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What Drives Financial Inclusion at the Bottom of the Pyramid?

Empirical Evidence from Microfinance Panel Data

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Abstract

Microfinance has played a key role in including the poor in financial markets. This paper uses microfinance data to approximate financial inclusion in the poorer segments of the population and proposes a quantile regression approach to study the development of microfinance markets. Our approach accounts for the dynamic and heterogeneous impacts that key drivers may have across different stages of market development. It also allows us to go beyond correlations and gets us closer to identifying causal relationships. Our key findings indicate that: i) Microfinance markets are more responsive to the needs of the bottom of the pyramid than to potential growth opportunities. ii) Enabling institutions that provide credit information become increasingly important with higher market complexity. iii) Formal financial development is a complement of microfinance development. iv) Technologies can help to overcome market entry barriers, and to enable a higher inclusion in markets with a high degree of complexity. Our results could help policymakers and investors better understand and influence financial inclusion at the bottom of the pyramid across different stages of market development.

Key words: financial inclusion, microfinance, market penetration, quantile regression.

JEL: G21, O16, L16.

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1 Introduction

Despite the trillions of dollars managed by the financial industry worldwide, half the world still remains unbanked (Chaia et al, 2009). This lack of financial inclusion disproportionately affects the poorer and more vulnerable segments of the population (Demirgüç-Kunt and Klapper, 2012). Nevertheless, we still do not have the necessary data to understand which are the causal drivers of financial inclusion at the bottom of the pyramid. In order to address this failure, this paper uses microfinance data of different countries across the world in the last decade. We use this data[1] to identify the causal drivers that policymakers and investors should target in order to increase financial inclusion at the bottom of the pyramid. We provide a quantile regression approach that gives appropriate insights across different stages of market development, and reduces potential endogeneity concerns.

We build on Krauss et al. (2012) methodology to create an indicator of microfinance market penetration in the working age population below the national poverty line, considering the information reported by microfinance institutions (MFIs) to the *Microfinance Information Exchange* (MIX)[2] in 109 countries between 2003 and 2012. This kind of financial inclusion information is currently not widely available. This lack of data is particularly acute at the poorer segments of the population. As of today, only two comparable datasets offer relevant information, but they are limited to only a subset of countries and years: The World Bank *Global Findex* survey provides demand-side data by income quantiles only for 2011[3], and the IMF *Financial Access Survey* provides supply-side information for households and SMEs only for some country-years[4].

This lack of adequate panel data makes it difficult to understand what are the causal drivers of

[1]Our dataset is available in our Online Data Appendix. Please refer to: http://www.cmf.uzh.ch/penetrationdata.html.

[2]Original, underlying data provided by Microfinance Information eXchange, Inc. (MIX). The *MIX* is a web platform to which microfinance institutions can report their financial and performance information to gain visibility and attract investors.

[3]The 2014 survey results will be published in April 2015. We consider the 2011 results to validate our data, as it is described in our Data Appendix. We will also consider the 2014 *Findex* results once they become available.

[4]Country-specific surveys have also been undertaken by institutions such as Finscope, FinMark and the Bill and Melinda Gates Foundation (Financial Inclusion Tracker Surveys and Financial Inclusion Insight Surveys), but they are not comparable across different countries.

financial inclusion at the bottom of the pyramid. Indeed, focusing only on a particular year does not allow controlling for unobservables that may change over time. Similarly, focusing only on a subset of countries does not allow controlling for unobservables that may change across different countries. A panel dataset like ours helps to better identify which are the causal drivers of financial inclusion. The quantile regression approach that we use allows us to examine how these drivers become less or more important across different stages of market development.

Due to the lack of comparable cross-country panel data, most of the existing studies on the determinants of financial inclusion (Demirgüç-Kunt and Klapper, 2013; Allen et al., 2012; Beck and Brown, 2011; Chaia et al., 2009; Honohan, 2008; Beck et al., 2007) use simple cross-sectional specifications with which it is difficult to address potential endogeneity concerns. There have been a few panel dataset studies for a subset of countries and years (Honohan and King, 2009) that have merged country surveys across different years. However, they have found difficulties in comparing information across countries, which has limited their scope and external validity.

There are only a few studies using microfinance data to explore the determinants of financial inclusion at the bottom of the pyramid. For example, Vanroose and D'Espallier (2009) examine the determinants of microfinance development using a random effects model across different countries between 1997 and 2006. Ahlin et al. (2011) examine the determinants of microfinance performance with an OLS approach, using macroeconomic indicators for 74 countries between 1996 and 2007. Hermes and Meesters (2011) do a similar study focusing on the macroeconomic determinants of MFIs' cost-efficiency. Javoy and Rozas (2013) predict microfinance penetration rates with an OLS approach using *Findex* and *UNDP Human Development Indicators* for 2011. They identify saturated markets comparing actual values with the predictions from their estimation using only this year. We contribute to this last stream of the literature by using Krauss et al. (2012) panel dataset on microfinance market penetration[5] and proposing several methodological strategies to disentangle causal relationships from correlations. This allows us to produce more precise estimators than those from previous studies.

[5]We provide a description of this index of microfinance market penetration in our methodology and data sections. In our Data Appendix, we also examine how the relevant *MIX* information that we use to calculate our *MF Penetration Rate* compares with the available and comparable information from the World Bank *Findex* and the IMF *FAS* datasets.

In particular, we propose a quantile regression approach with country and year fixed effects that accounts for the dynamic and heterogeneous impacts that key drivers may have across different stages of market development, while reducing potential endogeneity biases. The detailed insights provided in this paper are specific for different stages of microfinance market development. Thus, they can guide policymarkers and investors on how to best prioritize their efforts in a particular context, making the most effective and efficient impact on financial inclusion at the bottom of the pyramid.

Our robust specification is also able to address potential endogeneity concerns. This is very important to guarantee that policymakers and investors' efforts are focused on the key causal drivers of microfinance market development, and not only on those factors that may have a high correlation but play no causal role. In addition, by shedding light on the dynamics of microfinance market development, our results can help microfinance funders and investors to identify and forecast which microfinance markets constitute the best investment opportunities.

Our key findings indicate that: i) Microfinance markets are more responsive to the needs of the bottom of the pyramid than to potential growth opportunities. ii) Enabling institutions providing credit information become increasingly important with higher market complexity. iii) Formal financial development is a complement of microfinance development. iv) Technologies can help to overcome market entry barriers, and also to enable a higher inclusion in markets with a high degree of complexity.

2 Methodology

2.1 Definition of *MF Penetration Index*

In order to examine the drivers of microfinance market development, this paper considers the indicator of microfinance market penetration proposed by Krauss et al. (2012). This indicator is based on *MIX* data and on *World Development Indicators* (WDI). The index is defined as follows:

$$MF\ Penetration\ Rate_{i,t} = \frac{MFI\ Borrowers_{i,t}}{Working\ age\ population\ below\ the\ national\ poverty\ line_{i,t}} \quad (1)$$

where *MFI Borrowers*$_{i,t}$ is the total number of active borrowers reported by all MFIs[6] in country i for year t, and *Working age population below the national poverty line*$_{i,t}$ is the share of the adult (age 15 and over) population of country i in year t below the national poverty line according to *WDI* data[7].

Even if the *MIX* data is available since 1995, in order to calculate the *MF Penetration Index* developed by Krauss et al. (2012), we consider only the data for the period between 2003 and 2012. We start in 2003 because around this year *MIX* became a consolidated and representative information platform. We stop in 2012 because this year is the last most complete and consolidated period. Indeed, MFIs take time to report their figures and this information needs to be standardized by the *MIX*, which needs further time. In addition, by including the global financial crisis in our sample, we are able to assess the robustness of our results to global shocks that may affect microfinance market development.

Table 1 ranks countries according to their *MF Penetration Index* for 2012. It also includes the index compound average growth rate (CAGR) for the last 5 years when available, and the index average for the same period. Figure 1 maps our *MF Penetration Index* for 2012. An interactive version of this map is available in our Online Data Appendix[8]. We will discuss our *MF Penetration Index* in more detail in the next section.

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[6] There are 4 countries that do not have data on the number of microfinance borrowers for any of the years in the *MIX* sample, i.e. Belarus, Grenada, Slovakia, and Vanuatu. Thus, for these countries we cannot calculate our microfinance penetration index.

[7] For those years in which *WDI* indicators are not available, the last available observation and the observed annual growth rate are used as a proxy. If the annual growth rate cannot be calculated, then the last and next available observation are used. There are some countries that have no poverty headcount ratio at the national poverty line, but have it at the 2 USD PPP a day poverty line instead. These include Argentina, Belize, Guyana, Saint Lucia, Suriname, and Trinidad and Tobago. In order to preserve these countries in our sample, we use the 2 USD PPP poverty line in these particular cases. There are five countries that have no poverty headcount ratio information, i.e. Grenada, Myanmar, Samoa, Tonga and Vanuatu. Thus, for these countries we cannot calculate our microfinance penetration index.

[8] Please refer to: http://www.cmf.uzh.ch/penetrationdata.html. Table 1 and Figure 1 exclude the outliers that we have identified in our detailed Online Data Appendix, and are discussed in our Data section.

2.2 Potential Explanatory Variables

We use the following specification to describe microfinance market development across different countries in the world during the last decade (2003-2012):

$$MF\ Penetration\ Rate_{i,t} \ = \ X\beta_1 + \ \alpha_i + \ \delta_t + \ \epsilon_{i,t} \tag{2}$$

$$\begin{aligned} x_{i,t} \ = \{ \ & Income_{i,t}, \ Enabling\ Institutions_{i,t}, \ Formal\ Financial\ Development_{i,t}, \\ & Macroeconomic\ Environment_{i,t}, \ Geography\ and\ Technology_{i,t}, \ Knowledge_{i,t} \} \end{aligned} \tag{3}$$

We consider Krauss et al. (2012) index for microfinance market penetration as our dependent variable, *MF Penetration Rate*$_{i,t}$ (MFPR) for country i and year t. Our vector of explanatory variables X includes relevant *Income* indicators, such as GDP per capita and GDP growth, which we expect to be important drivers of the decision of microfinance institutions (MFIs) to enter a particular market or increase their presence in them. For example, we could expect MFIs to enter and penetrate markets with low GDP per capita but high GDP growth. We also consider the impact that inequality indicators may have on microfinance market development, expecting a positive relationship between inequality and microfinance market penetration, unless inequality creates too many barriers to market development.

We examine the influence that key *Enabling Institutions* have in the development of microfinance. In particular, we study the role of legal rights that ease credit transactions, and the prevalence of credit bureaus and public registries. We expect that a better quality of credit information would help the microfinance market development process.

We are also interested in understanding if *Formal Financial Development* can be a complement of or a substitute for microfinance development. In order to address this question, we explore different indicators of financial depth, including the penetration of commercial bank branches and ATMs, which reflect the existing supply of formal financial services. We also consider how the characteristics of the formal financial market may affect microfinance market development. In particular, we include indicators of concentration, competition, and marginal returns of formal financial institutions.

We also consider more general indicators of financial depth, such as the share of domestic credit provided by the financial sector. An interesting variable for the target population of microfinance is the GDP share of received remittances, which can influence the demand that the poor have for microfinance services. We also include this indicator in our matrix of explanatory variables.

We study how *Macroeconomic Environment* indicators may influence microfinance market development. In particular, we examine the role of inflation, employment, informality, interest rate (deposit, lending and real), exchange rate, and net aid inflows.

Moreover, we include indicators of *Geography and Technology* that may influence MFIs' ability to enter and develop in a given market. In particular, we consider population density, prevalence of rural population, mobile phone penetration, and internet access.

Likewise, the *Knowledge* in a given economy is also considered, controlling for schooling years and completion rates in primary, lower secondary and secondary school, across men and women. We also consider the importance of literacy rates.

2.3 Fixed effects

All these variables allow us to model the development of microfinance markets in a very complete way. However, the biggest advantage of our study with respect to previous studies, is not the amount of variables included in the model, but the fact that these variables can be tracked for a long period of time and across different countries. Indeed, by using a panel dataset on microfinance market penetration, we are able to perform fixed effects that control for omitted characteristics, thus limiting potential endogeneity issues. This allows us to go beyond correlation and brings us closer to identifying causal relationships, which can help policymakers and investors to better understand and influence the dynamics of microfinance market development.

We exploit our panel dataset to achieve this goal in several ways. First, we include country and year fixed effects. Country fixed effects control for time-invariant and country-specific characteristics, such as country-specific cultural values that may evolve over time but do not tend to change very quickly. Thus, introducing country fixed-effects reduces the importance of the error term α_i in equation (2), and limits the potential correlation between our explanatory variables and this error term $cov(X, \alpha_i)$. In addition, we cluster the standard errors of our estimations at the country level.

Second, we use year fixed effects to control for country-invariant and year-specific events, such as the global financial crisis. Year fixed effects allow us to reduce the error term δ_t in equation (2), and limit the potential correlation between our explanatory variables and this error term $cov(X, \delta_i)$. We also introduce a variable for the *Crisis* years, specifically for 2008 to 2010.

2.4 Non-Normality of *MF Penetration Rate*

It is important to consider that *MF Penetration Rate*, our dependent variable, has a zero-inflated distribution. Indeed, many countries in our sample have had no microfinance penetration for all or several of the years under consideration. Even if most of the low and middle-income countries tend to have some microfinance presence, there are cases where no MFIs have entered a specific country at all. In addition, in some low and middle-income countries, MFIs are present only for some years in the sample, for instance, when microfinance has entered a particular market relatively late.

Our study aims precisely at identifying which are the key factors that could explain this. In particular, we are interested in understanding the differences between the determinants of market entry and market penetration, and in providing useful insights to policymakers and microfinance investors in each particular case. Therefore, is very important for us to understand the key factors explaining the many zeros in our variable of interest.

Many of these zeros correspond to countries where microfinance markets will never develop, such as high-income countries, where MFIs have never been present, and most likely will never go. However, even if we take the high-income countries out of our sample, we are still left with a large amount of zeros. Indeed, our dependent variable does not have a normal distribution, as can be seen in Figure 2[9]. This can be problematic if an OLS model is used in the regression analysis. If errors are not normal, their expected value is not zero, which biases the expected value of β_1 according to the OLS estimation.

We contribute to the existing literature by addressing this problem with other estimation techniques. In particular, we address this problem by proposing two estimation strategies. The first one uses a two-stage sample selection approach, as proposed by Heckman (1979). The second one takes a quantile regression approach with fixed effects, using the penalising procedure proposed by Koenker (2004).

[9] We will discuss this in more detail in the summary statistics session.

2.5 Heckman Selection Approach

The Heckman selection approach allows us to disentangle the determinants of market entry from those of market penetration, and also reduces the potential bias introduced by the non-normality of our dependent variable. In addition, when we estimate our selection model, we first consider the full sample of countries, and second we exclude high-income countries from it. By examining only the countries where microfinance is more likely to develop in the future, we reduce the variation of our explanatory variables and focus only on the relevant variation driving *MF Penetration Rate*.

Our selection approach is described in equations (4) and (5), which imply that we observe a positive microfinance penetration rate in our database, $MFPR_{i,t} > 0$, only for those country-years that have the necessary characteristics for microfinance to be present in that particular context, $MFPR^*_{i,t} > 0$. The probability of a given country-year having any microfinance presence is modelled as in the right hand side of equation (5). If we did not control for this, our OLS estimates for equation (4) would be biased, since we would need to consider also $E[u_{i,t} \mid X, \eta_{i,t}]$ in equation (6) in order to correctly estimate β_1 in equation (4).

$$MFPR_{i,t} \;=\; X\beta_1 + \; u_{i,t} \tag{4}$$

$$MFPR_{i,t} = \begin{cases} MFPR^*_{i,t} > 0 & if \quad X\beta_2 + \; \eta_{i,t} > 0 \\ 0 & if \quad X\beta_2 + \; \eta_{i,t} \leq 0 \end{cases} \tag{5}$$

$$E[MFPR_{i,t} \mid X, \eta_{i,t}] \;=\; X\beta_1 + \; E[u_{i,t} \mid X, \eta_{i,t}] \tag{6}$$

In the first stage of our Heckman selection model, we estimate a selection equation in which the probability of microfinance entering in a given country-year is given by a Probit model. Since most of the countries with zero observations are upper-middle-income and high-income countries, with the exception of 11 cases[10], we use the *World Bank Income Classification* as the exclusion restriction in this selection equation. Indeed, we argue that while the income classification of a country can influence the decision of a MFI to enter a country or of its investors/donors to finance

[10]Low-income countries: Eritrea, North Korea and Somalia. Lower-middle-income countries: Micronesia, Solomon Islands, Kiribati, Djibouti, Lesotho, Sao Tome and Principe, Mauritania, and Cape Verde.

such market entry, income classification should not influence the degree of market penetration once market entry has taken place.

After we estimate this first stage, we calculate a relevant Mills Ratio that we include in the second stage. This second stage estimates an OLS model to explain the determinants of microfinance penetration in a given country-year. The Mills Ratio allows controlling for the probability of microfinance being present in that country-year in the second stage of the estimation. This analysis is particularly useful for examining the differences between the determinants of market entry and market penetration, thus leading to more precise insights for each particular case.

When we take the full sample into account, this approach helps us to differentiate between cases like Switzerland and Somalia, both with no microfinance penetration, but because of obviously different reasons. When we exclude high income countries from the sample, this approach can more precisely differentiate between cases like Somalia, with no microfinance, and Ethiopia, with some microfinance penetration, which are more interesting both from a policy perspective and from the perspective of microfinance investors.

2.6 Quantile Regression Approach

An alternative to deal with the non-normality of our dependent variable is to consider a quantile regression model. Quantile regressions make no distributional assumption about the error in the model. Therefore, the non-normality of our dependent variable is not problematic for the estimation of β_1 across different quantiles in the distribution of *MF Penetration Rate*.

The quantile approach is also very useful to understand the heterogeneous effects of our variables of interest across different stages of microfinance market development. It examines how our explanatory variables predict different segments of the *MF Penetration Rate* distribution. This analysis is particularly relevant for investors evaluating which are the main barriers or potentials of different markets in different development stages, and forecasting which development path markets are more likely to follow. It is also interesting for policymakers to understand which issues to prioritize depending on the level of microfinance market development in their particular countries.

We can introduce fixed effects in the quantile regression approach using the penalising procedure proposed by Koenker (2004). This allows us to control the error term α_i in equation (1). We also include year fixed effects in our estimations, helping us to reduce the importance of δ_t. The estimations behave very similarly when we use year fixed effects or when we replace them with a dummy variable for the years of the financial *Crisis* in our sample (2008-2010)[11]. The *Crisis* dummy allows us to preserve the degrees of freedom of our estimations, which are considerably reduced when year fixed effects are used. In addition, the *Crisis* dummy allows us to assess the impact of external global shocks to microfinance market development.

2.7 Potential Endogeneity Concerns

Including country and year fixed effects reduces potential endogeneity problems arising from omitted variables. We also examine if, after performing these fixed effects, there still might be endogeneity caused by simultaneity or reverse causation between *MF Penetration Rate* and our explanatory variables. In our particular case, these concerns may be relevant for the *Enabling Institutions* and the *Formal Financial Development* indicators in the right-hand side of our main equation.

Indeed, we expect that the presence of *Enabling Institutions* will help MFIs entering a particular market; but it could also be possible to imagine that countries that already have a high *MF Penetration Rate* may develop lobbies to increase the quality of relevant *Enabling Institutions* for the industry. This would mean that $cov(\textit{Enabling Institutions}, u) > \mathit{0}$ and $\beta_{\widehat{\textit{Enabling Institutions}}}$ would be biased upwards. Thus, we would be likely to overestimate the effect that *Enabling Institutions* have on microfinance market development.

However, this is likely to happen only in those countries with a very high microfinance penetration where MFIs are key players in the overall financial market. These countries constitute a very small group. By estimating the impact of *Enabling Institutions* in an heterogeneous way for countries in different stages of microfinance market development, our quantile approach mitigates this potential endogeneity concern. This approach is able to distinguish between the group of countries where there might be a potential endogeneity issue (in the highest percentiles of the distribution) and the rest of the countries. In particular, the quantile regression approach fits the observations not with respect to the mean of *MF Penetration Rate*, as OLS would do, but with respect to different moments of its distribution. Thus, the effect that *Enabling Institutions* have across different percentiles will be estimated differently across the distribution, and this limits po-

[11]We discuss this in more detail in our robustness checks section.

tential endogeneity concerns only to the highest percentiles of the distribution.

Similarly, while we expect the level of *Formal Financial Development* to act as a complement or a substitute of microfinance market development, it could also be the case that countries that already have a high *MF Penetration Rate* may crowd-in our crowd-out formal financial institutions. This would mean that $cov(\textit{Formal Financial Development}, u) > 0$ in the case of crowding-in or $cov(\textit{Formal Financial Development}, u) < 0$ in the case of crowding-out. However, this is likely to happen only in those countries where the microfinance industry has a very predominant role in the overall financial market, which again constitutes a small group. Just as we explained before, the quantile approach is also effective in mitigating the potential endogeneity of the *Formal Financial Development* variables.

It is very hard to argue that similar simultaneity concerns hold for our remaining right-hand side variables. Indeed, they are all macroeconomic or structural factors that cannot be easily influenced by microfinance development in the short and medium term, as widely documented in the extensive literature on the impacts of microfinance (Banerjee et al., 2015; Cull et al., 2014; Banerjee, 2013a; Bauchet et al., 2011).

3 Data

3.1 Existing Financial Inclusion Data

As we have discussed above, cross-country financial inclusion panel data is still not widely available, in particular for the poorer segments of the population. Currently, only two comparable datasets offer relevant information: The IMF *Financial Access Survey* (FAS) provides cross-country supply-side data but it is available only for some country-years[12]. On the other hand, the Gates Foundation, the World Bank, and Gallup World Poll produce the *Financial Inclusion Database* (Global Findex) that includes cross-country demand-side data, available for 148 countries in 2011 (Demirguc-Kunt

[12] *FAS* data is fed with information coming from financial regulatory entities of 189 jurisdictions across the world between 2004 and 2012. This dataset provides indicators of geographical outreach and use of financial services. The data is disaggregated by type of financial institution, including deposit-taking and non-deposit-taking MFIs; and by type of customer, including households and SMEs. Nevertheless, *FAS* is an unbalanced panel and some of the statistics are not available for all the covered country-years. Moreover, *FAS* financial inclusion indicators are provided at the country level and it is not possible to disentangle how they vary across the income distribution.

and Klapper, 2012)[13]. While *FAS* includes microfinance-specific indicators for an unbalanced panel of 15 countries between 2004 and 2012, *Findex* does not[14].

Findex is a demand-side dataset that measures financial inclusion by asking potential clients of financial service providers whether they use certain products or not. On the other hand, *FAS* is a supply-side dataset that measures financial inclusion based on the reports that different financial institutions give to their financial supervisors. Since they use different information sources, demand and supply-driven datasets lead to different financial inclusion figures.

We expect supply-side data to imply higher figures of financial inclusion than demand-side data in countries with higher financial complexity. Financial complexity can be defined in this case by high incidence of multiple borrowing, high incidence of cross-borrowing across different institutions, and by the presence of foreign borrowing. When these phenomena occur, households will have several accounts that will be recorded in FAS but not in *Findex*. Thus, *FAS* supply-driven indicators of financial inclusion will be higher than *Findex* demand-driven indicators.

We expect countries with higher income levels to have higher financial complexity. We show evidence supporting this claim in our Data Appendix. Moreover, we also expect that countries with a high share of unregulated institutions will have lower supply-based financial inclusion indicators when compared to the demand-based ones. For example, in a country with a high amount of unregulated institutions, *FAS* information may be under-representative of the overall financial inclusion landscape.

[13] *Global Findex* data is the result of a comprehensive set of household surveys performed in 164 countries across the world in 2011 (the 2014 data will be released in April 2015). The country-level version of the dataset includes information on the use of financial services of adults at the country level, such as the ratio of adults with an account or a loan at a formal financial institution. The household-level version of the dataset includes information on the quantile of the country income distribution attributable to each particular household, as well as on gender, age and education of the adult responding the survey. The data is not disaggregated by type of financial institution.

[14] *Findex* excluded from their public data release the answers to a question asking households whether they had borrowed or saved in a MFI in the last 12 months. According to *Findex*, the survey results indicated that households cannot always clearly distinguish if the provider of their formal account is a bank, a MFI, a credit union or a cooperative.

3.2 Comparison of *MF Penetration Index* with Existing Financial Inclusion Data

We use microfinance data on the total number of borrowers from *MIX* and combine it with *WDI* indicators on the share of the population below the national poverty line, as per Krauss et al. (2012), to build our *MF Penetration Rate*. In our detailed Data Appendix we propose a battery of tests to check the quality of the *MIX* data used to build our *MF Penetration Rate*. We use the best comparable *FAS* and *Findex* indicators. Despite these datasets' weaknesses, they are the best available sources of information that we can use to check the reliability of *MIX* data, and thus to assess how useful the panel dataset developed by Krauss et al. (2012) is to understand the drivers of microfinance market penetration.

Comparing relevant financial inclusion indicators from the supply-side *FAS* dataset and the demand-side *Findex* dataset[15] allows us to assess the complexity of the overall financial market in a given country. Similarly, we examine the complexity of the microfinance segment of the financial market by comparing the supply-driven microfinance penetration implied by *MIX* data with the demand-driven microfinance penetration implied by *Findex*[16]. We describe these calculations in our Data Appendix section.

Based on these comparisons, we can classify countries into four groups. We include a list of these country groups in our Data Appendix. In the first group, countries present high financial complexity both in the overall financial market and in the microfinance market segment. For these countries, we argue that if the *MIX* indicator of the national share of microfinance borrowers is higher than the relevant proxy from *Findex*, it may not be due to data issues, but rather to multiple borrowing, which may also be present in the overall financial market.

The second group includes countries in which both the microfinance market segment and the overall financial market show a low level of complexity. In these cases, we argue that if the *MIX* indicator of the national share of microfinance borrowers is lower than the relevant proxy from *Findex*, it may not be due to data issues, but rather to the low complexity of the overall financial market. In particular, there might be under-reporting of microfinance institutions, or a high share

[15] We do this in our Data Appendix, in particular in Figure 16.

[16] We do this in our Data Appendix, in particular in Figure 15.

of unregulated institutions, which is likely to also be present in the overall financial market.

Countries in the third group have a higher complexity in the microfinance segment than in the overall financial market. As can be seen in our Data Appendix, most of these countries, especially Bolivia and Kenya, are clear leaders in the development of financial services at the bottom of the pyramid and are lower middle-income and low-income countries. It is thus plausible that in these cases complexity is higher in the microfinance segment than in the overall financial market.

Countries in the fourth group have a higher complexity in the overall financial system than in the microfinance segment. This is plausible for countries with high income levels, as these countries can have complex overall financial systems that also may serve the needs of the bottom of the pyramid, and thus crowd-out specialized microfinance market players. In such countries, overall financial development is a substitute for and not a complement to microfinance market development.

However, this is more difficult to understand in countries with low income levels. Indeed, even if these countries have high overall financial market complexity, their low income levels suggest that a high proportion of the poor population may still lack access to financial services. Thus, it seems less clear why microfinance market development is low in these cases. This paper aims precisely at understanding these anomalies better.

All these countries are plotted in our Online Data Appendix[17]. There it is easy to see graphically in which cases there are important outliers in *MIX* data. As it is explained in our Data Appendix, we have identified the following country-years as outliers: Nigeria 2009, Burkina Faso 2011, Mali 2012, Comoros 2011, Ethiopia 2010, Kosovo 2011 and 2012, Congo Republic 2009 and 2010, Guinea 2011 and Thailand. We will discuss the robustness of our results when considering these observations in and out of the sample, in the robustness checks section.

We also consider in this section if our results are robust when controlling for the groups that we have just defined. Indeed, while Groups 1 and 2 suggest that overall financial complexity is a complement of microfinance market development; Groups 3 and 4 suggest that it can be a substitute for it. The determinants for microfinance development may be thus structurally different for different country-groups, and this is something that we examine in more detail in the robustness

[17]Please refer to: http://www.cmf.uzh.ch/penetrationdata.html.

checks section.

3.3 Sources of Explanatory Variables

We include different indicators for the main variables of interest and use those that have the highest explanatory power and present less missing values for the countries under consideration. Table 2 summarizes a detailed description of each of the variables that we use in our specifications. This Table also includes the main summary statistics of all the variables that we examine. As can be seen in the Table, some of the variables that are discussed here would have diminished considerably our observations, thus reducing our degrees of freedom and compromising the precision of our estimations. For this reason, we focus on those variables that have the highest number of observations.

For example, as *Income* indicators, we use *WDI* data on *GDP per capita* (constant 2005 USD) and *GDP growth* (annual %). We also consider using poverty gap[18] indicators, such as *Poverty gap at 2 USD a day (PPP) (%)* and *Poverty gap at national poverty line (%)*. We also consider using the *Gini Index* of inequality and several other measures of the share of income in different percentiles of the population. However, many countries have missing observations for these variables, which makes us focus only on *GDP growth* and *GDP pc* as our main *Income* indicators. We do not include any poverty incidence indicator since our dependent variable already includes one in its denominator.

In order to describe the relevant *Enabling Institutions* for microfinance development, we use *Doing Business* data on credit information. In particular, we use information on the *Getting Credit* ranking of the *Doing Business report*, which is composed of the following variables: *Strength of Legal Rights Index (0-10)*[19], *Depth of Credit Information Index (0-6)*[20], *Public Registry Coverage*

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[18]The poverty gap is the mean shortfall from the poverty line. The higher it is, the higher poverty depth is.

[19]This indicator measures up to what extent collateral and bankruptcy laws protect the rights of borrowers and lenders.

[20]This indicator measures the coverage, scope and accessibility of credit information available through credit bureaus or credit registries. One point is assigned for each of the following features: 1) Data on firms and individuals is distributed. 2) Positive and negative credit information is distributed. 3) Data from utility and retailers is distributed. 4) Data for at least 2 years is distributed. 5) Data on loans below 1% of income per capita is distributed. 6) Borrowers have the right to access their data.

(% of adults), and *Private Bureau Coverage (% of adults)*[21]. It would have been ideal to differentiate if these institutions specifically hold creditworthiness data of MFI clients in some particular countries, but we could not find comparable information for the country-years in our sample. It would also be important to include comparable indicators on the quality of countries' microfinance regulatory framework, but this data is not available for most of the country-years in our sample.

Formal Financial Development is described using *WDI* data on commercial *Bank Branches* (per 100,000 adults), automated teller machines *ATM* (per 100,000 adults), *Domestic Credit* provided by the financial sector (% of GDP), and personal received *Remittances* (% of GDP). We also include relevant variables from the *Global Financial Development Database* (GFDD) that could describe in more detail the specific characteristics of the formal financial market across different countries. In particular, we consider the Boone indicator of *Competition*, which is based on the profit-efficiency of the banking market[22]. We also include the degree of bank *Concentration*, which measures the assets of the three largest commercial banks as a share of total commercial banking assets. In addition, we examine the banks' *Net interest margin*, which represents banks' net interest revenue as a share of their total earning assets, and banks' *Non Rate Income*, which measures the income generated by non-interest related activities as a percentage of total income[23].

The *Macroeconomic environment* is measured using *WDI* data on consumer prices *Inflation* (annual %), ILO estimates on *Employment* to population ratio (%, ages 15-24 over total), official exchange rate *FX* (LCU per USD, period average), and *Net official development assistance and official aid received* (constant 2011 USD). The growth of these variables with respect to the previous year is included in the estimations. We also examine the impact that *Interest Rate* (lending, deposit and real, %) has on microfinance market development. In addition, we consider including *Doing Business* and *UNDP Human Development* indicators of the relevance of *Informality*, but find few available observations also in this case.

[21]Both types of organisations, public registries and private bureaus, collect information on the creditworthiness of borrowers and facilitate the exchange of credit information among lenders. The former is managed by the public sector and the latter is managed by the private sector.

[22]The GFDD Boone indicator of competition is calculated as the elasticity of profits to marginal costs, using a regression of the log of profits (measure by return on assets) on the log of marginal costs. The more negative the indicator, the higher the degree of competition, because the effect of reallocation to more efficient banks is stronger.

[23]Non-interest income includes net gains on trading and derivatives, net gains on other securities, net fees and commissions and other operating income

Geography and Technology includes measures of geographical isolation provided by *WDI* such as *Population Density* (people per sq. km of land area, hundreds) and *Rural Population* (% of total population). It also includes measures of technological innovation, such as *WDI* data on *Mobile Phones* subscriptions (per 100 people) and *Internet Users* (per 100 people).

Knowledge is described using *WDI* data on *Primary Years* and *Secondary Years* of schooling; *Primary* completion rate for the total population (% of relevant group) and of the female population, *Primary Female*; and *Lower Secondary* completion rate for the total population (% of relevant group) and of the female population, *Lower Secondary Female*. We also examine including relevant *Literacy* information, but find again too many missing values.

4 Summary Statistics

4.1 Relevant Sample of *MF Penetration Rate*

We take a sample of 214 countries recognised by the World Bank and follow them for 10 years (2003-2012). *MIX* data is available for 120 countries[24] and we observe no microfinance penetration for the remaining 94 countries that are not in the *MIX* sample[25]. Out of the 120 countries in the *MIX* sample, 7 do not have the necessary information to calculate the *MF Penetration Rate*[26]. At this stage, we consider all the observations and do not disregard any of the outliers identified in our previous section. However, we take out Montenegro 2008 from our sample, because it has a *MF Penetration Rate* that is more than two standard deviations away from the mean, which leaves us with 2069 country-years.

[24] As of 2012, 32 are low-income countries (26.7%), 40 lower-middle-income countries (33.3%), 40 upper-middle-income countries (33.3%), 7 high income countries (5.8%), and 1 country with no income classification (0.9%), i.e. South Sudan.

[25] Out of the 94 countries with no *MIX* data, as of 2012, 3 are low-income countries (3.2%), 8 lower-middle-income countries (8.5%), 15 upper-middle-income countries (16%), 65 high income countries (69.1%), and 3 countries with no income classification (3.1%).

[26] Besides 4 countries that do not have data on the number of microfinance borrowers for any of the years in the *MIX* sample (Belarus, Grenada, Slovakia, and Vanuatu), there are 3 countries that have such information but no poverty headcount (national or 2USD PPP) data: Myanmar, Tonga and Samoa.

Out of the countries with *MIX* data, 32 of them show no microfinance penetration during some of the years under examination, resulting in 132 zeros of our dependent variable. In total, out of our 2069 observations, 1072 are zeros, representing 52% of the observations. If we exclude high-income country-years from our sample, it is reduced to 1390 observations, out of which 423 are zeros, representing 30% of the observations. This zero-inflated distribution of our variable of interest *MF Penetration Rate* can be seen in Figure 2 for all the countries in the basic model sample[27] and for all countries except those classified as high-income economies. This Figure also includes the percentiles of our dependent variable for these two samples.

As can be seen in the Figure, in the first sample, *MF Penetration Index* starts to be positive only in the 40th percentile. In the second sample, it is positive already in the 20th percentile. The median in all countries in the basic model sample is 0.69%, while this increases to 2.96% when high-income countries are excluded. The 90th percentile in the first sample has an average of 21.8%, while that in the second sample has an average of 31.74%.

4.2 Recent Trends of *MF Penetration Rate*

Figure 1 plots a map of the *MF Penetration Rate* index as of 2012, together with its growth rate between 2007 and 2012[28]. We exclude outlier countries identified in the previous section. Table 1 shows the statistics used in this map, including also the average for the *MF Penetration Rate* between 2007 and 2012.

Azerbaijan, Cambodia, Paraguay, Peru, Vietnam, Mongolia, Bangladesh, Bhutan, Bosnia and Herzegovina, and Jordan are the 10 countries with the highest penetration rates in 2012, ranging between 47.7% and 126%. Most of these countries (7 out of 10) are also among those with the 10 highest averages of *MF Penetration Rate* between 2007 and 2012, which are Bosnia and Herzegovina, Bangladesh, Vietnam, Sri Lanka, Mongolia, Morocco, Azerbaijan, Peru, Cambodia and Armenia.

[27] This refers to the sample in the basic model, which we will describe in the results section. We choose to focus on this sample because it is the most relevant for the quantile regressions that we will present in what follows.

[28] An interactive version of this map is available at our Online Data Appendix. Please refer to: http://www.cmf.uzh.ch/penetrationdata.html.

Countries in both of these two lists have had a very high and stable microfinance market penetration in the last years. Interestingly, only one of these countries, Azerbaijan, is among those with the 10 highest growth rates in the period between 2007-2012, which are Ivory Coast, Turkey, China, Burundi, Iraq, Azerbaijan, Kazakhstan, Brazil, Argentina and Tunisia. This indicates that most of the countries with the highest microfinance penetration have reached a saturation level of penetration beyond which there are limited growth opportunities. The dynamics of microfinance market penetration across these different groups of countries are likely do be structurally different, and this is precisely what we will be able to examine in the next section with our Heckman and quantile regression approaches.

4.3 Explanatory Variables

Table 2 includes the descriptions and summary statistics of the variables that we consider in these specifications. These summary statistics are presented for the sample in which our *MF Penetration Index* is available between 2003 and 2012. As possible to see in Table 2, while our index is available for 2069 country years, all the variables of interest are available for a lower number of observations. This limits the sample that we can use for our estimation and reduces our degrees of freedom. Therefore, we select the variables with the most available observations and the best possible explanatory power for our basic model.

5 Results

In our basic model, we consider *GDP growth* and *GDP per capita* (USD thousands) as our *Income* variables. *Enabling Institutions* are captured with the *Depth of Credit Information* Index (*DBdepthcreditinfo*), which takes values from 0 to 6. Relevant barriers related to *Geography and Technology* are captured using *Population Density*, which represents hundreds of people per squared kilometer (*PopDenHun*). We use *Bank Branches* (per 100,000 adults) to capture *Formal Financial Development*. We also consider ILO estimates on *Employment* (*EmplILO*) to population ratio (%, ages 15-24 over total) as an important *Macroeconomic Environment* characteristic. *Knowledge* is represented by *Primary Years* of schooling.

5.1 Results of the Heckman Selection Approach

Table 3 presents our Heckman model using these variables. The first two columns consider all countries, while the last two columns exclude high-income countries. Columns 2 and 4 focus on the selection equation, showing the marginal effects resulting from the Probit model that estimates the probability of microfinance being present in a given country-year. Columns 1 and 3 take the resulting Mills ratio and estimate an OLS model on the determinants of microfinance market penetration. The results for market entry and market penetration are very similar for both samples, suggesting that the reduction of observations induced by excluding high-income countries does not bias our results.

We can see that having a higher income *Classification* (*classif*) by the World Bank reduces the probability to have microfinance in a given country-year, which is as expected. Also as expected, *GDP growth* increases the probability of microfinance market entry, while a higher *GDP per capita* reduces it, as well as does the level of education measured by *Primary Years* of schooling. The direction of the effect of these three variables is the same in the market entry phase and in the microfinance market penetration phase. However, the negative effect of *GDP per capita* is stronger in the market penetration phase.

In the Heckman specification in Table 3 , it is also possible to see that a higher *Depth of Credit Information* Index (0-6) increases both market entry and market penetration, but is more important during the penetration phase. *Formal Financial Development* measured with *Bank Branches* matters only in the penetration phase, suggesting that the complementarity between the formal financial system and the microfinance industry really develops as MFIs increase their presence in a particular market, and not before they enter it.

On the other hand, the *Employment* level has a positive and significant effect on the decision to enter a market. This shows that the level of employment in a given country is a good indicator of the potential clients that a MFI may have in that context. Indeed, even if MFIs mostly provide consumer loans and do not have a strong influence in the loans that SMEs need to increase their business, the level of employment is also an indicator of the level of credit-worthiness that potential borrowers may have, as it indicates how many available income sources are present in a given economy.

5.2 Results of the Quantile Regression Approach

While the Heckman specification is useful as a preliminary analysis, there might be important sources of bias in it, since we are not able to consistently include fixed effects due to the Probit performed in the first stage. We overcome this problem in our quantile regression approach. Indeed, in this approach we are able to introduce country fixed effects. We also include a dummy variable for the *Crisis* years between 2008 and 2010. This variable, as we discuss in the robustness checks section, performs similarly to conducting an estimation with year fixed effects, and helps us to preserve our degrees of freedom. With our quantile approach, we are also able to examine the heterogeneous effects of our explanatory variables across different stages of microfinance market penetration.

We start by considering all the countries in the sample in Table 4. We then exclude high-income countries and report the results in Table 5. In the first sample, *MF Penetration Index* starts being positive only in the 40th percentile, while in the second sample this happens already in the 20th percentile. The first sample includes high income countries where microfinance markets will never develop, thus they may introduce noise in the specification. Indeed, as we had argued before, in the lowest quantiles we will have countries such as Switzerland and Somalia, which are clearly very difficult to fit in any single meaningful regression.

We test the robustness of our results in the reduced sample by comparing the shape of the coefficient plots reported after each of the corresponding tables. These plots include the beta coefficient for each of the variables under consideration across different percentiles and the corresponding 95% confidence intervals. This comparison suggests that excluding high-income countries does not bias the results, as we already saw in the Heckman approach. *Population Density* is the only variable that behaves differently in the two samples, however it is insignificant in both.

5.2.1 Income

The first row of the Heckman estimation with high-income countries in Table 4 shows that *GDP growth* has a positive and significant effect across the entire distribution, which increases considerably in the 90th percentile. *GDP per capita*, on the other hand, has a negative and significant effect across all the distribution that gets stronger as *MF Penetration Rate* is higher. It is interesting to note that the coefficient of *GDP per capita* is always more significant and larger than that of *GDP growth*. This suggests that rather than responding to economic opportunities reflected in high *GDP growth*, microfinance markets develop the most where there are unmet needs, which are reflected in lower *GDP per capita* levels.

The effect of *GDP per capita* is stronger in countries with stronger microfinance market development. This heterogeneous effect across different stages of microfinance market development shows that as markets develop, MFIs may already have the tools that allow them to respond strongly to unmet needs, when compared with less developed markets, where more barriers to reach the poor may be in place. A similar interpretation is valid for the coefficients of *Primary Years* of schooling across different percentiles, however these are not significant.

In the sample without high-income economies, more interesting results emerge, as can be seen in Table 5. Indeed, once we focus on the countries where microfinance markets should and are more likely to develop, we take out noise in the specification coming from countries where MFIs will never go. Interestingly, in this specification in Table 5, *GDP growth* becomes insignificant. Once high-income economies with relatively low growth rates are taken out of the sample, the high growth rates of developing countries are no longer perceived in the estimation as a differentiating factor of countries where microfinance has a high penetration. These findings compare with those of Ahlin et al. (2011), who do not find significant effects of real GDP growth on a MFI-level measure of borrower growth.

On the contrary, the coefficients of *GDP per capita* become much larger with respect to the ones achieved using the full sample. Once the noise introduced by high-income countries is cancelled out, this variable becomes more important in explaining the variation of microfinance market penetration across different countries. In particular, while in the 10th percentile a reduction of *GDP per capita* of 1,000 USD increases *MF Penetration Rate* by 0.5 percentage points, in the 90th percentile it increases *MF Penetration Rate* by 1.2 percentage points.

5.2.2 Enabling Institutions

Our main measure of *Enabling Institutions*, i.e. *Depth of Credit Information* (*DBdepthcreditinfo*), has a positive and increasing effect as microfinance markets develop. This suggests that *Enabling Institutions* are increasingly more important as microfinance market penetration increases. This may be due to increasing complexity of microfinance services, which may require better support from the existing range of *Enabling Institutions.* This is in line with the findings of Assefa et al. (2013) suggesting that credit information sharing among lenders could have a positive effect on microfinance.

Similar to our *Income* indicators, *Depth of Credit Information* is not significant in the full sample and it becomes significant once high-income countries are excluded. In particular, *Depth of Credit Information* is significant in Table 5 in the 10th, 20th and 30th percentiles, and in the 70th, 80th and 90th percentiles, i.e. the extremes of the distribution. This is an interesting finding as it confirms the intuition that better enabling *Institutions* are important both for MFIs choosing markets to enter, and for MFIs expanding in already penetrated markets, where there might be a higher financial complexity in the microfinance subsegment, for example due to multiple borrowing, cross-borrowing and risk of over-indebtedness.

The change in the magnitude of this effect across different levels of microfinance market development suggests also that enabling *Enabling Institutions* are key to help MFIs deal with the increasing complexity of the market. Indeed, according to our basic sample results in Table 5, an increase in the Doing Business *Credit Information Depth* index (0-6) of one unit increases *MF Penetration Rate* by 0.2 to 0.3 percentage points in the lowest percentiles where *MF penetration Rate* is between 0.0% and 0.54%; and by 0.7 to 1.1 percentage points in the highest percentiles where *MF penetration Rate* is between 8.65% and 31.74%.

These findings are complemented with those from Table 6, which considers additional measures to capture the effect of *Enabling Institutions* in the quantile approach. It is possible to see that the strength of *Legal Rights* Index (*DBlegalrights*), with values from 0 to 10, the *Private Bureau* (*DBprivatebureau*) coverage (% of adults), and the *Public Registry* (*DBpublicregistry*) coverage (% of adults) have a positive and increasing effect as microfinance markets develop.

Interestingly, *Legal Rights* and *Public Registry* are only significant in the highest levels of the *MF Penetration Rate* distribution, while the overall index of *Depth of Credit Information* (*DB-depthcreditinfo*) is only significant in the lowest levels of the distribution. As we explained in the description of our variables, this index encompasses several indicators on the quality of the credit information institutions available in a given country. The importance of such an overall indicator at the lowest percentiles of *MF Penetration Rate* suggests that when MFIs decide to enter a market they care mostly about generic indicators of the country's *Enabling Institutions*.

On the other hand, the importance of *Legal Rights* and *Public Registry* at higher percentiles of *MF Penetration Rate* suggests that MFIs become more concerned with specific institutional settings as markets become more complex, as we have discussed above. It is possible to argue that

Public Registries are more important than *Private Bureaus* at these stages of market development because with these public institutions, MFIs can more easily make sure that it is possible to enforce credit information sharing. Indeed, this may not be possible in the case of private credit information agencies. This suggests that in more complex markets, MFIs should have access to all relevant credit information.

It is also very interesting to note that the coefficient of *Credit Information Depth* in the second stage of the Heckman approach was much higher than any of the coefficients that we estimate in our quantile regression. Indeed, according to the Heckman results of Table 3, an increase in the Doing Business *Credit Information Depth* index (0-6) of one unit increases the probability of having microfinance in the first place by 24-26%, and our *MF Penetration Rate* by 3.6 to 3.8 percentage points. This last figure compares to a quantile estimation of 1.1 percentage points in the 90th percentile of the distribution, and lower figures in the other percentiles.

This confirms the hypothesis that as *MF Penetration Rate* increases, MFIs are in a better position to lobby and achieve a better regulatory environment. As we have explained before, this implies that $cov(\mathit{Enabling\ Institutions}, u) > \mathit{0}$. This implies that an OLS estimation of $\beta_{\widehat{\mathit{Enabling\ Institutions}}}$ would be biased upwards, overestimating the effect that *Enabling Institutions* have on microfinance market development.

Thus, previous studies using this technique may have over-estimated this effect. We are able to address this issue in our quantile regression approach. Indeed, the fact that the highest quantile coefficient for *Credit Information Depth* is lower than the OLS one from the Heckman procedure suggests that this potential upward bias is reduced in the quantile regression approach. This is achieved because this approach considers the heterogeneity of the effect across different stages of microfinance market development.

5.2.3 Formal Financial Development

We also had endogeneity concerns regarding $cov(\mathit{Formal\ Financial\ Development}, u) > \mathit{0}$. However, the difference between the Heckman and the quantile coefficients for *Bank Branches* (per 100,000 adults) is not as dramatic in this case. Indeed, according to the Heckman results reported in Table 3, an increase of *Bank Branches* by 10 units, which corresponds to half of a standard deviation, increases *MF Penetration Index* by 2.8 percentage points. The quantile results in Table 5 show an effect between 1.7 to 3.1 percentage points, depending on the level of microfinance market development. The small difference between these two estimators shows that the potential concern of reverse causation due to microfinance markets crowding-in or out formal financial markets does not seem to have empirical support.

Similar to *Income* and *Enabling Institutions* indicators, our *Formal Financial Development* indicator is also not significant in the full sample, but becomes significant once high-income countries are taken out. The positive sign of *Bank Branches* across all quantiles of the distribution in Table 5 suggests a strong complementarity between the formal market and the microfinance market. This indicates that MFIs find it easier to penetrate markets where there is already some financial infrastructure available. Formal providers do not constitute a direct competition to MFIs, typically because their target markets are different. This is confirmed when we examine other indicators of *Formal Financial Development* in Tables 7 and 8.

Table 7 includes characteristics that may shape the *Formal Financial Development* in a given country year, such as the GFDD Boone indicator of *Competition* (*bcompetition*), the degree of bank *Concentration*, bank's *Net interest margin* (*netinterestmg*), and banks' *Non Rate Income* (*nonrincome*). We find that none of these variables play an important role in microfinance market development, confirming the hypothesis that formal providers are not direct competitors of MFIs. The only exception is the *Non Rate Income*, which is weakly significant and negative.

In Table 8, besides considering the effect that more commercial *Bank Branches* (per 100,000 adults) may have on *MF Penetration Rate*, we also consider the effect that automated teller machines *ATM* (per 100,000 adults) may have. Both effects are positive and increasing in the highest quantiles, but only that of *Bank Branches* is significant. Indeed, in developing economies, the amount of transactions that can be done at *ATMs* tends to be lower than the amount of transactions that are usually performed in physical offices, often due to bureaucracy or security concerns.

Another important indicator of *Formal Financial Development* is the *Domestic Credit* provided by the financial sector (% of GDP). This variable is positive and significant only at the highest levels of microfinance penetration. Indeed, this variable relates to the macroeconomic financial complexity of a country, and can be more important in those countries where the microfinance segment is more complex. This variable was also studied in Hermes et al. (2009), finding a positive influence on microfinance efficency.

Finally, we consider received *Remittances* (% of GDP) as an indicator of *Formal Financial*

Development. *Remittances* are very important in developing countries and affect the need for microfinance services that the poor have, as they directly impact their available income. Interestingly, we find that there is a positive and significant effect at the lowest levels of microfinance market penetration, and a negative and insignificant one at higher levels of microfinance market penetration.

The positive and significant effect when microfinance penetration is low suggests that *Remittances* are a complement and not a substitute of microfinance markets when they are starting to develop. It is possible to think that at lower stages of microfinance market development, *Remittances* act in the same way as more formal sources of finance would do in higher stages of market development. Both sources of financial resources, i.e. *Remittances* as an informal source, and other more formal sources from the financial markets, such as *Bank Branches* and *ATMs*, as we saw before, act as complements for microfinance. The first one is important when microfinance markets are starting to develop. The second one is relevant once they mature.

5.2.4 Geography and Technology

Barriers relating to *Geography and Technology* are considered in more detail in Table 9. The share of *Rural Population* has a positive and significant effect only for those country-years with a *MF Penetration Index* close to the median of the distribution. This suggests that in countries in which penetration is not very low or very high, having a higher rural population helps microfinance market development, implying that only at this stage of market development, MFIs may find it easier to reach rural clients.

Mobile Phones subscriptions (per 100 people) and *Internet Users* (per 100 people) have a positive and increasing effect on microfinance penetration across different stages of market development. In particular, both these variables are significant in the 70th, 80th and 90th percentiles of the distribution. This suggests that in more developed markets, information technologies may play a more important role than in less developed markets.

It is very interesting to see that *Mobile Phones* subscriptions also have a significant effect in the 20th and 30th percentile. This relates nicely with the developments in e-money solutions that use different mobile technologies to increase financial inclusion at the bottom of the pyramid. It suggest that these technologies can be important enablers in the early stages of market development, as they can help MFIs overcome potential geographical constraints and transaction costs that may limit their ability to reach the poor with affordable services.

5.2.5 Macroeconomic Environment

Our main measure of *Macroeconomic Environment*, i.e. *Employment*, has high explanatory power at market entry and in the lowest percentiles of *MF Penetration Rate*. This means that this indicator is important at the market entry stages, as we expected. Indeed, this indicator reflects the available income and creditworthiness of potential microfinance clients.

We also explore if alternative *Macroeconomic Environment* indicators have an important role. In particular, in Table 10, we consider the growth of the CPI *Inflation* with respect of the previous year (*GInflation*). We expect this variable to capture which markets are more unstable than others, and thus to negatively affect microfinance penetration. However, we find no significant coefficients across any of the percentiles of *MF Penetration Rate*.

Another important *Macroeconomic Environment* indicator is the exchange rate *FX*. We include the growth of this variable with respect to the previous year (*GFX*). *FX* is defined as local currency units (LCU) per USD. Thus, an increase in *GFX* would indicate a depreciation. We would expect that MFIs operating in countries with depreciating currencies would find it harder to fund their operations, as MFIs' debt is generally denominated in hard currencies. However, we find no statistically significant relationship in this case.

We examine the role of *Net official development assistance and official aid received* (constant 2011, USD) on microfinance market development. We consider the growth of these net inflows with respect to the previous year (*GOdaAid*). We would expect this variable to play a more important role at the market entry stage, as some MFIs could finance their initial operations in under-developed markets using aid. However, we also find in this case no statistically significant relationship.

We also examined if the level of these variables, i.e. *Inflation*, *FX*, and *Net official development assistance and official aid received*, could play a significant role, but found no such empirical evidence. Also, the variance of these variables for the last 5 years was found to be insignificant. This suggests that besides macroeconomic factors that may influence the ability that MFIs have to find funding to their operations, other factors, such as the ones we discussed above, play a more important role. This is somewhat in line with the results of Vanroos and D'Espallier (2009), althought they find a significant effect of inflation on MFIs' outreach.

We also examine the role of different *Interest Rates* on microfinance market development. In particular, in Table 11, we considered the role of the lending rate (*LendingRate*), deposit rate (*DepositRate*), and real rate (*RealRate*). Interestingly, we find no significant relationship between microfinance market development and any of these *Interest Rates*. This suggests a decoupling of microfinance prices from those of the overall financial market.

Our dummy variable for the global financial *Crisis* is the only macroeconomic indicator that has a significant effect. Indeed, this variable presents a positive and significant effect. This effect is more important at market entry, in the lowest percentiles of *MF Penetration Rate*. This offers support to some studies suggesting that during the global financial *Crisis* microfinance was an interesting diversification opportunity for investors (Krauss and Walter, 2008) and as MFIs become more commercialized they are more affected by global financial markets (Wagner and Winkler, 2013). Interestingly, this effect is the strongest in the least penetrated markets because these are the most decoupled from the global financial markets, and thus the ones offering the highest diversification potential.

5.2.6 Knowledge

In our baseline specification, our main *Knowledge* indicator is the average *Primary Years* of schooling of the overall population. When the whole sample is considered this variable is insignificant. It becomes significant when we exclude high-income countries and reduce the noise of the specification. In particular, a higher average of *Primary Years* in a given country year has a negative impact on microfinance market development. Such negative impact gets stronger as microfinance markets develop. Similar to *GDPpc*, a low average *Primary Years* is related to important development needs, and our results indicate that MFIs tend to enter those markets where these needs are more important, and are better placed to respond to those needs in markets that already have some microfinance market structure in place.

We consider different measures of *Knowledge* in Table 12 to explore this in more detail. We include *Secondary Years* of schooling, *Primary* completion rate for the total population (% of relevant group) and of the female population *Primary Female*, as well as *Lower Secondary* completion rate for the total population (% of relevant group) and of the female population *Lower Secondary Female*. However, when we consider all these variables, the effect that we captured before is blurred.

This may be because MFIs need some human capital in order to reach the poor, but also tend to go where human capital is the lowest and there are higher development needs. Our results suggest that it is hard to disentangle these two effects from each other.

6 Robustness Checks

6.1 Lags

In order to address potential endogeneity concerns even further, we propose to consider the lagged values of our measures of *Enabling Institutions* and *Formal Financial Development*. In particular, we consider a one year lag for *Depth of Credit Information* (*lDBdepthcreditinfo*) and *Bank Branches* (*lBankBranches*). Table 13 shows the Heckman results, and Table 18 shows the quantile results. The Heckman results are very similar to the ones without lagged values presented in Table 3. The quantile results are also very similar to the ones without lagged values presented in Table 5. This confirms the robustness of our results.

6.2 Country Groups

In the sections above, we discussed that the complementarity or substitutability between microfinance and formal financial inclusion could depend on the similarities or differences between the complexity of the microfinance market segment and the complexity of the overal financial market. In particular, we argued that in group 1 and 2 countries, where complexity in the microfinance segment is similar to the overall financial market complexity, it is more likely to find a complementary relationship between microfinance development and formal financial inclusion. On the contrary, in group 3 and 4 countries, a substitution effect may be more plausible.

We examine this issue further by including dummies for *group 2* (low complexity in the microfinance segment and in the overall market) , *group3* (high complexity in the microfinance segment and low in the overall market) and *group 4* (low complexity in the microfinance segment and high in the overall market), as well as their interactions with *Bank Branches* (*BankBranches2*, *BankBranches3*, and *BankBranches4*). We exclude group 1, which represents countries with high complexity both in the microfinance segment and in the overall market, in order to avoid multicollinearity issues.

The Heckman results are presented in Table 14. The results of column (2) and (4) suggest that the marginal effect of increasing the number of *Bank Branches* at the market entry stage is still not significant, as we have found in Table 3, where no interactions are included. The results of column (1) and (3) suggest that the marginal effect of increasing the number of *Bank Branches* at the market penetration stage is positive and significant, indicating complementarity, as we have found in Table 3, where no interactions are included. This confirms the robustness of our result indicating a complementarity between microfinance and the formal financial market.

Interestingly, the marginal effect of increasing the number of *Bank Branches* at the market penetration stage increases when countries belong to *group 2*, as *BankBranches2* is significant and positive. These countries, with low complexity both in the microfinance segment and the overall market, could be countries where many institutions are un-regulated and where financial markets overall are not very well developed. Our Heckman results indicate that MFIs find important synergies and collaborations with formal financial institutions in those countries in particular. However, this result is no longer significant in the quantile approach with group interactions presented in Table 18.

It is also interesting to see that in our Heckman approach of Table 14, *BankBranches4* has a negative sign. This is also true in some of the percentiles of the quantile approach in Table 18. This indicates that in these countries, with low complexity in the microfinance segment and high complexity in the overall market, there might be a slight substitution effect between microfinance and formal financial inclusion, as we had anticipated. This would indicate that in these countries, MFIs would find it harder to create synergies with the formal financial sector. It also suggests that there might be a threshold level of microfinance market development after which it is easier for MFIs to create synergies with formal institutions. However, this effect is not significant and thus cannot be considered as a strong determinant of *MF Penetration Rate*.

6.3 Outliers

We also consider if our results would change when we disregard the outliers that we identified when comparing *MIX* data with *Findex* and *FAS*, as described in our Data Appendix. The results are shown in Table 15 for the Heckman Model and in Table 20 for the quantile approach. Our results are robust in both cases.

6.4 Replacing Missing Values Using Other *MIX* Data

There is an important amount of missing observations in the *MIX* dataset in the number of active borrowers that MFIs report, i.e. $MFI\ Borrowers_{j,i,t}$ for MFI j in country i and year t. Between 1995 and 2013, 10% of MFIs did not report any information on their number of active borrowers. Nevertheless, this information can be constructed using other available *MIX* data. In particular, for the institutions that do not report their number of active borrowers but report their gross loan portfolio, we can consider the country average of MFIs' average loan balance and calculate the following proxy:

$$MFI\ Borrowers\ Proxy\ 1_{j,i,t} = \frac{Gross\ Loan\ Portfolio_{j,i,t}}{Average\ Loan\ Balance_{i,t}} \tag{7}$$

Replacing missing observations in the original dataset with proxy 1 reduces the number of institutions with no information on their number of active borrowers from 10% to 3%. Moreover, for the institutions that do not report their gross loan portfolio, we can consider the country average of both the MFIs' gross loan portfolio and their average loan balance to calculate the following proxy:

$$MFI\ Borrowers\ Proxy\ 2_{j,i,t} = \frac{Gross\ Loan\ Portfolio_{i,t}}{Average\ Loan\ Balance_{i,t}} \tag{8}$$

Replacing missing observations in the original dataset with proxies 1 and 2 reduces the number of institutions with no information on their number of active borrowers from 10% to 0.5%.

We use *MFI Borrowers Proxy 1* and *MFI Borrowers Proxy 2* and re-run our results in Tables 16 and 17 for the Heckman approach, and in Tables 21 and 22 for the quantile approach. Also in this case, our results are robust.

6.5 Year Fixed Effects and *Crisis* Dummy

As we have argued, performing fixed year effects or using a dummy for the years of the global financial *Crisis* in our sample performs very similarly. Table 23 shows a simple OLS estimation in which this can be seen. Column (2) shows the results with year fixed effects, while column (3) shows the results when using the *Crisis* dummy instead. All the coefficients behave very similarly, and in the third column we preserve the degrees of freedom in our estimation. Thus we use our *Crisis* dummy in our analysis.

7 Conclusions

Half the world is still unbanked. This lack of financial inclusion affects disproportionately the bottom of the pyramid. Until now, the data to understand how to include the poorer segments of the population in financial markets has been lacking. We use microfinance data to provide this information. In particular, we consider the methodology proposed by Krauss et al. (2012) to calculate an index of microfinance market penetration *MF Penetration Rate*, considering the total number of microfinance borrowers as a share of working age population below the national poverty line. We provide this index for 109 countries around the world during the last decade in an Online Data Appendix[29], together with a detailed comparison with the best proxies from the currently available *Findex* and *FAS* datasets.

We use a quantile regression approach with fixed effects to understand the dynamics of our *MF Penetration Rate*. This methodology has several advantages: 1) It accounts for the dynamic and heterogeneous impacts that key drivers of microfinance market penetration have across different stages of market development. 2) It correctly acknowledges the non-normality of our variable of interest and helps us better understand the outliers in the sample. 3) It allows us to address potential endogeneity concerns. By using our panel dataset on microfinance market penetration and the quantile regression methodology, we are able to contribute to the literature with a more precise and robust understanding on the key drivers and dynamics of microfinance penetration across different stages of market development.

Our findings indicate that microfinance institutions (MFIs) are more responsive to the needs of the bottom of the pyramid, reflected in lower *GDP per capita* and lower *Primary Years* of schooling, than to potential growth opportunities reflected in higher *GDP growth*. The ability that MFIs have to respond to these needs is higher once microfinance markets are more mature, and a relevant market infrastructure is already in place. However, the overall level of *Employment* in the economy is a criterion that MFIs consider both at market entry and at higher market penetration stages.

Our results also indicate that at market entry, overall indicators of credit information quality are very important. At higher levels of microfinance market development, a more refined institutional setting must be in place to help MFIs deal with increasing levels of complexity, which could be due

[29] Please refer to: http://www.cmf.uzh.ch/penetrationdata.html.

to multiple and cross-borrowing and could imply a risk of over-indebtedneess. Interestingly, while *Public Registry* coverage is significant at high levels of microfinance market development, *Private Bureau* coverage is not. With the public institutions, MFIs may find more chances to enforce credit information sharing, which may not be possible in the case of the private credit information agencies.

We also find that financial development, both informal and formal, is a complement of and not a substitute for microfinance development. At market entry and the lower levels of market penetration, received *Remittances* (% of GDP) act as a complement for microfinance development. At higher levels of market development, Bank Branches (per 100,000 adults) play the same role. Our results indicate that MFIs find important synergies and collaborations with other financial institutions particularly in countries with low complexity both in the microfinance segment and the overall market. These could be countries where many institutions are un-regulated and where financial markets overall are not very well developed. On the contrary, in countries with low complexity in the microfinance segment and high complexity in the overall financial market, there is a statistically insignificant substitution effect between microfinance and formal financial inclusion. This suggests that there might be a threshold level of microfinance market development after which it is easier for MFIs to create synergies with other financial institutions.

We consider indicators of the competition and concentration in the formal financial sector and find no statistically significant relationship with microfinance market development. Similarly, factors such as inflation, FX, and aid inflows are not important determinants of microfinance market development. We also consider different interest rates (deposit, lending and real) of the formal financial sector and find no significant relationship. This suggests a decoupling of the microfinance market prices from the overal financial market prices, and constitutes an interesting research avenue for further studies. Indeed, it would be important to detemine to what extent microfinance prices respond to costs, value added services and risks, or if they are more driven by market power. It would also be important to better understand how exactly microfinance prices have managed to decouple from the overall financial system prices.

We also find that technologies can help to overcome market entry barriers, in particular, *Mobile Phones* subscriptions. This suggests that e-money solutions can be important enablers in the early stages of market development, as they can help MFIs overcome potential geographical constraints and transaction costs that may limit their ability to reach the poor with affordable services. At higher levels of market development, *Mobile Phones* subscriptions and *Internet Users* are also important. This suggests that technologies enable MFIs to have a more timely relationship with their customers, which may be crucial as markets mature and become more complex.

The detailed insights provided in this paper are specific for different stages of microfinance market development and can better guide policymarkers and investors to prioritize their efforts in a particular context to increase financial inclusion at the bottom of the pyramid. Our robust specification is able to address potential endogeneity concerns. This is very important to guarantee that these efforts are focused on the key causal drivers of microfinance market development, and not only on those factors that may have a high correlation but play no causal role. Our findings are also important for other industries reaching the poor with products, services and opportunities in commercially viable ways. Using the rich and widely available microfinance data, our results can guide industries for which less comparable information is available. In particular, our findings can shed light on which are the most important barriers to scale-up other inclusive innovations, and how they evolve across different stages of market development.

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8 *MF Penetration Rate*

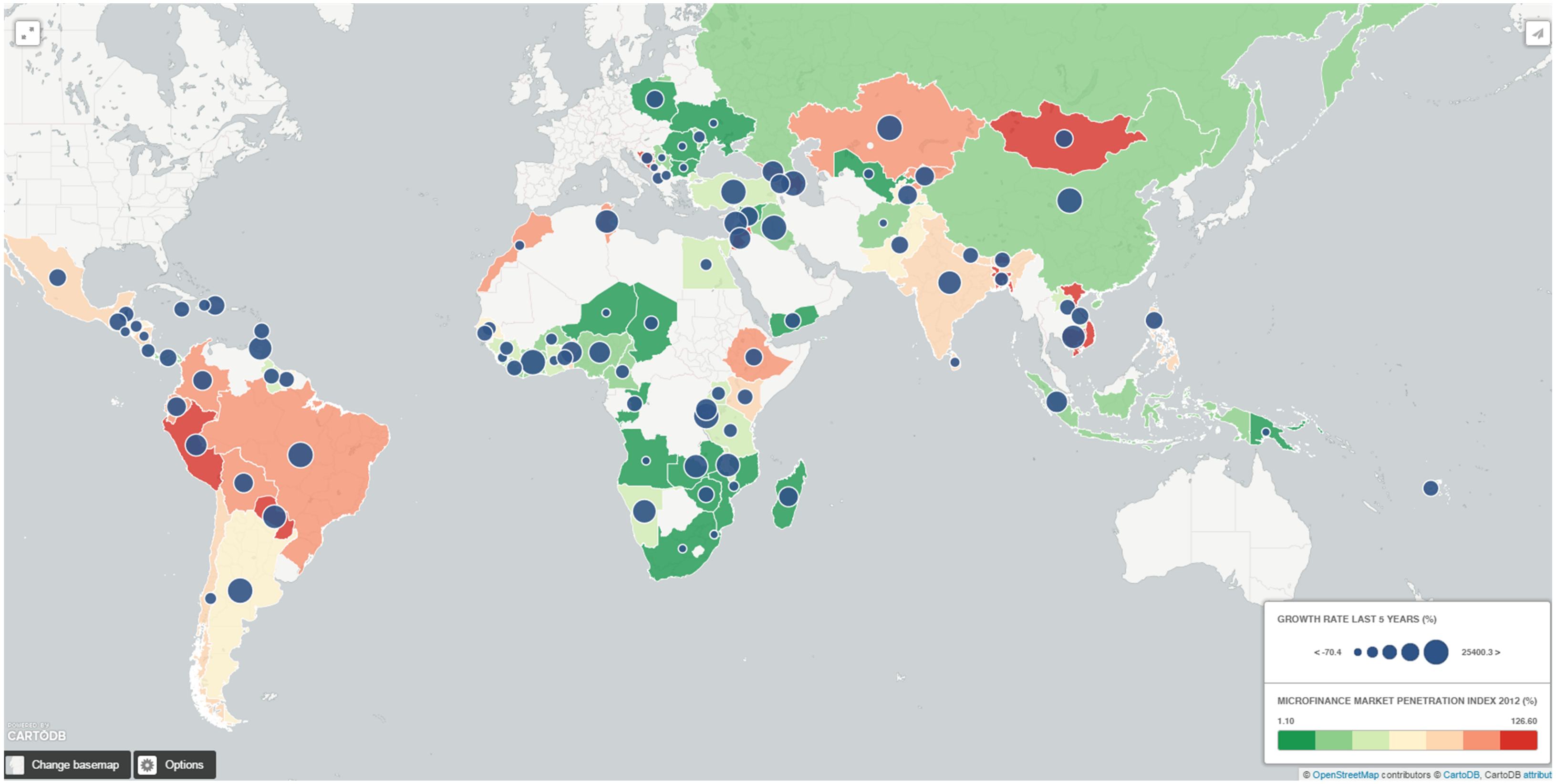
Table 1: **MF Penetration Index, 2012**

		MF Penetration Index		
Ranking	Country	2012	CAGR 5y	Average 5y
1	Azerbaijan	126.6	41.6	52.6
2	Cambodia	81.4	31.0	49.0
3	Paraguay	74.5	28.1	27.2
4	Peru	73.6	17.0	49.6
5	Vietnam	71.0	7.5	59.1
6	Mongolia	64.3	4.8	55.0
7	Bangladesh	62.1	-0.4	63.4
8	Bhutan	56.1		16.8
9	Bosnia and Herzegovina	49.8	-8.1	71.4
10	Jordan	47.7	18.1	30.4
11	Georgia	47.1	17.5	25.7
12	Bolivia	39.3	11.4	28.8
13	Ecuador	35.8	13.7	23.7
14	Armenia	35.5	12.9	35.2
15	Morocco	34.8	-14.1	54.2
16	Montenegro	34.8	-23.3	
17	Kyrgyzstan	29.4	13.0	26.3
18	Kazakhstan	28.0	39.9	8.5
19	Colombia	23.7	10.7	17.9
20	Brazil	19.1	39.0	7.2
21	Ethiopia	18.1	9.4	9.4
22	Tunisia	18.0	35.8	9.5
23	Philippines	17.9	6.4	18.0
24	Nicaragua	17.4	-12.1	26.5
25	Albania	16.6	-4.6	30.5

		MF Penetration Index		
Ranking	Country	2012	CAGR 5y	Average 5y
26	Sri Lanka	15.8	-14.9	57.3
27	Nepal	15.8	4.2	17.1
28	India	15.5	33.6	8.8
29	Benin	15.2	16.3	10.1
30	Mexico	14.8	5.2	13.6
31	Chile	14.7	-5.9	14.7
32	Dominican Republic	11.8	14.6	10.7
33	Kenya	11.2	2.8	11.9
34	Jamaica	10.7		3.9
35	Pakistan	10.3	7.6	8.8
36	Guatemala	9.5	6.2	7.5
37	El Salvador	9.0	-9.7	12.5
38	Tajikistan	8.6	13.9	5.5
39	Argentina	7.8	36.0	6.2
40	Suriname	7.8		2.2
41	Senegal	7.1	-0.6	8.3
42	Honduras	6.1	-6.0	7.2
43	East Timor	5.8	0.6	5.4
44	Lebanon	5.7	20.1	4.1
45	Togo	5.0	1.9	5.1
46	Trinidad and Tobago	4.8	23.7	1.2
47	Ghana	4.7	-11.0	8.1
48	Uganda	4.7	-3.2	8.0
49	Turkey	4.6	147.2	1.5
50	Guyana	4.5		1.9
51	Egypt	4.5	-9.5	8.4
52	Saint Lucia	4.4		0.0
53	Malawi	4.0	19.2	3.4
54	Tanzania	3.9	-0.5	4.6
55	Palestine	3.3	-2.1	6.3
56	Namibia	3.3	35.6	0.4
57	Macedonia	3.2	-21.4	9.5
58	Rwanda	2.9	14.9	2.2
59	Burundi	2.9	52.4	1.1
60	Laos	2.9		0.6
61	Guinea	2.9	-3.4	2.4
62	Nigeria	2.6	17.8	2.8
63	Cameroon	2.5	-0.8	3.8
64	Panama	2.5	4.3	3.0
65	Serbia	2.5	-26.4	8.8

		MF Penetration Index		
Ranking	Country	2012	CAGR 5y	Average 5y
66	Burkina Faso	2.5	-8.7	4.8
67	Haiti	2.4	-3.8	3.1
68	Afghanistan	2.2	-23.1	5.8
69	Costa Rica	2.1	-1.7	3.1
70	Indonesia	2.1	18.1	5.4
71	Ivory Coast	1.9	202.9	1.0
72	Moldova	1.7	-9.2	3.4
73	Liberia	1.6		1.4
74	Fiji	1.4		0.3
75	Sierra Leone	1.3	-14.7	2.2
76	Russia	1.3	2.2	1.0
77	Iraq	1.2	52.4	1.2
78	China, People's Republic of	1.2	74.8	2.1
79	Zambia	1.1	22.0	0.5
80	Madagascar	1.0	14.8	0.9
81	Uzbekistan	0.9	-12.0	2.5
82	Syria	0.7	10.6	0.4
83	Congo, Democratic Republic of the	0.6	18.1	0.4
84	Yemen	0.6	1.5	0.9
85	Chad	0.5	-1.6	0.6
86	Congo, Republic of the	0.5		2.6
87	South Sudan	0.5	2.5	0.4
88	Romania	0.5	-21.6	1.5
89	Poland	0.5	5.7	0.3
90	Mozambique	0.4	-17.5	1.0
91	Niger	0.4	-30.2	1.8
92	Zimbabwe	0.4		0.1
93	Bulgaria	0.3	-46.4	4.5
94	Gambia, The	0.2	2.6	2.4
95	Papua New Guinea	0.1	-29.1	0.5
96	South Africa	0.1	-61.9	6.5
97	Ukraine	0.0	-50.8	1.3
98	Angola	0.0	-100.0	0.3
99	Belize	0.0		8.1
100	Swaziland	0.0	-100.0	1.5

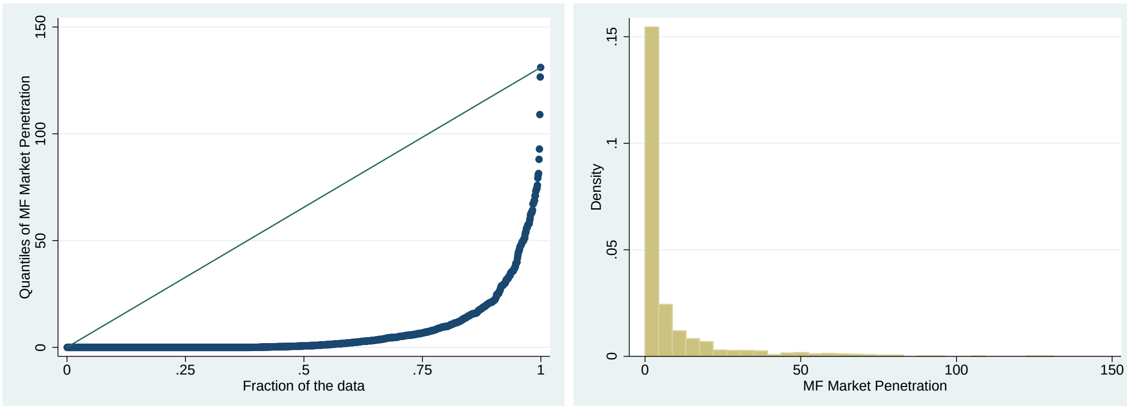
Figure 1: **MFI Penetration Rate and Growth in the Last 5 Years**



(a) Interactive map available at http://www.cmf.uzh.ch/penetrationdata.html.

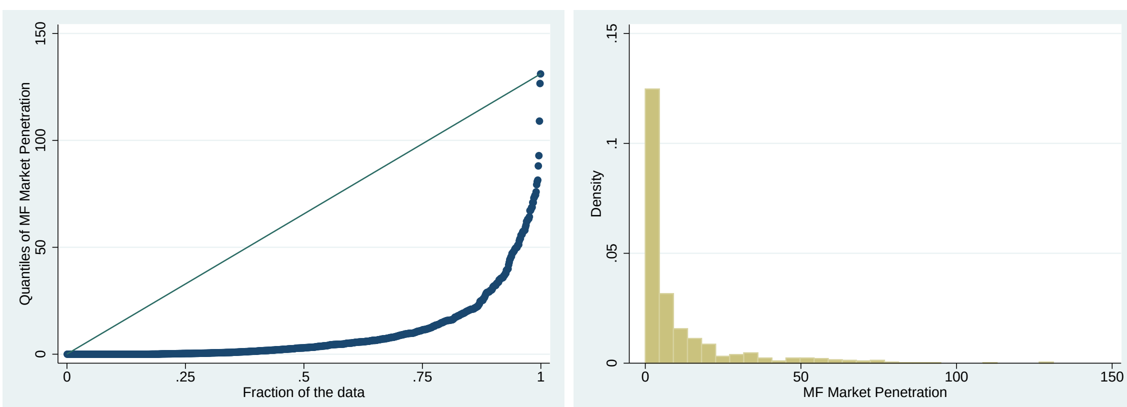
9 Summary Statistics

Figure 2: **MFI Penetration Rate - Basic Model Sample**



All Countries

p10	p20	p30	p40	p50	p60	p70	p80	p90
0.00	0.00	0.00	0.05	0.69	2.20	4.95	9.79	21.80



Without High Income Countries

p10	p20	p30	p40	p50	p60	p70	p80	p90
0.00	0.13	0.54	1.45	2.96	5.23	8.65	15.54	31.74

Table 2: **Description of the variables and Summary Statistics**

Description of the variables

MF Penetration Rate	Share of microfinance borrowers, % of the working age population (age 15+) under the national poverty line	MIX and WDI
Income		
GDPgrowth	*GDP growth* (annual %)	WDI
GDPpcTh	*GDP per capita* (constant 2005 USD, thousands)	WDI
classif	*Income Classification*	World Bank
Enabling Institutions		
DBdepthcreditinfo	*Depth of Credit Information* Index (0-6)	Doing Business
DBlegalrights	Strength of *Legal Rights* Index (0-10)	Doing Business
DBprivatebureau	*Private Bureau* Coverage (% of adults)	Doing Business
DBpublicregistry	*Public Registry* Coverage (% of adults)	Doing Business
Geography and Technology		
PopDenHun	*Population Density* (people per sq. km of land area, hundreds)	WDI
RurPop	*Rural Population* (% of total population)	WDI
MobilePhones	*Mobile Phones* subscriptions (per 100 people)	WDI
InternetUsers	*Internet Users* (per 100 people)	WDI
Formal Financial Development		
BankBranches	*Bank Branches* (per 100,000 adults)	WDI
ATM	*ATM* (per 100,000 adults)	WDI
RemitReceivedGDP	Personal Received *Remittances* (% of GDP)	WDI
DomCreditByFin	*Domestic Credit* provided by the financial sector (% of GDP)	WDI
Formal Financial Market Characteristics		
netinterestmg	Banks' *Net interest margin*	GFDD
nonrincome	Banks' *Non Rate Income*	GFDD
concentration	Degree of bank *Concentration*	GFDD
bcompetition	Boone indicator of *Competition*	GFDD
Macroeconomic Environment		
EmplILO	*Employment* to population ratio (%, ages 15-24 over total, ILO)	WDI
GInflation	Growth of consumer prices *Inflation* (annual %)	WDI
GFX	Growth of official exchange rate *FX* (LCU per US$, period average)	WDI
GOdaAid	Growth of *Net official development assistance and official aid received* (constant 2011 US$)	WDI
Interest Rates		
DepositRate	*Deposit Interest Rate* (%)	WDI
LendingRate	*Lending Interest Rate* (%)	WDI
RealRate	*Real Interest Rate* (%)	WDI
Knowledge		
PrimaryYears	*Primary Years* of education	WDI
Primary	*Primary* completion rate, total (% of relevant age group)	WDI
PrimaryFemale	*Primary* completion rate, female (% of relevant age group)	WDI
LowerSecondary	*Lower Secondary* completion rate, total (% of relevant age group)	WDI
LowerSecondaryFemale	*Lower Secondary* completion rate, female (% of relevant age group)	WDI
SecondaryYears	*Secondary Years* of education	WDI

Summary Statistics

	N	Mean	Sd	P10	P25	P50	P75	P90	Min	Max
MF Penetration Index	2'069	4.9	12.5	0.0	0.0	0.0	3.6	14.7	0.0	131.1
Income										
GDPgrowth	1'882	4.3	5.9	-1.0	1.9	4.2	6.7	9.1	-62.1	104.5
GDPpcTh	1'868	11.6	18.4	0.4	0.9	3.4	14.2	36.5	0.1	158.8
classif	2'006	2.6	1.1	1.0	2.0	3.0	4.0	4.0	1.0	4.0
Inequality										
Gini	353	42.2	9.1	30.9	34.8	41.1	49.0	55.2	24.2	67.4
IncShSecond20	351	10	2	7	8	10	12	13	4	15
IncShThird20	351	14.5	2.1	11.5	13.1	14.8	16.1	17.0	7.1	18.7
IncShFourth20	351	21.1	1.5	19.0	20.3	21.4	22.2	22.5	12.7	23.4
IncShHigh20	352	48.6	7.4	39.5	42.8	47.2	53.8	59.4	33.7	72.2
IncShHigh10	352	33.1	7.1	24.9	27.7	31.8	38.0	43.3	19.5	60.2
IncShLow10	352	2.3	1.0	0.8	1.4	2.4	3.2	3.6	0.3	4.4
IncShLow20	352	5.8	2.1	2.8	3.9	6.0	7.7	8.6	1.5	9.9
Institutions										
DBdepthcreditinfo	1'365	2.9	2.2	0.0	0.0	3.0	5.0	6.0	0.0	6.0
DBlegalrights	1'365	5.3	2.5	3.0	3.0	5.0	7.0	9.0	0.0	10.0
DBprivatebureau	1'365	20.2	32.0	0.0	0.0	0.0	32.9	78.7	0.0	100
DBpublicregistry	1'365	5.6	12.8	0.0	0.0	0.0	3.1	20.5	0.0	100.0
Geography and Technology										
PopDenHun	2'059	3.9	18.6	0.1	0.3	0.8	2.0	4.2	0.0	198.9
RurPop	2'029	42.7	24.2	8.7	23.2	42.3	62.7	77.3	0.0	91.1
MobilePhones	1'948	68.1	46.6	6.3	25.8	67.0	102.8	126.4	0.0	289.8
InternetUsers	1'924	28.1	26.6	1.1	4.6	19.7	47.7	70.0	0.0	96.2
Formal Financial Development										
BankBranches	1'469	18.7	19.6	1.9	4.6	13.0	24.5	40.4	0.1	126.1
ATM	1'343	39.6	43.6	1.1	5.4	27.4	56.7	99.5	0.0	282.5
RemitReceivedGDP	1'534	4.5	7.0	0.1	0.4	1.7	5.3	13.9	0.0	57.5
DomCreditByFin	1'691	62.9	60.8	8.1	19.9	46.2	90.6	146.3	-114.7	349.0
Formal Financial Market Characteristics										
netinterestmg	1'529	4.8	3.0	1.4	2.6	4.3	6.4	8.8	0.0	20.5
nonrincome	1'548	39.2	14.6	22.8	29.1	37.7	47.7	58.9	0.0	95.7
concentration	1'331	71.5	19.3	45.0	56.6	72.1	87.7	98.0	21.8	100.0
bcompetition	1'385	0.0	0.3	-0.1	-0.1	-0.1	0.0	0.0	-2.2	5.7

Summary Statistics

	N	Mean	Sd	P10	P25	P50	P75	P90	Min	Max
Macroeconomic Environment										
EmplILO	1'709	40.0	15.0	21.2	28.4	39.1	50.9	59.8	11.4	78.8
InformalCompet	143	57.7	17.8	33.1	45.9	60.3	70.4	78.1	10.7	90.1
FormalFirms	127	87.9	13.0	74.0	82.6	91.3	97.3	98.6	17.9	100.0
InformalYears	127	0.9	1.8	0.0	0.2	0.5	1.0	2.0	0.0	17.2
InformalConstr	152	33.1	15.9	12.2	22.0	31.1	41.3	55.0	0.0	76.0
GInflation	1'671	0.2	12.9	-0.8	-0.4	0.0	0.5	1.4	-390.2	208.5
GFX	1'686	415.8	16903.5	-0.1	0.0	0.0	0.0	0.1	-0.3	694043.6
GOdaAid	1'423	0.2	2.8	-0.4	-0.2	0.0	0.2	0.6	-34.2	72.8
Interest Rates										
DepositRate	1'470	5.6	5.4	1.3	2.9	4.1	7.5	11.1	0.0	103.2
LendingRate	1'370	14.6	23.9	5.5	7.8	11.5	16.6	22.6	0.5	579.0
RealRate	1'357	7.3	24.1	-2.7	1.7	5.1	9.7	15.4	-41.9	572.9
Knowledge										
PrimaryYears	1'984	5.7	0.9	4.0	5.0	6.0	6.0	7.0	3.0	8.0
Primary	1'234	87.9	19.9	57.1	79.8	94.8	100.1	104.5	21.3	189.1
PrimaryFemale	1'203	86.9	22.0	51.7	78.2	95.1	100.5	105.1	17.4	187.5
LowerSecondary	1'100	78.5	38.9	20.6	51.3	82.1	107.2	125.4	2.8	203.0
LowerSecondaryFemale	1'068	78.6	40.2	16.9	48.4	83.3	107.6	125.0	2.1	205.7
SecondaryYears	1'939	6.3	0.9	5.0	6.0	6.0	7.0	7.0	4.0	9.0
LiteFemMale	316	94.7	12.2	75.1	95.7	100.0	100.5	101.5	43.6	124.1
LiteYoung	316	89.4	16.9	65.1	87.1	97.8	99.0	99.7	23.5	100.0
LiteAdult	316	81.9	19.9	50.6	73.7	90.6	95.4	98.7	15.5	100.0

10 Results

Table 3: **Heckman Model - Basic Model**

	(1)	(2)	(3)	(4)
VARIABLES	index1	select	index1	select
classif		-0.356***		-0.391***
		(0.131)		(0.148)
GDPgrowth	0.296*	0.041***	0.284	0.042***
	(0.178)	(0.012)	(0.198)	(0.013)
GDPpcTh	-3.825***	-0.160***	-3.832***	-0.173***
	(0.699)	(0.026)	(0.799)	(0.038)
DBdepthcreditinfo	3.671***	0.240***	3.773***	0.262***
	(0.609)	(0.033)	(0.705)	(0.036)
PopDenHun	1.527***	-0.057*	1.477***	-0.079**
	(0.478)	(0.031)	(0.526)	(0.032)
BankBranches	0.277***	-0.001	0.268***	-0.003
	(0.064)	(0.006)	(0.071)	(0.006)
EmplILO	0.084	0.011**	0.089	0.009*
	(0.056)	(0.005)	(0.065)	(0.005)
PrimaryYears	-4.776***	-0.424***	-5.416***	-0.543***
	(1.184)	(0.074)	(1.470)	(0.084)
lambda	20.306***		21.982***	0
	(5.851)		(7.529)	0
Constant	22.377***	3.491***	25.523***	4.360***
	(5.793)	(0.503)	(6.765)	(0.570)
Observations	1,164	1,164	846	846
Censored obs	449	449	144	144
Uncensored obs	715	715	702	702

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: **Quantile Model - Basic Model - Full Sample**

	p10	p20	p30	p40	p50	p60	p70	p80	p90
GDPgrowth	0.007 *	0.005 *	0.005 *	0.007 *	0.007 *	0.008 *	0.005	0.008	0.029 ***
GDPpcTh	-0.035 **	-0.036 **	-0.036 **	-0.068 ***	-0.068 ***	-0.069 ***	-0.107 ***	-0.109 ***	-0.117 ***
DBdepthcreditinfo	0.098	0.096	0.096	0.136	0.135	0.139	0.174	0.178	0.236
PopDenHun	0.005	0.005	0.005	0.003	0.004	0.004	0.004	0.004	0
BankBranches	0.012	0.012	0.012	0.026	0.026	0.026	0.028	0.028	0.028
EmplILO	0.008 *	0.009 *	0.009 *	0.006	0.007	0.007	0.02	0.02	0.021
PrimaryYears	-0.115	-0.121	-0.12	-0.093	-0.091	-0.099	-0.08	-0.107	-0.146
(Intercept)	0.578 *	0.75 **	0.756 **	1.478	1.5	1.601	2.319	2.579	3.045
crisis	0.155 *	0.071	0.073	0.105 **	0.077 *	0.083 *	0	-0.062	-0.088
Country FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	1164	1164	1164	1164	1164	1164	1164	1164	1164

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

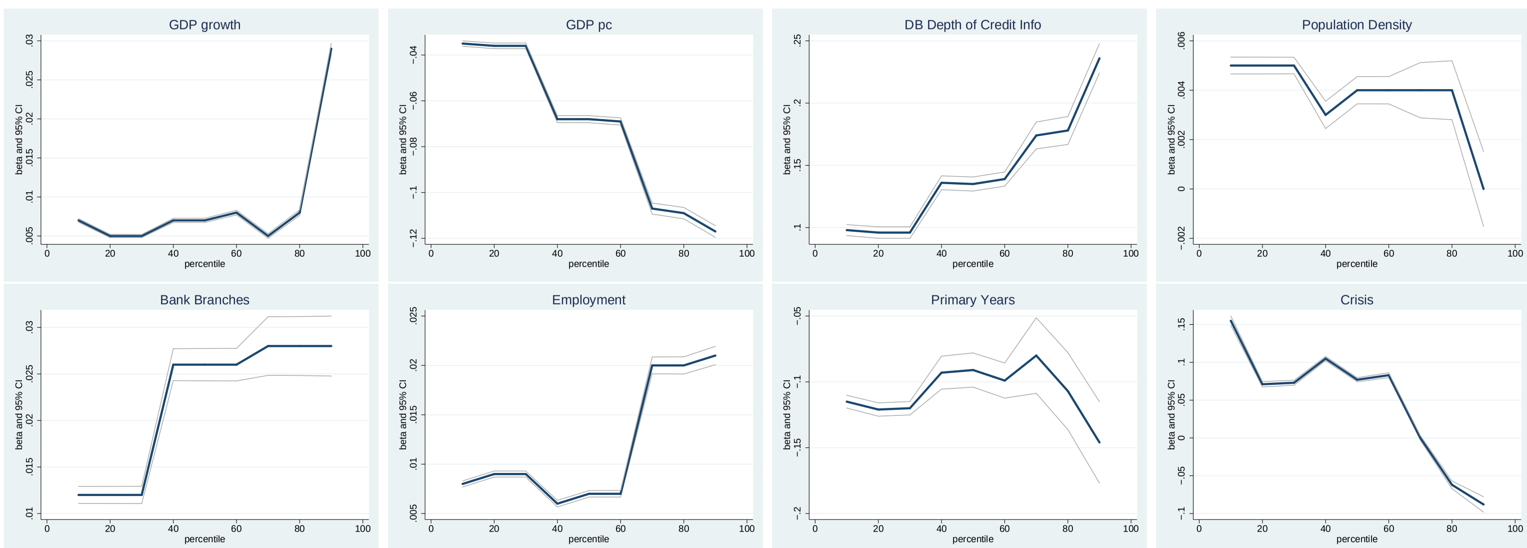


Table 5: **Quantile Model - Basic Model - Without High Income Countries**

	p10		p20		p30		p40		p50		p60		p70		p80		p90	
GDPgrowth	0.005		0.009		0.006		0.003		0.005		0.008		0.005		0.006		0.028	
GDPpcTh	-0.458	**	-0.542	***	-0.557	***	-0.571	***	-0.587	***	-0.612	***	-1.045	***	-1.109	***	-1.189	***
DBdepthcreditinfo	0.254	*	0.31	**	0.317	**	0.2		0.214		0.242		0.76	*	0.915	**	1.103	**
PopDenHun	0.168		0.163		0.158		0.417		0.432		0.422		-0.065		-0.052		-0.045	
BankBranches	0.16	*	0.175	**	0.177	**	0.244	*	0.247	*	0.251	*	0.301	**	0.299	**	0.312	**
EmplILO	0.014		0.007		0.006		0.017		0.015		0.015		0.021		0.019		0.023	
PrimaryYears	-0.39	**	-0.408	**	-0.406	**	-0.432	**	-0.394	*	-0.382		-0.715		-0.917	*	-1.119	*
(Intercept)	1.669		2.349	*	2.483	*	2.348		2.324		2.36		6.183	*	7.719	**	8.889	**
crisis	0.541	***	0.315	*	0.365	**	0.409	***	0.349	**	0.339		0.033		-0.08		0.021	
Country FE	yes		yes		yes		yes		yes		yes		yes		yes		yes	
Observations	846		846		846		846		846		846		846		846		846	

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 6: **Quantile Model - Credit Information - Without High Income Countries**

	p10	p20	p30	p40	p50	p60	p70	p80	p90
GDPgrowth	0.007	0.008	0.007	0.004	0.004	0.007	0	0.006	0.029
GDPpcTh	-0.506 **	-0.6 ***	-0.606 ***	-0.621 ***	-0.631 ***	-0.661 ***	-1.129 ***	-1.181 ***	-1.229 ***
DBdepthcreditinfo	0.247 *	0.305 *	0.306 *	0.112	0.121	0.165	0.306	0.381	0.565
Dblegalrights	0.079	0.109	0.109	0.123	0.12	0.137	0.483 *	0.518 *	0.595 **
Dbprivatebureau	0.003	0.006	0.007	0.016	0.015	0.015	0.019	0.02	0.022
Dbpublicregistry	-0.004	-0.011	-0.012	0.001	0.001	0.008	0.091	0.122 *	0.15 **
PopDenHun	0.2	0.216	0.217	0.491	0.502	0.494	0.093	0.1	0.115
BankBranches	0.155	0.169 *	0.171 *	0.239 **	0.242 **	0.243 **	0.338 ***	0.328 ***	0.322 **
EmplILO	0.01	0.004	0.003	0.013	0.012	0.014	0.013	0.013	0.012
PrimaryYears	-0.35	-0.425 *	-0.427 *	-0.347	-0.348	-0.395	-0.724	-0.933	-1.064
(Intercept)	1.32	2.24	2.298	1.699	1.886	2.109	4.877	6.234	6.85
crisis	0.624 ***	0.412 **	0.459 ***	0.39 **	0.31	0.324	0.016	-0.034	0.07
Country FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	846	846	846	846	846	846	846	846	846

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

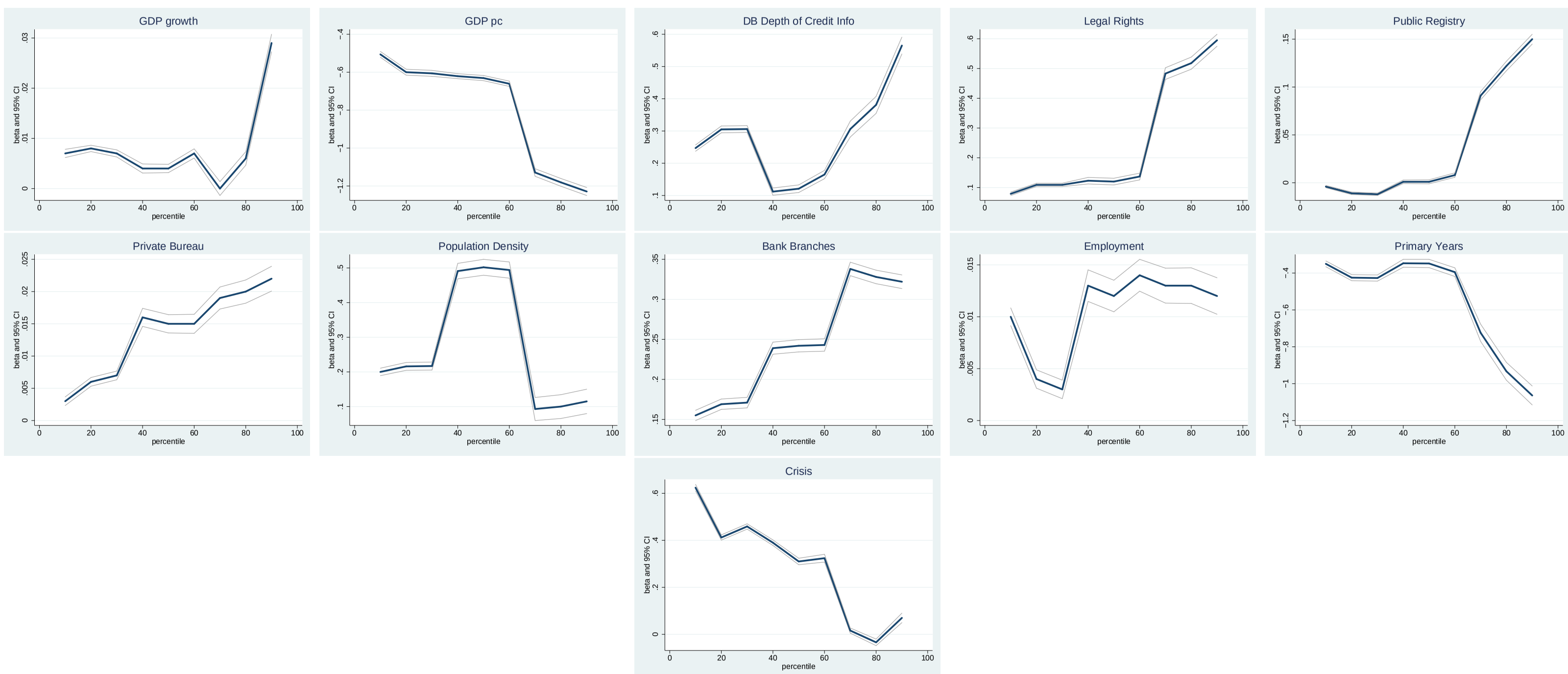


Table 7: **Quantile Model - Formal Financial Market Characteristics - Without High Income Countries**

	p10		p20		p30		p40		p50		p60		p70		p80		p90	
GDPgrowth	0.038	*	0.020		0.020		0.015		0.024		0.021		0.019		0.027		0.036	
GDPpcTh	-0.633	**	-0.671	***	-0.682	***	-0.751	***	-0.811	***	-0.823	***	-1.222	***	-1.264	***	-1.330	***
DBdepthcreditinfo	0.389	**	0.464	**	0.452	**	0.283		0.385		0.427	*	1.037	***	1.134	***	1.207	***
PopDenHun	1.600	**	1.618	**	1.644	**	1.920	**	1.992	**	1.993	**	0.941		0.992		1.066	
BankBranches	0.157		0.153		0.154		0.210		0.209		0.206		0.287	*	0.280		0.279	
netinterestmg	-0.078		-0.072		-0.072		-0.093		-0.095		-0.098		-0.106		-0.134	*	-0.156	*
nonrincome	-0.031		-0.033	*	-0.035	*	-0.039	*	-0.046	**	-0.050	**	-0.049		-0.059	*	-0.077	**
concentration	0.004		0.004		0.002		0.004		-0.001		-0.002		-0.006		-0.008		-0.010	
bcompetition	-0.767		-0.912		-0.944		-0.013		-0.021		0.121		0.196		0.151		0.023	
EmplILO	0.011		0.007		0.006		0.013		0.008		0.009		0.012		0.014		0.009	
PrimaryYears	-0.394		-0.416		-0.429		-0.356		-0.334		-0.382		-0.480		-0.597		-0.736	
(Intercept)	2.931		3.785		4.233		4.386		5.306		5.829	*	8.575	*	10.259	**	12.591	**
crisis	0.829	***	0.494	**	0.536	**	0.672	**	0.837	***	0.890	***	0.246		0.167		0.166	
Country FE	yes		yes		yes		yes		yes		yes		yes		yes		yes	
Observations	621		621		621		621		621		621		621		621		621	

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

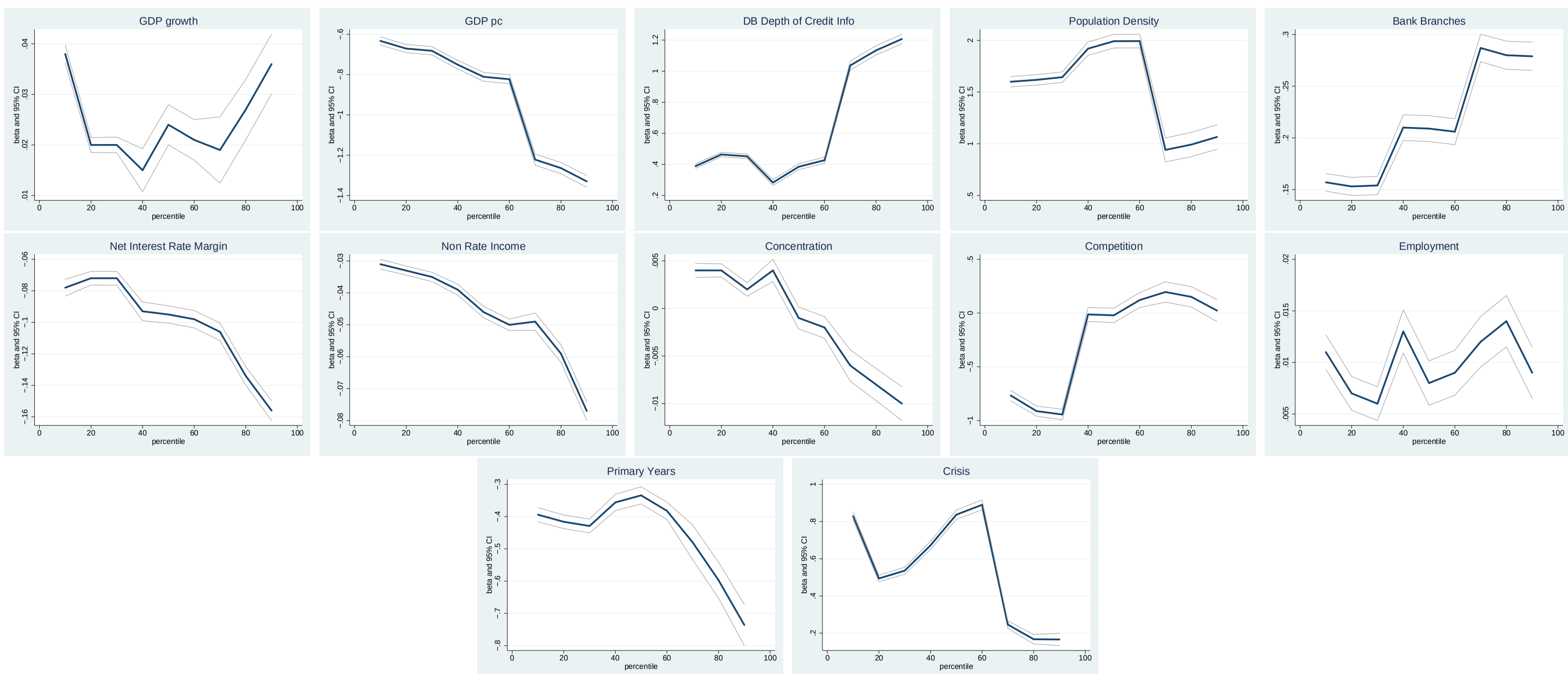


Table 8: **Quantile Model - Formal Financial Development - Without High Income Countries**

	p10	p20	p30	p40	p50	p60	p70	p80	p90
GDPgrowth	0.006	0.014	0.016	0.009	0.017	0.013	0.023	0.013	0.023
GDPpcTh	-0.457*	-0.494*	-0.510**	-0.812**	-0.840**	-0.906***	-1.488***	-1.656***	-1.758***
DBdepthcreditinfo	0.269	0.338*	0.343*	0.201	0.214	0.257	0.903**	1.075***	1.245***
PopDenHun	0.161	0.229	0.224	0.960	0.953	0.974	-0.102	-0.101	-0.038
BankBranches	0.173	0.173	0.174	0.280*	0.283*	0.281*	0.327*	0.325*	0.337*
ATM	-0.015	-0.016	-0.015	-0.009	-0.007	0.004	0.020	0.031	0.035
RemitReceivedGDP	0.057***	0.059***	0.057***	0.031	0.028	0.030	-0.002	-0.005	-0.002
DomCreditByFin	0.000	-0.002	-0.002	0.006	0.005	0.005	0.037**	0.036*	0.035*
EmplILO	0.008	0.004	0.002	0.023	0.024	0.024	0.065**	0.067**	0.073**
PrimaryYears	-0.451*	-0.501*	-0.504*	-0.381	-0.386	-0.389	-1.036	-1.215	-1.466*
(Intercept)	1.959	2.759	2.892	2.376	2.475	2.610	6.379	7.863	9.306*
crisis	0.767***	0.550**	0.594***	0.411**	0.359	0.286	-0.129	-0.226	-0.134
Country FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	836	836	836	836	836	836	836	836	836

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

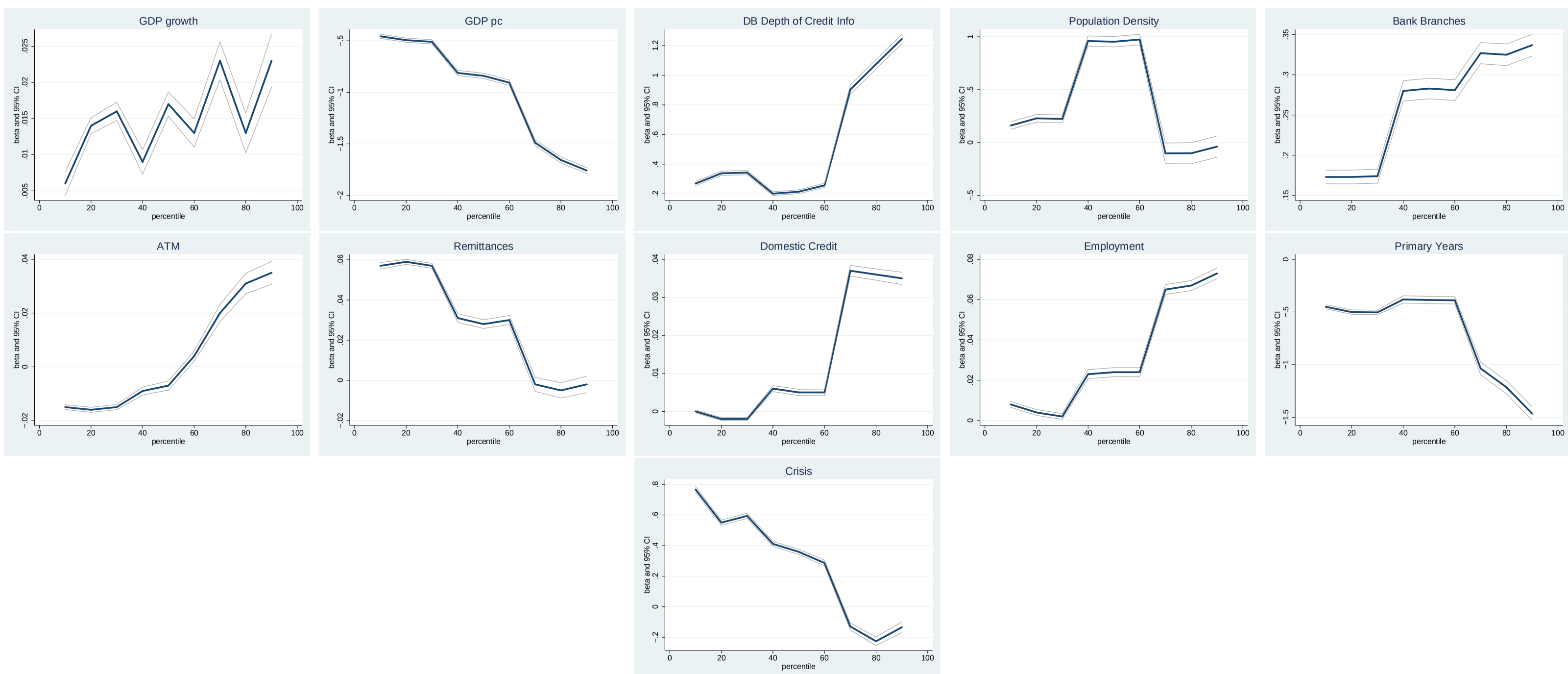


Table 9: **Quantile Model - Geography and Technology - Without High Income Countries**

	p10		p20		p30		p40		p50		p60		p70		p80		p90	
GDPgrowth	0.001		0.007		0.007		0.019		0.02		0.029		0.023		0.021		0.016	
GDPpcTh	-0.444	**	-0.517	***	-0.525	***	-0.704	***	-0.735	***	-0.77	***	-1.324	***	-1.436	***	-1.582	***
DBdepthcreditinfo	0.197		0.28	*	0.275	*	0.091		0.088		0.111		0.468		0.537		0.631	*
PopDenHun	0.272		0.274		0.285		0.188		0.187		0.216		-0.351		-0.366		-0.348	
RurPop	0.008		0.013		0.012		0.05	***	0.047	***	0.043	**	-0.018		-0.018		-0.01	
MobilePhones	0.007		0.009	**	0.009	**	0.005		0.005		0.005		0.022		0.029	*	0.044	**
InternetUsers	-0.006		-0.009		-0.006		0.05		0.052		0.059		0.124	**	0.147	**	0.157	**
BankBranches	0.136		0.145	*	0.146	*	0.232	*	0.238	*	0.235	*	0.176		0.175		0.181	
EmplILO	0.017		0.01		0.009		0.007		0.008		0.008		0.046	*	0.048	*	0.048	*
PrimaryYears	-0.365	*	-0.445	**	-0.442	**	-0.445	*	-0.409		-0.372		-0.3		-0.186		-0.161	
(Intercept)	0.924		1.599		1.693		0.482		0.617		0.689		3.412		2.683		2.068	
crisis	0.541	***	0.346	**	0.439	***	0.401	**	0.298	*	0.27		-0.168		-0.334		-0.614	
Country FE	yes		yes		yes		yes		yes		yes		yes		yes		yes	
Observations	846		846		846		846		846		846		846		846		846	

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

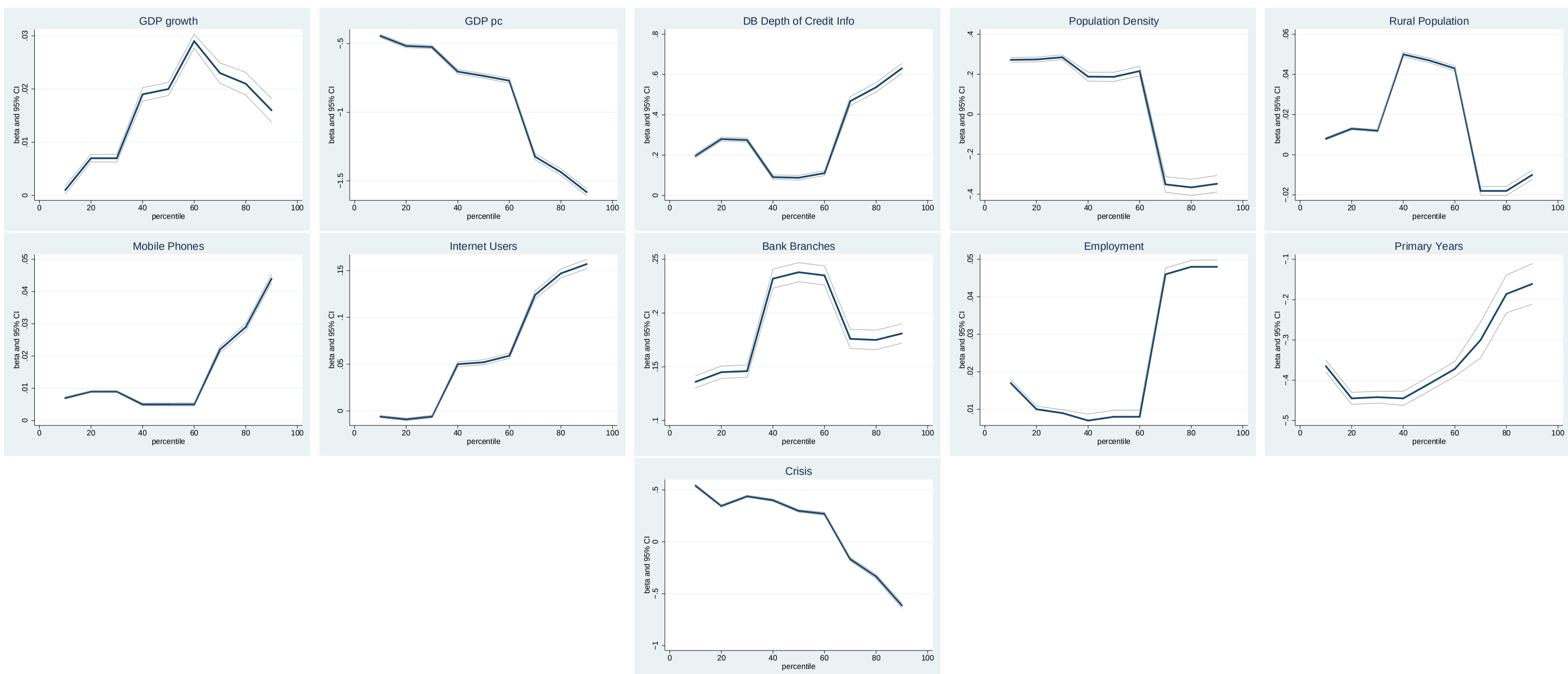


Table 10: **Quantile Model - Macroeconomic Environment - Without High Income Countries**

	p10		p20		p30		p40		p50		p60		p70		p80		p90	
GDPgrowth	0.005		0.006		0.004		-0.003		0.012		0.014		-0.008		0.016		0.028	
GDPpcTh	-0.903	*	-1.009	**	-1.009	**	-1.139	***	-1.148	***	-1.172	***	-1.384	***	-1.449	***	-1.558	***
DBdepthcreditinfo	0.321		0.391	*	0.400	*	0.294		0.292		0.385	*	1.085	***	1.228	***	1.468	***
PopDenHun	-0.208		-0.220		-0.207		-0.009		-0.020		0.010		-0.498		-0.481		-0.448	
BankBranches	0.371	*	0.392	*	0.399	*	0.655	***	0.672	***	0.676	***	0.740	***	0.744	***	0.738	***
EmplILO	-0.002		-0.009		-0.009		0.007		0.008		0.011		0.027		0.026		0.025	
GInflation	0.001		0.002		0.002		0.002		0.002		0.002		0.003		0.003		0.005	
GFX	-0.003		-0.005		-0.006		-0.006		-0.007		-0.012		-0.059		-0.058		-0.063	
GOdaAid	-0.001		-0.016		-0.022		-0.019		-0.020		-0.043		-0.004		-0.032		-0.074	
PrimaryYears	-1.093	***	-1.150	***	-1.147	***	-1.051	*	-1.056	*	-1.084	*	-2.402	*	-2.629	**	-2.904	**
(Intercept)	6.730	***	7.635	***	7.622	***	6.032		6.031		6.197		14.925	*	16.438	**	18.619	**
crisis	0.651	***	0.434	**	0.482	***	0.533	***	0.456	***	0.39	*	0.061		-0.005		-0.36	
Country FE	yes		yes		yes		yes		yes		yes		yes		yes		yes	
Observations	749		749		749		749		749		749		749		749		749	

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

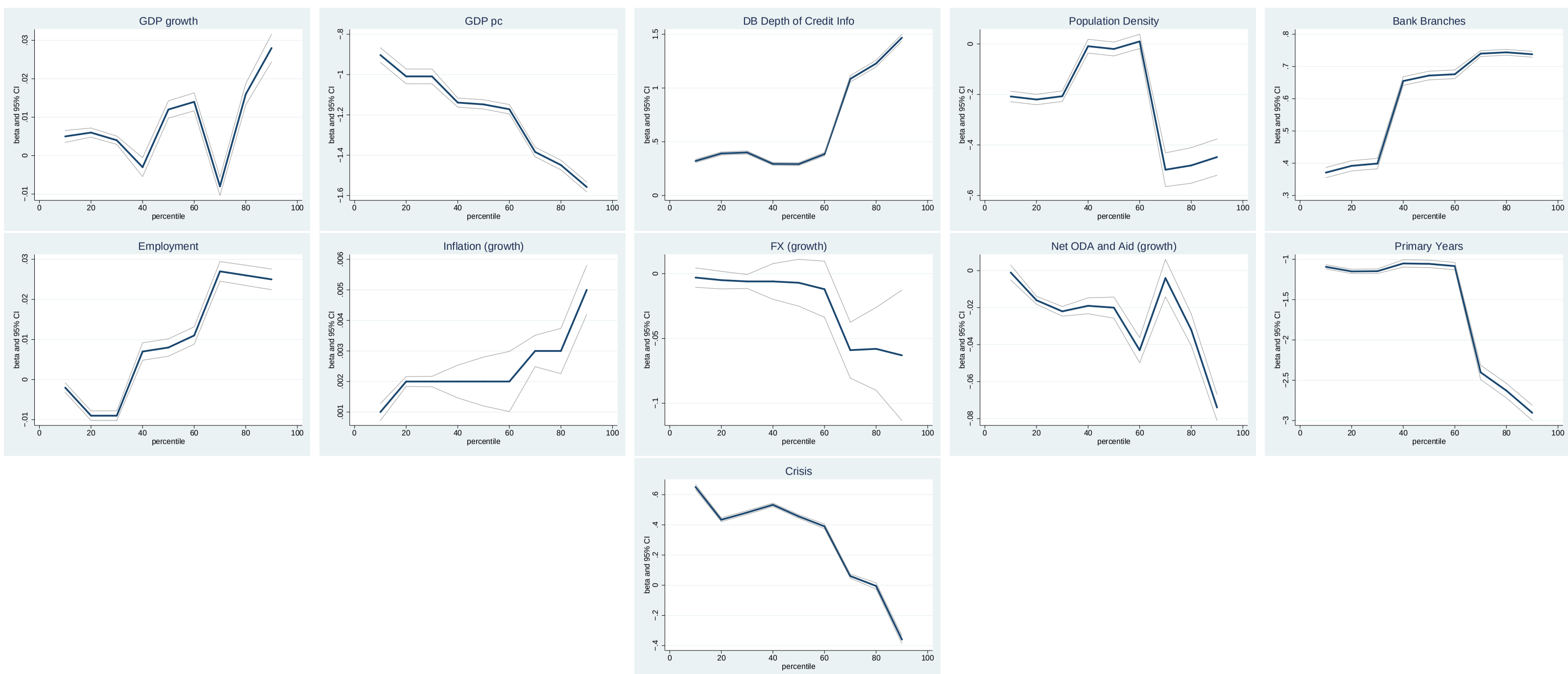


Table 11: **Quantile Model - Interest Rates - Without High Income Countries**

	p10	p20	p30	p40	p50	p60	p70	p80	p90
GDPgrowth	-0.001	0.009	0.006	0.001	0.004	-0.002	0.011	0.014	-0.021
GDPpcTh	-0.380	-0.441	-0.453	-0.540 *	-0.557 *	-0.581 *	-1.039 ***	-1.112 ***	-1.214 ***
DBdepthcreditinfo	0.132	0.193	0.195	0.142	0.156	0.185	0.519	0.666 *	0.802 *
PopDenHun	0.488	0.490	0.507	0.406	0.420	0.417	-0.043	-0.064	0.016
BankBranches	0.150	0.154	0.156	0.230	0.234	0.236	0.391 **	0.409 **	0.404 **
EmplILO	0.030 **	0.022	0.023	0.029	0.028	0.026	0.068 **	0.065 **	0.067 **
LendingRate	0.000	0.002	0.000	-0.008	-0.008	-0.003	-0.002	0.006	-0.002
DepositRate	0.014	0.005	0.010	-0.006	-0.006	-0.019	-0.049	-0.072	-0.041
RealRate	-0.011	-0.009 *	-0.009	0.001	0.001	0.000	-0.001	0.000	-0.007
PrimaryYears	-0.334	-0.349	-0.362	-0.333	-0.340	-0.327	-1.007	-1.150	-1.485 *
(Intercept)	0.689	1.411	1.497	1.763	1.879	2.045	5.833	6.907	9.435 *
crisis	0.520 **	0.320	0.363 *	0.302 *	0.269	0.272	0.076	-0.002	0.035
Country FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	654	654	654	654	654	654	654	654	654

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

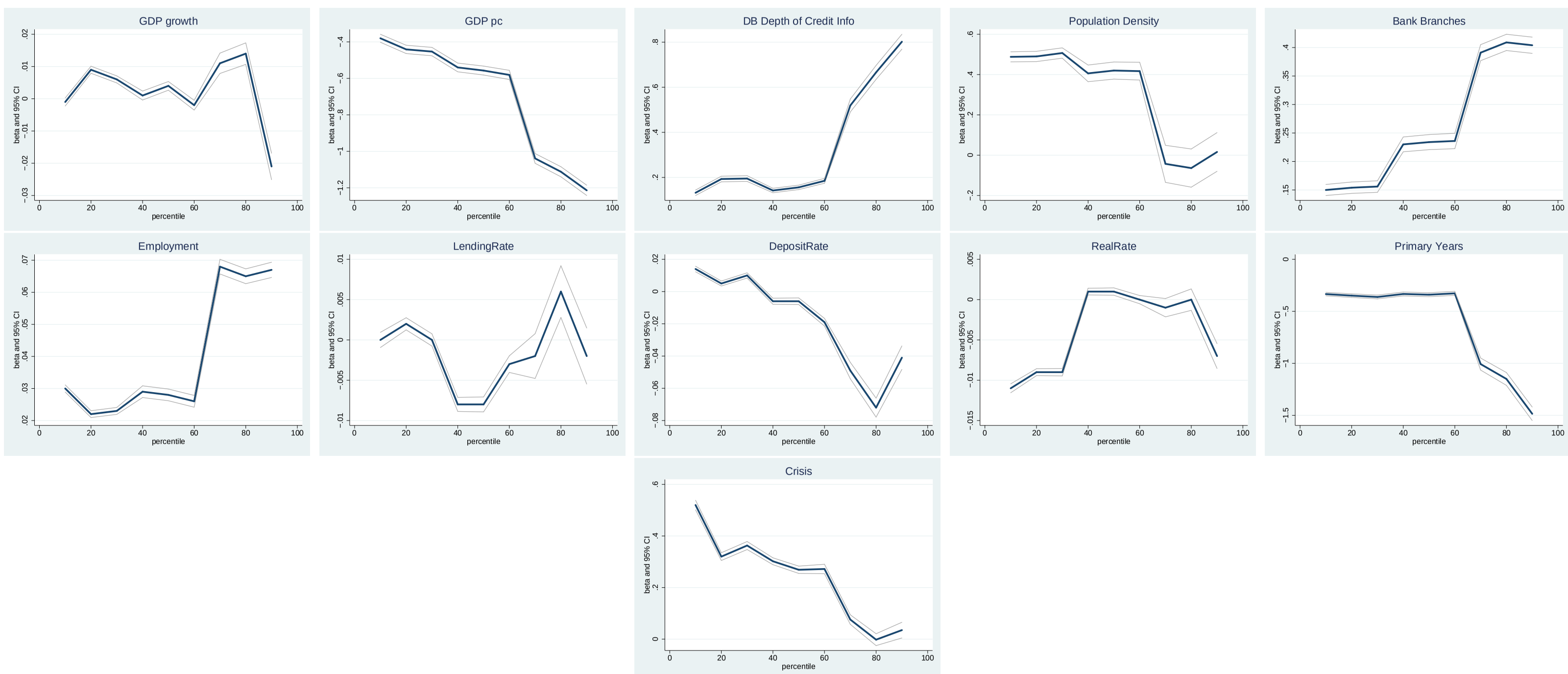
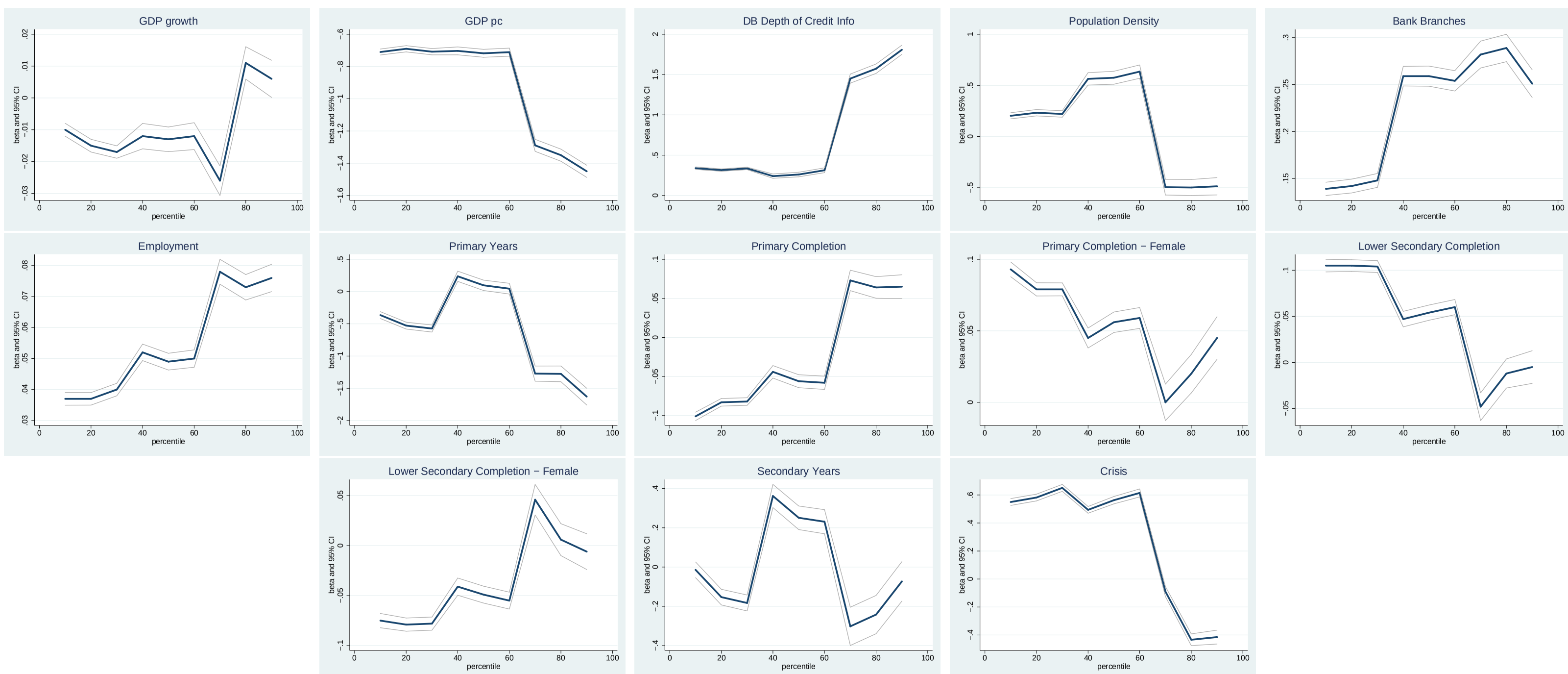


Table 12: **Quantile Model - Knowledge - Without High Income Countries**

	p10		p20		p30		p40		p50		p60		p70		p80		p90	
GDPgrowth	-0.01		-0.015		-0.017		-0.012		-0.013		-0.012		-0.026		0.011		0.006	
GDPpcTh	-0.71	***	-0.69	***	-0.708	***	-0.703	***	-0.718	***	-0.711	**	-1.289	***	-1.35	***	-1.45	***
DBdepthcreditinfo	0.339	*	0.315	*	0.336	**	0.24		0.26		0.313		1.45	**	1.573	**	1.808	***
PopDenHun	0.203		0.233		0.221		0.564		0.575		0.635		-0.495		-0.498		-0.486	
BankBranches	0.139	*	0.142	*	0.148	*	0.259	**	0.259	**	0.254	**	0.282	*	0.289	*	0.251	
EmplILO	0.037	*	0.037	*	0.04	*	0.052	*	0.049		0.05		0.078	*	0.073		0.076	
PrimaryYears	-0.365		-0.528		-0.573		0.237		0.097		0.045		-1.272		-1.276		-1.629	
SecondaryYears	-0.014		-0.153		-0.183		0.362		0.251		0.231		-0.302		-0.242		-0.073	
Primary	-0.101	*	-0.083		-0.082		-0.044		-0.056		-0.058		0.073		0.064		0.065	
PrimaryFemale	0.093	*	0.079		0.079		0.045		0.056		0.059		0		0.02		0.045	
LowerSecondary	0.105		0.105		0.104		0.047		0.054		0.06		-0.048		-0.012		-0.005	
LowerSecondaryFemale	-0.075		-0.079		-0.078		-0.041		-0.049		-0.055		0.046		0.006		-0.006	
(Intercept)	0.885		2.808		3.154		-5.181		-3.171		-2.846		4.353		3.829		3.807	
crisis	0.55	**	0.582	**	0.651	**	0.494	*	0.563	*	0.615	**	-0.09		-0.434		-0.415	
Country FE	yes		yes		yes		yes		yes		yes		yes		yes		yes	
Observations	462		462		462		462		462		462		462		462		462	

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1



11 Robustness Checks

Table 13: **Heckman Model - Basic Model - With Lags**

	(1)	(2)	(3)	(4)
VARIABLES	index1	select	index1	select
classif		-0.377***		-0.450***
		(0.139)		(0.161)
GDPgrowth	0.467**	0.041***	0.519*	0.044***
	(0.236)	(0.013)	(0.308)	(0.014)
GDPpcTh	-4.318***	-0.157***	-4.355***	-0.142***
	(0.906)	(0.028)	(1.145)	(0.044)
lDBdepthcreditinfo	4.326***	0.230***	4.621***	0.248***
	(0.779)	(0.036)	(1.041)	(0.039)
PopDenHun	1.307**	-0.066**	1.209	-0.090***
	(0.616)	(0.033)	(0.787)	(0.034)
lBankBranches	0.216**	0.001	0.191*	-0.003
	(0.085)	(0.006)	(0.110)	(0.007)
EmplILO	0.092	0.009*	0.120	0.007
	(0.072)	(0.005)	(0.099)	(0.005)
PrimaryYears	-5.592***	-0.423***	-6.956***	-0.555***
	(1.538)	(0.080)	(2.278)	(0.093)
lambda	24.454***		30.768***	
	(7.500)		(11.689)	
Constant	26.385***	3.648***	31.155***	4.622***
	(7.649)	(0.549)	(10.427)	(0.634)
Observations	1,164	1,164	846	846
Censored obs	449	449	144	144
Uncensored obs	715	715	702	702

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 14: **Heckman Model - Basic Model - With Country Group Interactions**

VARIABLES	(1) index1	(2) select	(3) index1	(4) select
classif		-0.404***		-0.441***
		(0.135)		(0.155)
GDPgrowth	0.177	0.045***	0.148	0.045***
	(0.169)	(0.013)	(0.170)	(0.014)
GDPpcTh	-3.369***	-0.153***	-3.278***	-0.171***
	(0.652)	(0.026)	(0.665)	(0.039)
DBdepthcreditinfo	3.290***	0.245***	3.283***	0.270***
	(0.555)	(0.034)	(0.568)	(0.037)
PopDenHun	1.598***	-0.043	1.570***	-0.063*
	(0.443)	(0.032)	(0.448)	(0.033)
BankBranches	0.277***	0.001	0.272***	-0.002
	(0.061)	(0.006)	(0.062)	(0.007)
BankBranches2	2.205*	18.595	2.194*	24.361
	(1.238)	(0.000)	(1.239)	(0.000)
BankBranches3	0.456	-0.013	0.451	-0.014
	(0.299)	(0.036)	(0.299)	(0.037)
BankBranches4	-0.272	-0.012	-0.258	0.014
	(0.222)	(0.026)	(0.230)	(0.040)
EmplILO	0.081	0.012**	0.078	0.010*
	(0.053)	(0.005)	(0.055)	(0.005)
PrimaryYears	-4.422***	-0.464***	-4.836***	-0.595***
	(1.113)	(0.076)	(1.229)	(0.087)
group2	-7.915	143.951	-7.808	187.394
	(6.208)	(0.000)	(6.226)	(0.000)
group3	2.579	0.282	2.825	0.278
	(3.945)	(0.414)	(3.948)	(0.418)
group4	3.394	1.180**	2.871	0.928
	(4.470)	(0.510)	(4.495)	(0.575)
lambda	17.121***		17.222***	
	(5.442)		(5.968)	
Constant	21.812***	3.616***	24.446***	4.579***
	(5.353)	(0.511)	(5.721)	(0.585)
Observations	1,164	1,164	846	846
Censored obs	449	449	144	144
Uncensored obs	715	715	702	702

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: **Heckman Model - Basic Model - Without Outliers**

VARIABLES	(1) index1	(2) select	(3) index1	(4) select
classif		-0.354***		-0.419***
		(0.125)		(0.142)
GDPgrowth	0.306	0.038***	0.294	0.038***
	(0.193)	(0.012)	(0.220)	(0.013)
GDPpcTh	-3.949***	-0.150***	-3.950***	-0.153***
	(0.778)	(0.024)	(0.921)	(0.037)
DBdepthcreditinfo	3.743***	0.211***	3.846***	0.228***
	(0.649)	(0.032)	(0.778)	(0.034)
PopDenHun	1.518***	-0.054*	1.456**	-0.076**
	(0.506)	(0.030)	(0.569)	(0.031)
BankBranches	0.290***	0.003	0.284***	0.002
	(0.068)	(0.006)	(0.076)	(0.006)
EmplILO	0.074	0.006	0.077	0.003
	(0.058)	(0.004)	(0.068)	(0.005)
PrimaryYears	-4.970***	-0.396***	-5.704***	-0.499***
	(1.310)	(0.071)	(1.717)	(0.079)
lambda	21.551***		23.739***	0
	(6.670)		(9.125)	0
Constant	22.947***	3.418***	26.432***	4.237***
	(6.241)	(0.487)	(7.575)	(0.548)
Observations	1,164	1,164	846	846
Censored obs	464	464	159	159
Uncensored obs	700	700	687	687

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 16: **Heckman Model - Basic Model - With Proxy1**

	(1)	(2)	(3)	(4)
VARIABLES	index1	select	index1	select
classif		-0.352***		-0.387***
		(0.131)		(0.148)
GDPgrowth	0.209	0.042***	0.127	0.042***
	(0.367)	(0.012)	(0.372)	(0.013)
GDPpcTh	-3.841**	-0.160***	-3.322**	-0.173***
	(1.573)	(0.026)	(1.599)	(0.038)
DBdepthcreditinfo	3.889***	0.238***	3.587***	0.259***
	(1.293)	(0.033)	(1.353)	(0.036)
PopDenHun	1.768*	-0.058*	1.794*	-0.080**
	(0.983)	(0.031)	(0.994)	(0.032)
BankBranches	0.455***	-0.000	0.456***	-0.003
	(0.127)	(0.006)	(0.128)	(0.006)
EmplILO	-0.153	0.011**	-0.175	0.009*
	(0.116)	(0.005)	(0.122)	(0.005)
PrimaryYears	-5.315**	-0.426***	-5.103*	-0.546***
	(2.497)	(0.074)	(2.822)	(0.084)
lambda	15.265		10.646	
	(13.883)		(15.811)	
Constant	38.089***	3.498***	39.123***	4.369***
	(11.709)	(0.503)	(12.553)	(0.570)
Observations	1,165	1,165	847	847
Censored obs	449	449	144	144
Uncensored obs	716	716	703	703

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 17: **Heckman Model - Basic Model - With Proxy2**

VARIABLES	(1) index1	(2) select	(3) index1	(4) select
classif		-0.352***		-0.387***
		(0.131)		(0.148)
GDPgrowth	0.235	0.042***	0.152	0.042***
	(0.371)	(0.012)	(0.376)	(0.013)
GDPpcTh	-3.951**	-0.160***	-3.430**	-0.173***
	(1.589)	(0.026)	(1.616)	(0.038)
DBdepthcreditinfo	3.985***	0.238***	3.677***	0.259***
	(1.307)	(0.033)	(1.368)	(0.036)
PopDenHun	1.795*	-0.058*	1.818*	-0.080**
	(0.995)	(0.031)	(1.005)	(0.032)
BankBranches	0.455***	-0.000	0.456***	-0.003
	(0.128)	(0.006)	(0.129)	(0.006)
EmplILO	-0.155	0.011**	-0.178	0.009*
	(0.118)	(0.005)	(0.124)	(0.005)
PrimaryYears	-5.474**	-0.426***	-5.259*	-0.546***
	(2.525)	(0.074)	(2.853)	(0.084)
lambda	15.779		11.023	
	(14.029)		(15.982)	
Constant	38.998***	3.498***	40.103***	4.369***
	(11.844)	(0.503)	(12.694)	(0.570)
Observations	1,165	1,165	847	847
Censored obs	449	449	144	144
Uncensored obs	716	716	703	703

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18: **Quantile Model - Basic Model - Without High Income Countries and With Lags**

	p10	p20	p30	p40	p50	p60	p70	p80	p90
GDPgrowth	-0.001	0.003	0.01	0.008	0.016	0.02	0.025	0.025	0.034
GDPpcTh	-0.401 ***	-0.472 ***	-0.482 ***	-0.558 *	-0.572 *	-0.594 **	-1.345 ***	-1.419 ***	-1.532 ***
lDBdepthcreditinfo	0.261	0.32 *	0.327 **	0.153	0.221	0.246	1.015 **	1.182 ***	1.353 ***
PopDenHun	0.243 *	0.247 *	0.245 *	0.362	0.35	0.345	-0.434	-0.444	-0.45
lBankBranches	0.088 *	0.095 *	0.097 *	0.203	0.204	0.208	0.345 ***	0.347 ***	0.387 ***
EmplILO	0.028 *	0.024	0.024	0.026	0.027	0.026	-0.011	-0.014	-0.016
PrimaryYears	-0.632 ***	-0.673 ***	-0.726 ***	-0.461	-0.496	-0.522	-1.021	-1.079	-1.168
(Intercept)	3.069 *	4.086 **	4.491 **	3.087	3.292	3.55	9.858 **	10.708 **	11.459 **
crisis	0.824 ***	0.341 **	0.297 *	0.254 **	0.219 **	0.187 *	-0.133	-0.429	-0.52
Country FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	846	846	846	846	846	846	846	846	846

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 19: **Quantile Model - Basic Model - Without High Income Countries and With Country Group Interactions**

	p10	p20	p30	p40	p50	p60	p70	p80	p90
GDPgrowth	0.005	0.009	0.006	0.004	0.006	0.008	-0.003	-0.003	0.018
GDPpcTh	-0.428 **	-0.502 ***	-0.516 ***	-0.56 **	-0.576 **	-0.593 **	-0.939 ***	-0.954 ***	-1.062 ***
DBdepthcreditinfo	0.224	0.264 *	0.266 *	0.164	0.176	0.205	0.745 *	0.85 **	1.044 **
PopDenHun	0.215	0.214	0.219	0.385	0.393	0.391	-0.03	0.005	0.007
BankBranches	0.146 *	0.158 *	0.16 *	0.251 *	0.253 *	0.254 *	0.269 *	0.26 *	0.278 *
EmplILO	0.014	0.009	0.008	0.027	0.026	0.026	0.065 **	0.063 **	0.072 ***
PrimaryYears	-0.358 *	-0.396 **	-0.392 *	-0.438 *	-0.403	-0.388	-1.27 **	-1.433 ***	-1.687 ***
(Intercept)	1.343	2.192	2.307	1.99	1.978	1.983	7.147 **	8.343 **	9.753 ***
crisis	0.674 ***	0.339 **	0.403 **	0.488 ***	0.399 **	0.55 **	0.168	0.128	0.143
BankBranches2	0.078	0.071	0.069	0.022	0.036	-0.02	0.069	0.089	0.105
BankBranches3	0.224	0.2	0.197	0.064	0.058	0.052	-0.014	-0.021	-0.06
BankBranches4	0.005	-0.006	-0.01	-0.005	0.021	0.013	-0.043	-0.038	-0.052
group2	0.188	-0.117	-0.175	0.181	0.107	0.243	-0.687	-0.921	-1.388
group3	0.177	0.383	0.359	0.575	0.682	0.801	4.728 **	5.128 **	5.238 **
group4	0.24	0.258	0.292	0.502	0.53	0.8	2.664	2.637	2.676
Country FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	846	846	846	846	846	846	846	846	846

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 20: **Quantile Model - Basic Model - Without High Income Countries and Without Outliers**

	p10		p20		p30		p40		p50		p60		p70		p80		p90	
GDPgrowth	0.005		0.007		0.006		0.003		0.005		0.006		0.001		0.004		0.017	
GDPpcTh	-0.462	***	-0.546	***	-0.559	***	-0.576	**	-0.592	**	-0.617	**	-1.063	***	-1.136	***	-1.219	***
DBdepthcreditinfo	0.267	**	0.338	**	0.342	**	0.218		0.232		0.271		0.801	**	0.992	**	1.19	***
PopDenHun	0.175		0.17		0.167		0.433		0.429		0.423		-0.143		-0.142		-0.136	
BankBranches	0.161	**	0.173	**	0.177	**	0.244	*	0.248	*	0.251	*	0.337	**	0.337	**	0.35	***
EmplILO	0.017		0.011		0.011		0.016		0.015		0.015		0.053	*	0.052	*	0.055	*
PrimaryYears	-0.391	**	-0.438	**	-0.427	**	-0.433	**	-0.399	*	-0.403	*	-1.087	**	-1.323	**	-1.503	**
(Intercept)	1.556		2.413	*	2.452	*	2.365		2.313		2.41		6.592	**	8.245	**	9.37	***
crisis	0.577	***	0.349	**	0.367	**	0.381	**	0.329	*	0.329		0.015		-0.086		-0.103	
Country FE	yes		yes		yes		yes		yes		yes		yes		yes		yes	
Observations	831		831		831		831		831		831		831		831		831	

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 21: **Quantile Model - Basic Model - Without High Income Countries and With Proxy 1**

	p10		p20		p30		p40		p50		p60		p70		p80		p90	
GDPgrowth	0.006		0.008		0.007		0.002		0.002		0.001		-0.005		-0.002		-0.02	
GDPpcTh	-0.627	***	-0.68	***	-0.692	***	-0.705	***	-0.728	***	-0.741	***	-1.333	***	-1.379	***	-1.496	***
DBdepthcreditinfo	0.424	**	0.497	**	0.499	**	0.553	**	0.572	**	0.64	**	1.99	***	2.134	***	2.531	***
PopDenHun	0.089		0.083		0.079		0.32		0.32		0.322		-0.497		-0.492		-0.5	
BankBranches	0.197	**	0.2	**	0.202	**	0.25	*	0.254	*	0.25	*	0.372	**	0.376	**	0.375	**
EmplILO	-0.001		-0.005		-0.007		0.022		0.022		0.021		0.038		0.035		0.03	
PrimaryYears	-0.52	***	-0.555	***	-0.538	***	-0.381	*	-0.405	*	-0.479	**	-0.588		-0.681		-0.789	
(Intercept)	2.936	**	3.687	***	3.734	***	1.852		2.129		2.69		4.809		5.964		7.629	
crisis	0.656	***	0.359	**	0.414	**	0.318	**	0.216		0.231		-0.299		-0.684	*	-1.104	**
Country FE	yes		yes		yes		yes		yes		yes		yes		yes		yes	
Observations	847		847		847		847		847		847		847		847		847	

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 22: **Quantile Model - Basic Model - Without High Income Countries and With Proxy 2**

	p10		p20		p30		p40		p50		p60		p70		p80		p90	
GDPgrowth	0.003		0.008		0.008		0.004		0.006		0.004		-0.005		-0.003		-0.026	
GDPpcTh	-0.649	***	-0.685	***	-0.69	***	-0.703	***	-0.727	***	-0.746	***	-1.26	***	-1.377	***	-1.464	***
DBdepthcreditinfo	0.432	**	0.478	**	0.476	**	0.527		0.565	*	0.636	*	2.086	***	2.258	***	2.62	***
PopDenHun	0.144		0.139		0.133		0.302		0.3		0.307		-0.465		-0.454		-0.441	
BankBranches	0.197	**	0.201	**	0.204	**	0.242		0.245		0.244		0.368	**	0.382	**	0.374	**
EmplILO	0.001		-0.003		-0.003		0.019		0.019		0.018		0.045		0.042		0.04	
PrimaryYears	-0.535	***	-0.548	***	-0.535	**	-0.446	*	-0.462	*	-0.525	*	-0.512		-0.656		-0.899	
(Intercept)	3.003	**	3.668	**	3.66	**	2.422		2.604		3.142	*	3.644		5.367		7.648	
crisis	0.723	***	0.375	**	0.414	**	0.358	**	0.267		0.273		-0.148		-0.721	*	-1.032	**
Country FE	yes		yes		yes		yes		yes		yes		yes		yes		yes	
Observations	847		847		847		847		847		847		847		847		847	

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 23: **Year Fixed Effects and *Crisis* Dummy**

	(1)	(2)	(3)
GDPgrowth	0.211**	0.319***	0.258***
	(0.095)	(0.102)	(0.097)
GDPpcTh	-0.354***	-0.341***	-0.351***
	(0.035)	(0.035)	(0.035)
DBdepthcreditinfo	1.305***	1.202***	1.306***
	(0.216)	(0.217)	(0.215)
PopDenHun	0.038	0.034	0.037
	(0.054)	(0.054)	(0.054)
BankBranches	0.104***	0.103***	0.104***
	(0.028)	(0.028)	(0.028)
EmplILO	0.104***	0.103***	0.103***
	(0.030)	(0.030)	(0.030)
PrimaryYears	-3.029***	-3.117***	-3.035***
	(0.508)	(0.506)	(0.507)
crisis			1.985**
			(0.881)
Constant	17.436***	14.494***	16.514***
	(3.093)	(3.281)	(3.114)
Observations	1,164	1,164	1,164
R-squared	0.149	0.163	0.153
Year FE	No	Yes	No

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

12 Data Appendix

In this Data Appendix we propose a battery of tests to check the quality of the *MIX* data used to build our *MF Penetration Rate.* We start by comparing *MIX*, which is a supply-side database with *FAS*, which also corresponds to the supply side. Using *MIX* active borrowers data at the country level and *WDI* population statistics, it is possible to calculate an indicator of MFI borrowers by 1,000 adults (age 15 and older) based on *MIX* data[30]. This figure can be compared with the same statistic reported by the IMF in *FAS.* Even if this last figure is available only for 15 countries between 2004 and 2012, comparing it with the *MIX* indicator is a good exercise to assess the quality of this last dataset. As can be seen in Figure 14, most countries are very close to the 45 degree line, indicating that *MIX* and *FAS* estimates are very close.

Findex provides information for 164 countries across the world. However, it is not possible to make a direct comparison of *MIX* and *Findex* data. Indeed, while *MIX* provides supply-side data, *Findex* provides demand-side data. Moreover, *MIX* provides information only of MFIs, while *Findex* provides aggregated data that corresponds to the services provided by formal financial institutions, including but not limited to MFIs. In order to solve this problem, we proceed as follows: Using *MIX* and *WDI*, we create an indicator of the share of adults (age 15 and over)[31] that had borrowed from a MFI in a given year[32]. We consider the national share of adults with a formal loan reported by *Findex*[33]. We multiply this last figure by the market share of microfinance at the country level. We calculate this national microfinance market share using *FAS* data on the number

[30]We do not focus here on the poor population as we do in our *MF Penetration Rate* because we want this data to be comparable also to *FAS* indicators on microfinance penetration, which cannot be disaggregated by income level.

[31]We do not focus here on the poor population as we do in our *MF Penetration Rate* because we want this data to be comparable also to *FAS* indicators on microfinance penetration, which cannot be disaggregated by income level.

[32]There are 4 countries that do not have data on the number of microfinance borrowers for any of the years in the *MIX* sample: Belarus, Grenada, Slovakia, and Vanuatu. Other countries have no *MIX* data for 2011, which is the year in which *Findex* data is available: Croatia, Gabon, Guinea-Bissau, Hungary, Malaysia, Namibia and Zimbabwe. For these countries, the last available observation and the observed annual growth rate are used as a proxy. If the annual growth rate cannot be calculated, then the last and next available observation are used.

[33]Out of the 120 countries in the *MIX* sample, 16 have no *Findex* data. In order to approximate feasible values for *Findex* national shares of formal borrowers, we estimate a simple linear regression of this variable on countries' GDP per capita with country and year fixed effects, using *WDI* data. Myanmar and South Sudan do not have readily available *WDI* data on GDP per capita, thus this approximation is not possible for these two countries.

of microfinance borrower accounts over the total number of borrower accounts[34].

Once all of this information is taken into consideration, a closer comparison of *MIX* and *Findex* data is possible in Figure 15. As can be seen in the figure, in many countries, the *MIX* share of MFI borrowers is higher than the best proxy that we have for the *Findex* share of MFI borrowers (these countries are above the 45 degree line in Figure 15). In order to understand if these discrepancies are due to data failures or to country characteristics, it is useful to reproduce the picture that Figure 15 gives on the microfinance market segment for the overall financial market. We achieve this by using *FAS* data to calculate the total amount of formal borrower accounts for a given country year[35], and divide this number using *WDI* population data. The resulting numbers are plotted in Figure 16 together with the *Findex* share of formal borrowers. While Figure 15 depicts only the microfinance market segment, Figure 16 considers all the financial market.

According to their position in Figures 15 and 16, different countries can be classified into four groups, as we have explained in our paper. Tables 24 and 25 list countries in Group 1 and 2. The first column shows the ratio of the *MIX* indicator of the national share of microfinance borrowers over the corresponding *Findex* proxy, i.e. $\frac{MIX}{\text{Findex proxy}}$. The second column shows the ratio of the *FAS* indicator of the share of formal borrowers over the corresponding *Findex* figure, i.e. $\frac{FAS}{\text{Findex}}$. The third column shows the ratio between column 1 and 2. Higher values indicate that according to the figures there is more complexity in the microfinance market segment than in the overall financial market, suggesting that there might be more multiple borrowing in the former than in the

[34] The *FAS* indicator of the national microfinance share of the market is only available for 15 countries. Two of these countries do not have this information for 2011, which is the year for which *Findex* information is available: Benin has data only until 2009, which we use also for 2011. Zambia has only information for 2012, which we take also for 2011. For the remaining countries, we use the predicted values from a linear regression of this parameter on countries' GDP per capita with country and year fixed effects, using *WDI* data. In the cases where such prediction yields national microfinance market shares higher than 1 or lower than 0, the average of the corresponding World Bank country income classification is used. In the cases where this is not available, the average of the corresponding region is used.

[35] We replace missing values for countries with some *FAS* information, but not for 2011 and not for the years in which *MIX* information is present, the last available observation and the observed annual growth rate are used as a proxy. If the annual growth rate cannot be calculated, then the last and next available observation are used.. Out of the 120 countries in *MIX* sample, 36 have no *FAS* data for any year. In order to approximate feasible values for *FAS* national shares of formal borrowers in these cases, we estimate a simple linear regressions of this variable on countries' GDP per capita with country and year fixed effects, using *WDI* data. Since South Sudan does not have GDP per capita information, this procedure is not possible in this particular case.

latter. The last column shows the kurtosis of the *MIX* data under consideration. Figures higher than 3, indicate that *MIX* data presents fat tails[36].

All the countries in Groups 1 and 2 have a more similar behaviour in the microfinance market segment than in the overall financial market. However, in some countries the complexity in the microfinance market is much higher than in the overall financial market, showing a very high value in column 3. In particular, according to the figures in Table 24, the microfinance market is at least 10 times more complex than the overall financial markets for Brazil, Kyrgyzstan, Burkina Faso, Chad, Senegal, Benin, Pakistan, Mali and Comoros.

Moreover, some countries present *MIX* data with high kurtosis. This is the case of Moldova, Nigeria, and Sudan. We plot *MIX* and comparable *Findex* and *FAS* data in our Online Data Appendix[37]. Graphically it is easy to see those countries where *MIX* data presents unusual behaviour. In particular, Nigeria in 2009 has a very strong spike that could be considered as an outlier. The same is true for Burkina Faso in 2011. In the case of Mali, on the other hand, there is a sharp decrease in 2012 that could be considered as an outlier. Comoros, on the other hand has only information for 2011, which is not enough to judge its quality, so it could also be considered as an outlier. All the other countries in this group show a relatively stable behaviour of *MIX* data[38].

The remaining countries can be classified in Groups 3 and 4. These countries are listed in Tables 26 and 27. Most of the countries in Table 26 have a microfinance market complexity that is 10 times higher than the overall financial market, according to our measure in column 3. These countries, especially Bolivia and Kenya, are clear leaders in the development of financial services

[36] The normal distribution has a kurtosis value of 3.

[37] Please refer to http://www.cmf.uzh.ch/penetrationdata.html.

[38] Brazil shows a very high $\frac{MIX}{\text{Findex proxy}}$ ratio in Table X. Indeed, while the *MIX* indicator of the national share of microfinance borrowers for 2011 is of 1.51%, the corresponding *Findex* proxy is close to 0%. We find such a low figure because the *FAS* microfinance share of the market is close to 0%. According to *MIX* data only 29% of MFIs were regulated in Brazil in 2011, which means that most of the MFIs in the country report to *FAS*. Moreover, it is evident from the Brazilian plot in Figure X that *FAS* figure of formal borrowers, which for 2011 is close to 70%, reflects the upper-end Brazilian fast-growing financial market, which is not necessarily reflected into good financial inclusion indicators for the overall population. The share of formal financial borrowers according to *Findex* is of 6%, which means that the *MIX* figure of 1% microfinance borrowers is credible. Moreover, *MIX* data presents a very stable trend over all available years

at the bottom of the pyramid and are lower middle-income and low-income countries. Thus, it is feasible that complexity is higher in the microfinance than in the overall financial market. All these countries are plotted in our Online Data Appendix. Graphically it is easy to see that there are important outliers of *MIX* data for Ethiopia in 2010 and 2011. Kosovo, on the other hand, shows a sharp decrease in 2011 and 2012, following the microfinance crisis in this country. All the other countries present a rather smooth behaviour of *MIX* data, even in the cases of Guinea-Bissau and Zimbabwe, which have a high kurtosis value.

In Group 4 countries, the complexity of the overall financial system is higher than that of the microfinance segment. This could be plausible for countries with high income levels, as these countries can have complex overall financial systems that serve also the needs of the bottom of the pyramid and thus crowd-out microfinance market development. In our Online Data Appendix we plot countries in Group 4 in the upper-middle and high-income classifications as of 2011. *MIX* data presents no clear outliers. However, some cases need to be considered in further detail. For example, Thailand shows very low *MIX* figures because two mayor players are government organisations that do not report to the *MIX*. Thus, in this particular case the *MIX* indicator is inaccurate, and should be considered as an outlier.

We also consider in our Online Data Appendix countries in Group 4 that are classified by the World Bank as being low and lower-middle-income countries as of 2011. Visually it is possible to identify outliers in *MIX* data for Congo Republic 2009 and 2010, and Guinea 2011. All the other countries present a stable behaviour of the data.

In synthesis, we consider as outliers the following country-years: Nigeria 2009, Burkina Faso 2011, Mali 2012, Comoros 2011, Ethiopia 2010, Kosovo 2011 and 2012, Congo Republic 2009 and 2010, Guinea 2011 and Thailand. Please refer to our Online Data Appendix for further details.

Figure 13: **Findex (demand-side) and FAS (supply-side) share of formal borrowers, countries by income classification, 2011**

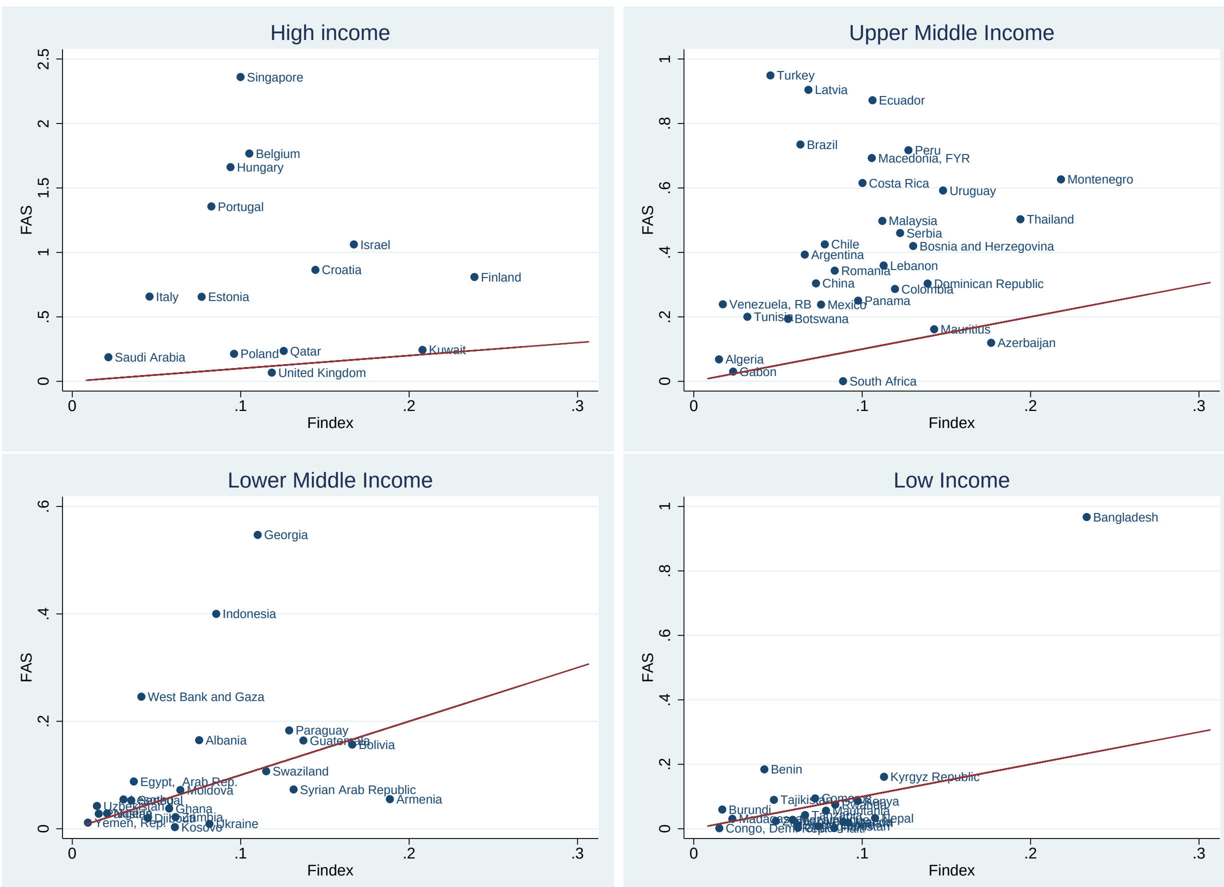


Figure 14: **MFI borrowers per 1000 adults: MIX and FAS, all country-years**

Figure 15: **National share of microfinance borrowers: Findex proxy (demand) and MIX (supply), 2011**

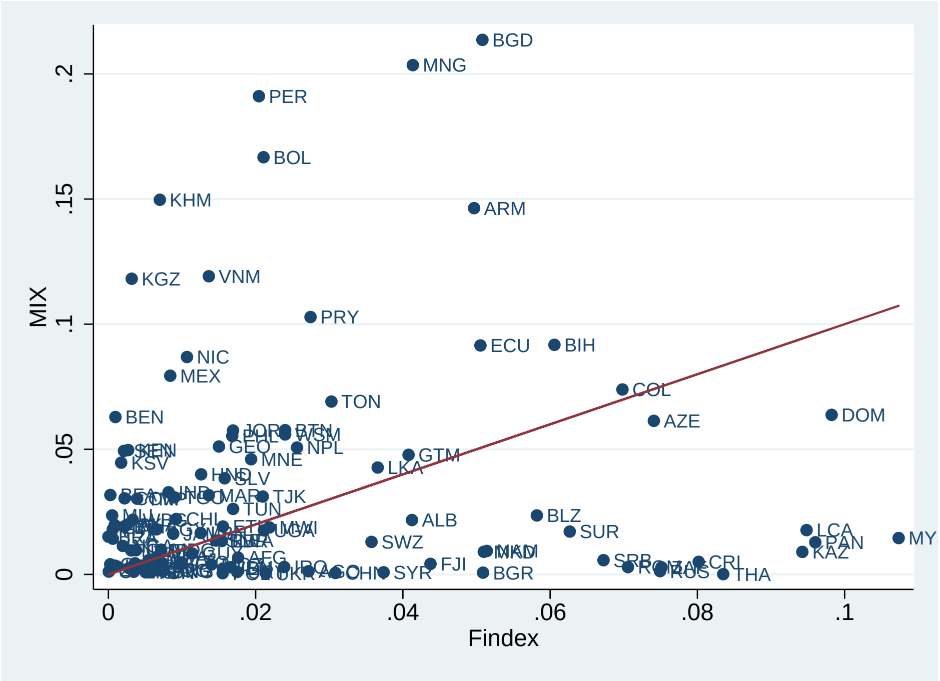


Figure 16: **National share of formal borrowers: Findex (demand) and FAS (supply), 2011**

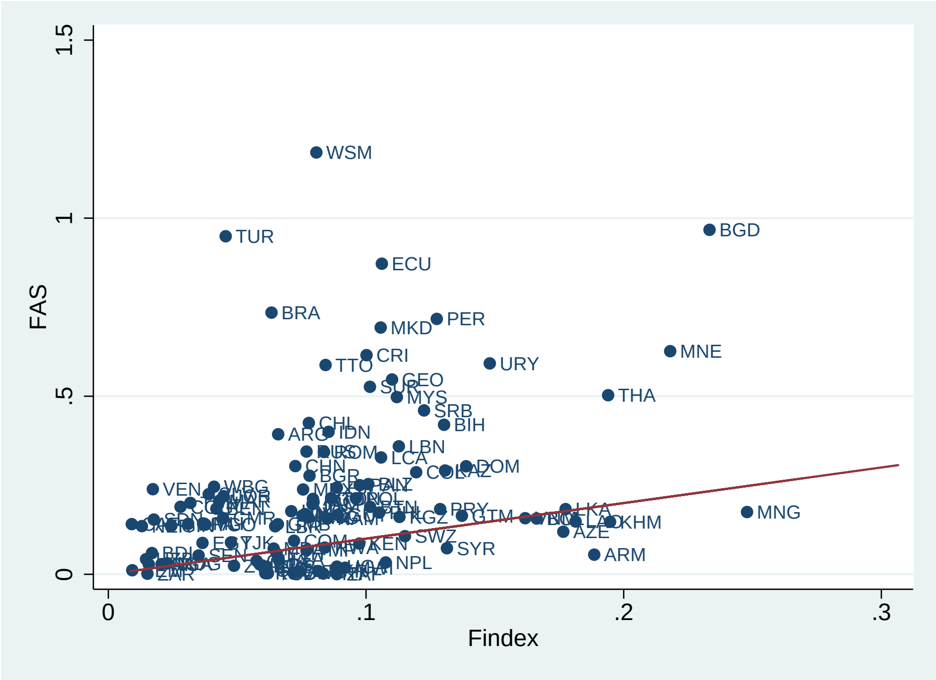


Table 24: **Countries in Group 1**

	Microfinance market segment	Overall financial market	Ratio	MIX Kurtosis
Country	MIX/Findex proxy	FAS/Findex	Col 1/Col 2	
Bangladesh	4.2	4.1	1.0	1.6
Benin	65.8	4.4	15.0	2.1
Bhutan***	2.4	1.9	1.3	1.8
Bosnia and Herzegovina	1.5	3.2	0.5	1.9
Brazil	4965.2	11.6	428.0	2.1
Burkina Faso**	119.4	4.6	26.1	2.6
Burundi	9.1	3.5	2.6	2.9
Cameroon**	2.6	3.5	0.7	2.1
Central African Rep.**	23.7	15.5	1.5	1.8
Chile	2.4	5.5	0.4	2.6
Colombia	1.1	2.4	0.4	1.4
Comoros	13.8	1.3	10.6	0.0
Ecuador	1.8	8.2	0.2	1.5
Egypt	2.8	2.4	1.1	1.7
El Salvador**	2.4	5.8	0.4	1.7
The Gambia***	16.0	2.1	7.5	1.4
Georgia	3.4	5.0	0.7	1.8
Guatemala	1.2	1.2	1.0	1.7
Honduras**	3.2	2.5	1.3	1.5
India**	4.0	2.1	1.9	2.3
Jamaica**	1.8	2.5	0.7	2.2
Jordan**	3.4	4.9	0.7	2.0
Kyrgyzstan	37.3	1.4	26.2	1.9
Lebanon	1.3	3.2	0.4	2.2
Madagascar	1.4	1.3	1.0	2.1
Mali**	46.2	3.9	11.9	2.5
Mexico	9.5	3.1	3.0	1.6
Moldova	1.0	1.1	0.9	1.5
Montenegro	2.4	2.9	0.8	3.9
Morocco**	2.3	4.8	0.5	2.0
Nicaragua**	8.1	2.2	3.7	1.7
Niger**	3.1	10.4	0.3	2.0
Nigeria	5.8	1.4	4.2	10.0
Pakistan	23.1	1.8	13.0	1.6
Palestine	6.6	6.0	1.1	2.0
Paraguay	3.7	1.4	2.6	2.8
Peru	9.3	5.6	1.7	1.6
Philippines**	3.3	1.6	2.0	1.5

Samoa*	2.3	14.7	0.2	1.8
Senegal	23.3	1.5	15.5	1.9
Sri Lanka**	1.2	1.0	1.1	2.1
Sudan**	2.7	8.7	0.3	4.8
Tajikistan	1.5	1.9	0.8	1.7
Togo**	3.4	3.7	0.9	1.6
Tonga***	2.3	2.5	0.9	2.3
Tunisia	1.5	6.3	0.2	2.1
Uzbekistan	4.0	2.9	1.4	1.6

* No Findex data available, predicted values reported

** No FAS data available, predicted values reported

*** No Findex or FAS data available, predicted values reported

Table 25: **Countries in Group 2**

	Microfinance market segment	Overall financial market	Ratio	MIX Kurtosis
Country	MIX/Findex proxy	FAS/Findex	Col 1/Col 2	
Afghanistan	0.4	0.1	3.6	1.5
Azerbaijan	0.8	0.7	1.2	1.4
Chad	0.9	0.0	18.5	2.4
Laos**	0.6	0.8	0.8	2.5
Malawi	0.9	0.2	4.3	2.2
Mozambique	0.3	0.5	0.6	2.0
Rwanda	0.9	0.9	1.0	1.5
Sierra Leone	0.9	0.2	4.8	2.2
South Africa	0.0	0.0	7.2	4.4
Swaziland	0.4	0.9	0.4	3.1
Syria	0.0	0.6	0.0	2.5
Uganda	0.8	0.2	3.4	2.2
Ukraine	0.0	0.1	0.2	1.9
Zambia	0.3	0.4	0.9	2.5

* No Findex data available, predicted values reported

** No FAS data available, predicted values reported

*** No Findex or FAS data available, predicted values reported

Table 26: **Countries in Group 3**

	Microfinance market segment	Overall financial market	Ratio	MIX Kurtosis
Country	MIX/Findex proxy	FAS/Findex	Col 1/Col 2	
Armenia	2.9	0.3	10.1	1.5
Bolivia	7.9	0.9	8.4	1.6
Cambodia**	21.4	0.8	28.3	1.9
Congo, Dem. Rep.	1.2	0.1	11.8	2.3
East Timor*	7.7	0.9	8.8	1.9
Ethiopia*	1.2	0.9	1.4	1.7
Ghana	7.9	0.7	12.1	1.5
Guinea-Bissau*	4.0	0.2	26.0	3.6
Haiti	30.4	0.0	1219.5	2.2
Ivory Coast*	1.0	0.1	15.6	2.2
Kenya	18.5	0.9	20.9	1.6
Kosovo	25.7	0.1	513.9	1.7
Mongolia**	4.9	0.7	7.0	1.4
Nepal	2.0	0.3	6.4	1.6
Tanzania	23.7	0.6	36.9	1.8
Vietnam**	8.7	1.0	9.0	1.7
Zimbabwe	8.3	0.5	16.8	3.4

* No Findex data available, predicted values reported

** No FAS data available, predicted values reported

*** No Findex or FAS data available, predicted values reported

Table 27: **Countries in Group 4**

	Microfinance market segment	Overall financial market	Ratio	MIX Kurtosis
Country	MIX/Findex proxy	FAS/Findex	Col 2/Col 1	
Albania	0.5	2.2	4.2	1.8
Angola**	0.0	2.7	57.5	4.6
Argentina	0.2	6.0	28.8	1.4
Belize*	0.4	2.5	6.2	2.0
Bulgaria**	0.0	3.5	252.5	1.8
China	0.0	4.2	221.9	5.1
Congo Rep**	0.3	6.8	26.7	3.9
Costa Rica	0.1	6.1	97.8	1.8
Croatia	0.0	6.0	4654.8	1.4
Dominican Republic	0.6	2.2	3.4	2.5
Fiji***	0.1	2.7	28.5	1.5
Gabon	0.1	1.3	15.1	1.5
Guinea**	0.2	5.6	30.1	2.7
Guyana***	0.7	1.9	2.6	1.5
Hungary	0.0	17.7	21306.6	2.0
Indonesia	0.2	4.7	26.9	1.7
Iraq**	0.1	2.5	20.5	1.6
Kazakhstan**	0.1	2.2	23.3	1.8
Liberia**	0.9	2.1	2.4	1.9
Macedonia	0.2	6.6	36.9	1.6
Malaysia	0.1	4.4	32.8	1.7
Namibia*	0.2	1.8	10.1	2.9
Panama	0.1	2.6	19.2	1.9
Papua New Guinea***	0.2	2.1	12.1	2.3
Poland	0.0	2.2	70.3	1.8
Romania	0.0	4.1	99.2	1.6
Russia**	0.0	4.5	256.0	2.4
Saint Lucia***	0.2	3.1	0.1	0.0
Serbia	0.1	3.8	44.4	1.5
Suriname*	0.3	5.2	19.0	1.5
Thailand	0.0	2.6	2025.5	4.5
Trinidad and Tobago**	0.5	7.0	14.5	2.3
Turkey	0.2	20.8	121.1	1.6
Uruguay	0.1	4.0	71.5	1.1
Venezuela	0.2	13.8	92.1	2.0
Yemen	0.9	1.2	1.4	2.8

* No Findex data available, predicted values reported

** No FAS data available, predicted values reported

*** No Findex or FAS data available, predicted values reported