(155.62)	(137.10)
Polity 2 score of 1	-94.076	43.919
	(162.05)	(148.16)
Polity 2 score of 10	180.802	275.815*
	(159.51)	(143.84)
Polity 2 score of 3	223.874	221.031

	(154.59)	(136.02)
Polity 2 score of 4	226.724	262.844*
	(154.30)	(135.86)
Polity 2 score of 5	109.785	45.44
	(151.01)	(133.14)
Polity 2 score of 6	232.314	208.274
	(151.61)	(133.61)
Polity 2 score of 7	192.837	167.448
	(150.15)	(132.07)
Polity 2 score of 8	161.121	134.115
	(154.31)	(136.10)
Polity 2 score of 9	108.128	130.492
	(153.60)	(135.29)
Subsidies and other transfers (% of expense)	1.274	2.991***
	(0.92)	(0.86)
Observations	950	889
R2	0.232	0.153
Adjusted R2	0.149	0.036
F Statistic	9.570*** (df = 27; 857)	142.998***

Appendix P - This appendix presents OLS and IV results using a squared poverty gap variable to emphasise the effect on the people furthest away from the poverty line. The data used in these regressions is obtained from the World Bank's MIX market database as well as the World Bank's World Development Indicators database and the World Bank's GovData 360 database.