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DOI:
10.1111/jmcb.12472

Competition, Loan Rates and Information Dispersion in Nonprofit and For-profit Microcredit Markets

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Abstract

We describe the competitive environment of microcredit markets globally and we study the effects of competition on loan rates of microfinance institutions (MFIs). We use a new database from rating agencies, covering 379 for-profit and nonprofit MFIs in 67 countries over 2002-2008. Controlling for interest rate ceilings and other country-specific factors, we first find that nonprofits are relatively insensitive to industry-wide concentration changes, while for-profits charge significantly lower rates in less concentrated markets. Second, we find spillover effects between the for-profit and nonprofit

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¶We acknowledge financial support of the National Research Fund, Luxembourg through CORE research project C08/IS/09. This research has been conducted as part of the project Labex MME-DII (ANR11-LBX-0023-01). We thank two anonymous referees for their many comments, which greatly improved the paper. We are grateful for comments and suggestions from Ronald W. Anderson, Bernd Balkenhol, Allen N. Berger, Steve Caudill, Hans Degryse, Scott Gaul, Simone Kohnz, Marc Labie, Evren Örs, Rich Rosenberg, Ariane Szafarz, Susan Chenyu Shan and Eric Strobl. We thank participants at the Financial Management Association, Orlando, 2015, the Financial Engineering and Banking Society conference at University of Surrey, June 2014, the ASSA Meetings in Philadelphia, January 2014, the Workshop on Institutions, Individual Behavior and Economic Outcomes in Porto Conte Ricerche, Alghero, June 2013, the Eastern Finance Association Annual Meetings in St. Pete Beach, April 2013, the Western Economic Association International & International Banking, Economics and Finance Association, 10th Biennial Pacific Rim Conference in Tokyo, March 2013, the Financial Management Association, Atlanta, 2012 (Semi-finalist for the best paper award in Financial Markets and Institutions), the European Financial Management Association 2012 in Barcelona, the Association of the Luxembourg Fund Industry Responsible Investing Conference, May 2012, the Asian Meeting of the Econometric Society in Seoul, August 2011, the Second European Research Conference on Microfinance, Groningen, June 2011, and the European Microfinance Week, December 2010. We thank Appui au Développement Autonome (ADA) for its continued support. Our special thanks go to Axel De Ville of ADA, Damian von Stauffenberg of MicroRate, Emmanuelle Javoy of Planet Rating and Aldo Moauro of MicroFinanza Rating. We thank Filipe de Lemos, Talida Manolache, Jurate Janaviciute, and Ioana-Valentina Rus for excellent research assistance. The usual disclaimers apply.

segments. Third, we show that the effects of concentration are consistent with an information dispersion mechanism.

Keywords: Loan rates, bank competition, microfinance, information dispersion, nonprofit institutions.

JEL Classification: D4, G21, L1, O1

1 INTRODUCTION

Proprietary information on borrowers is a key source of rents in credit markets (see e.g. Hauswald and Marquez, 2006; Santos and Winton, 2008; Schenone, 2009). The theoretical banking literature suggests, however, that banks' informational advantage can be vulnerable to competition, resulting in reduced market power of lenders (see e.g. Gehrig, 1998; Marquez, 2002; Hauswald and Marquez, 2003). In this paper we use a wide-reaching cross-country sample to investigate the effects of competition on loan rates in microcredit markets, where proprietary information is particularly valuable due to the general absence of information sharing institutions and the lack of collateral from borrowers. Moreover, proprietary information might be critical to sustain the costly lending technologies of microfinance institutions (MFIs henceforth), which require serving small loans, intensely gathering borrower-specific information and building close and personalized relations with very heterogeneous clients (in contrast to impersonal credit scoring methods used in consumer credit). Thus we further explore whether the effects of competition on loan rates are consistent with a mechanism of information dispersion, whereby the ability of a lender to exploit its proprietary information on borrowers reduces in a more competitive environment.

MFIs provide very small loans to clients who are predominantly poor and are excluded from the formal banking sector. The industry has experienced an impressive growth in recent years. In our sample period, between 2003 and 2008, the aggregate loan portfolio grew 34% per year on average to reach 44.2 US billion dollars globally in 2008, while the aggregate number of borrowers served reached 86.2 million (see Gonzalez, 2010).[1] MFIs typically use innovative lending mechanisms based on joint liability, such as group lending and village banking, while targeting mostly female borrowers. This type of lending model, which relies primarily on soft information and strong bank-borrower relations, allows to alleviate credit constraints more effectively in the absence of collateral and credit registries (see e.g. Berger, Miller, Petersen, Rajan and Stein, 2005; Berger, Frame and Ioannidou, 2011). Traditionally, MFIs have been established as nonprofit institutions that rely on capital from donors and development agencies. Increasingly, however, MFIs try to achieve a self-sustainable model, that is less dependent on donations and subsidies, and instead relies more on profits and commercial investors (see e.g. Garmaise and Natividad, 2010, 2013). BancoSol in Bolivia, Compartamos in Mexico and SKS in India are among the early prominent cases of for-profit MFIs. This model has prompted ethical questions, namely to what extent generating profits by lending to the poor is acceptable and consistent with a poverty alleviation objective. Further, having a profit objective could force MFIs to drift away from their traditional mission of serving the very poor in favor of serving higher-income clients while keeping high loan rates. The proponents of the for-profit model contend that sustainable operations and outreach complement each other. Under limited donor funding and demand in excess of supply of microfinance services, profits beyond cost coverage would attract additional funding and enable faster and wider outreach. Eventually, excessive profits would be moderated by competition (see Rosenberg, Gonzalez and Narain, 2009). In recent years, MFIs have certainly been subject to intense competitive pressures, with both for-profit and nonprofit MFIs entering the sector. Yet, with the notable exception of Gonzalez-Vega and Villafani-Ibarnegaray (2011), who provide evidence from the Bolivian market, there is little empirical evidence about the actual effects of competition on both nonprofit and profit-oriented MFIs and the mutual competitive pressures that arise between them.

In this paper we provide a description of the competitive environment of microcredit markets worldwide and we ask whether concentration matters for MFI lending rates. The classical competition paradigm in banking is the structure-conduct-performance hypothesis. It predicts that in more concentrated markets, banks engage in anticompetitive behavior, charging high loan rates and thus earning higher profits (see Bain, 1956). In general, the empirical literature in banking finds a positive relation between concentration and loan rates (for an overview, see e.g. Gilbert and Zaretsky, 2003). An important motivation for our study is the apparent insensitivity of microcredit lending rates to reduced concentration in several countries, which has often resulted in the imposition of interest rate ceilings (see e.g. Helms and Reille, 2004; Porteous, 2006). One possible explanation is that MFIs in certain markets are able to retain their informational advantage in spite of increased competition, for instance as a result of having captive borrowers due to higher switching costs or higher information asymmetries (see Dell'Ariccia, 2001; Hauswald and Marquez, 2003; Schenone, 2009).[2] Our results suggest that this is the case in nonprofit markets, that are likely to be more opaque, with slower information dissemination among lenders and where expertise in processing borrower-specific information is highly valuable.

We introduce a unique data set of 379 MFIs in 67 countries from 2002 to 2008, obtained from three main rating agencies. This allows us to cover an unusually large number of MFIs with high-quality data, that has been subject to a due diligence process, in the course of on-site visits by rating analysts. We carry out the necessary adjustments to guarantee consistency and comparability between the three data sets. This results in a total of 1452 MFI-year observations, which makes our sample the largest used in microfinance empirical studies to date, to our best knowledge.

The empirical evidence on the effects of competition in microfinance is relatively scant due to the lack of information about the market structure of this sector so far. Existing papers typically use proxies for the intensity of competition at a given point in time, collected from survey data. For example Cull, Demirgüç-Kunt and Morduch (2013) study competition between banks and microbanks using data on bank branch penetration collected in 2003/2004 by Beck, Demirgüç-Kunt and Martinez Peria (2007). Their proxy for the competitive pressure exercised by banks on MFIs is the number of bank branches in a country per geographical area or population. They do not, however, measure the intensity of competition among MFIs. Hartarska and Nadolnyak (2007) study the impact of regulation on MFI performance in 62 countries and use as a control variable the number of MFIs reporting to the Microcredit Summit Campaign in 2002, that serve clients below official poverty lines. Yet this variable of concentration is an unweighted measure, that does not account for the potential market power of larger MFIs in each country. Further, it is not feasible to reliably obtain the actual number of MFIs in most markets. McIntosh, de Janvry and Sadoulet (2005) study the effects of competition in Uganda between 1998 and 2002 using survey data collected in 2002 from group-members of one of the largest MFIs in Uganda. They use three alternative competition measures: the number of competitors, an indicator for the presence of a competitor, and the distance to the closest one. Navajas, Conning and Gonzalez-Vega (2003) use borrower level data to analyze the changes in lending technologies of incumbent MFIs in response to competition from a new entrant in the Bolivian market.

In contrast to the studies above, in this paper we characterize the changing competitive environment in microfinance by constructing a Herfindahl Hirschman Index (HHI) for every year and every country that captures not only cross-sectional variation but also time-variation in the organization of the industry. To this effect, we carefully construct a data set of market shares of MFIs in each country by combining our data from rating agencies with recently updated information from the Microfinance Information Exchange (MIX), an online platform founded by CGAP[3]. Together, these data sets provide a comprehensive picture of the industry, including the size and number of the largest and most important players, which is crucial to construct reliable measures of market share and HHI. Our combined data set of market shares contains a total of 7235 observations, corresponding to 1333 MFIs for the countries in our study.[4] Our paper also considers other dimensions of competition beyond industry structure that need to be controlled for. First, our empirical approach is designed to identify the mutual competitive pressures between for-profit and nonprofit MFIs. We capture this effect by calculating a variable that accounts for the share of microfinance loans issued by profit-oriented MFIs in each country and period. Second, we allow for the possibility that different environments with varying levels of institutional development affect competitive conditions differently. Third, we use measures of market penetration from the Financial Access Survey to control for a potential competitive pressure of main-stream banks. More specifically, we use the two measures employed by Cull et al. (2013), the number of commercial bank branches per 1000 km^2 and the number of commercial bank branches per

100000 adults.

We estimate a model explaining loan rates from concentration, controlling for a number of MFI and country-specific characteristics. We measure loan rates as the spread between the yield charged by an MFI and the average lending rate prevailing in a country in a given period taken from the World Bank.[5] Specifically, we test the hypothesis that concentration matters for MFI lending rates, even after taking into account potential spillover effects from the increasing relative presence of for-profits, the diversity of institutional environments and competitive pressures from main-stream banks. Further, in line with the model of Marquez (2002), using the size of the pool of borrowers as a proxy for information acquisition of MFIs, we investigate whether the ability of a lender to exploit this information reduces in a more competitive environment. Our paper is the first in the microfinance literature to incorporate as a control variable the interest rate ceilings imposed by regulators in specific countries and periods, depending on MFI status, which is an essential factor to understand the behavior of loan rates of MFIs. Methodologically, our study is close to several recent studies in banking that conduct international comparisons of the effects of competition (see e.g. Beck et al., 2007; Beck, Demirgüç-Kunt and Maksimovic, 2004; Claessens and Laeven, 2004; Demirgüç-Kunt, Laeven and Levine, 2004). We account for the fact that loan rates and HHI might be simultaneously determined by time-invariant unobserved effects by controlling for as many relevant variables as possible, both at the country level and MFI level, and with an instrumental variable approach on a smaller sample.

Our paper makes four main contributions to the literature. First, we provide a comprehensive picture of the competitive environment of MFIs worldwide and over time. Second, we find remarkably different competitive effects in nonprofit and for-profit MFIs. In general, loan rates of nonprofit MFIs are insensitive to changes in concentration. In contrast, with increased competition, for-profit MFIs charge significantly lower rates.[6] In particular, the effect of concentration on loan rates of for-profit MFIs is more than twice the one reported in previous studies in banking, even after controlling for interest rate ceilings. The size of this effect might be due to the particularly intense and dynamic movement towards cost-reducing innovations that took place in the microfinance sector, compared with the traditional banking sector. Third, our study reveals a competitive interplay between for-profit and nonprofit MFIs. Most notably, we find some evidence that the loan rates of nonprofit MFIs increase when there is a higher proportion of profit-oriented MFIs in the market. One possible explanation is that nonprofits are forced into niche markets with more excluded borrowers, where they have increased flexibility to adjust their prices and offer smaller and costlier loans. Alternatively, it could be that there is a composition effect because the most efficient MFIs graduate from non-regulated nonprofit to regulated for-profit status, which leaves the least efficient MFIs charging the highest rates in the pool of nonprofits. And fourth, we find some evidence suggesting an information-based competitive mechanism at work in the microfinance sector. Both for-profit and nonprofit MFIs with a large pool of borrowers appear to enjoy an information monopoly in concentrated markets, which allows them to charge higher rates compared to smaller MFIs. However, this informational advantage is apparently not sustainable in more competitive markets. This is consistent with lower incentives to invest in screening technologies, lower switching costs for borrowers and more fragmented or dispersed information among competing MFIs.

The paper is organized as follows. Section 2 describes our data. Section 3 describes the competitive environment in the microfinance sector worldwide and over time. Section 4 discusses our hypotheses and presents our model specification. Section 5 shows our empirical results. In Section 6 we present a number of robustness tests. Finally, Section 7 concludes.

2 DATA DESCRIPTION

We use an original data set collected from three global rating agencies of microfinance institutions, Planet Rating, MicroFinanza Rating and MicroRate.[7] The combination of these three sources results in a sample of 379 MFIs and 1452 MFI-years from 67 countries around the world between 2002 and 2008. To our best knowledge, our sample is the largest used in microfinance empirical studies to date.[8] Rating agencies offer evaluation services of risk profile, financial and social performance of MFIs wishing to attract new funding from donors or investors. This evaluation is based on an analysis of financial statements, portfolio quality reports and interviews with the different stakeholders (i.e. clients, credit officers, staff, board members, management team, etc.) conducted by rating analysts during the course of on-site visits. Thus, each rating report contains financial, social and managerial information that has been verified at its source.[9] We carry out the necessary adjustments and recalculate all financial ratios to guarantee consistency and comparability between the three data sets. The very high quality of the information differentiates our data set from other samples used in previous studies, typically based on self-reported information of the Microfinance Information Exchange (MIX). In addition, our data set contains 316 MFI-year observations from 140 MFIs that do not disclose to the MIX, but are covered by rating agencies. Furthermore, one major advantage of our database is that we track the changes in MFI legal status over time from rating reports for each MFI in our sample. These changes are ignored in other studies using MIX data, since the legal status of MFIs in MIX data is treated as a static variable, which corresponds to the latest updated status at the time the data is downloaded.

The rating report of each MFI includes the financial statements over at least two and up to seven years. The initial year in our database contains 81 MFIs. By the end of 2004 the database contained about 255 MFIs, and by 2006 nearly 290 MFIs were available, which illustrates the increasing importance of the sector and demand for reliable information. The large majority of observations in our data set are in Latin America and the Caribbean (43%), followed by Africa (26%), Eastern Europe (19%), Middle East and North Africa (6.5%) and Asia (5.5%).

MFIs constitute a heterogenous group in terms of mission (for-profit vs. nonprofit), legal status (non-governmental organization, bank, cooperative, etc.), services they provide (e.g. deposit-taking or not) and lending technologies. As stated above we track these characteristics over time for each MFI. Our sample reflects the heterogeneity of this industry. Overall, non-governmental organizations (NGOs, henceforth) represent the most common organizational form in our sample, around 40% of observations, followed by non-bank financial institutions (NBFIs henceforth, 39%), cooperatives (15%), banks (5%) and other (1%). About one third of observations in our database correspond to for-profit institutions, of which 80% are NBFIs and 18% have a bank status. The proportion of for-profit MFIs in our sample varies across regions. For example, most MFIs in Asia are for-profit institutions (around 61%), while we have none in the Middle East and North Africa. Their presence in other regions remains around 30% of the total. One question is whether this variation reflects differences in regulation or entry barriers preventing for-profit institutions from entering the microfinance sector. Regarding nonprofit MFIs, a large majority of observations (56%) are NGOs, 23% are NBFIs and 20% are cooperatives. Nonprofit institutions are significantly smaller, reflecting the fact that they are in general not regulated and therefore are constrained in the use of leverage, which limits their growth opportunities. Further, 44% of the nonprofits in our sample are allowed to take deposits. Nonprofit MFIs clearly focus on more financially disadvantaged clients by offering an average loan size of USD 866 which is small compared to USD 1403, or more, offered by for-profit, see Table 1 for descriptive statistics.[10] Our sample is also representative of the wide variation of MFIs in terms of age and size. It contains some of the oldest and largest MFIs in most countries, with assets above USD 500 million and more than one million borrowers. Yet, our sample also includes relatively small MFIs with a few dozens of borrowers, as well as young MFIs, some of which have started operations during our sample period. The average MFI in our sample is 10.3 years old, has total assets of about USD 18 million, and serves about 21300 active borrowers. Also, our average MFI charges a real interest rate of approximately 20% above the country rate. MFIs adopt specific lending technologies that differentiate them from traditional banks, namely, they institute joint liability mechanisms and strong relations between borrowers and credit officers. The latter have the responsibility of monitoring the individuals or groups that apply for credit in situ. This is different from the traditional lending methodology of banks, based on credit scoring and distance monitoring. As a result, MFIs enjoy better portfolio quality and have proven to be profitable. Table 2 shows the distribution of MFIs across status and lending technologies. Note that an MFI may use more than one lending technology. Only few NGOs and NBFIs engage exclusively in village or group lending, while the vast majority of MFIs have at least a fraction of their portfolio lent to individuals (1279 observations). MFIs that combine individual and group lending are the most prevalent. Finally, Table 3 (Panel A) shows the number of observations in our sample over time by profit status.

3 THE COMPETITIVE ENVIRONMENT OF MICROFINANCE ACROSS COUNTRIES

To assess the intensity of competition in the microfinance sector in each country, we rely on a second source of information, the Microfinance Information Exchange (MIX). The MIX operates since 2002, but collects self-reported information from MFIs back from 1995. The MIX has become the largest source of public information in the microfinance sector, although many MFIs that report to the MIX are not audited. Between 2002 and 2006 the number of MFIs tracked by the platform grew very rapidly, reaching a stable number of about 1160 MFIs in 2006.[11] The platform's growth partly reflects the fact that MFIs compete actively for scarce funding. Reporting to the MIX gives MFIs visibility and signals transparency, which helps them attract potential donors or investors. In this respect, the MIX mirrors the competitive environment and the structure of the industry across countries. It includes the total number and size of the largest and most important players in each country, and thus is likely to constitute a representative sample. These two pieces of information -number and size- allow us to construct a Herfindahl-Hirschman concentration index (HHI) for each year and for each country. To calculate HHI, we follow previous banking literature and compute market shares in terms of gross loan portfolio, of each individual MFI in our sample and in the MIX, with respect to the total in a given country and period.[12] Market shares are also included in our models to capture the degree of market power MFIs enjoy.

We implement two adjustments prior to the calculation of the concentration index. First, in 42 countries we correct the number of MFIs present in the MIX by adding 316 MFI-year observations, corresponding to 140 MFIs from our database from rating agencies that do not report to the MIX. Second, we correct the number of MFIs in the MIX by adding those MFIs in existence in the years prior to the first reporting date. For those years, we make an estimation of their size by linear extrapolation of the gross loan portfolio between their inception year and the year in which they first report to the MIX. Likewise we interpolate gaps in reporting in the 2002 to 2008 period. After these adjustments we obtain a total of 7235 market share observations, corresponding to 1333 MFIs, which is the sample we use to construct our concentration measures (see Table 3, Panel B).

Figure 1 shows the structure of the combination of the MIX and our sample for the countries in our data set, in 2002 and 2008. The figure reveals wide variation of the degree of development of the microfinance industry in the cross-section and over time. The combined data reflects the fact that countries with a long tradition of microfinance, like the Philippines, Peru, Brazil and Bolivia, have more mature markets, with many MFIs, while in countries like Tunisia, Gambia, Yemen and Chile, the industry is less developed, with only few important participants, due to different reasons. In the case of Yemen, for example, the fact that the country had no tradition of money lending and that people in rural areas in particular had no experience with credit, represented a significant barrier to the development of microfinance (see Lyman, Mahieux and Reille, 2005). Figure 2 shows the HHI per country in 2002 and 2008. The average HHI across countries in our database is 0.40 and the average market share is 7%. There is wide variation in market structure across countries, even among countries with a longer tradition of microfinance. Typically, in less concentrated markets we observe a few large MFIs that are clear market leaders, and dozens of smaller MFIs that follow their lead. This is the case of Vietnam. Other countries, like Bolivia, Peru and Nicaragua have instead very competitive markets, with no clear market leader. The figure also reveals increasingly competitive conditions over time in most countries, for example Mexico (from 0.75 in 2002 to 0.3 in 2008), Guatemala (from 0.3 in 2002 to 0.15 in 2008) and Ecuador (from nearly 0.4 in 2002 to 0.12 in 2008). Remarkably, in Russia, the sector has experienced a consolidation which resulted in an increase in Herfindahl from 0.55 in 2002 to about 0.70 in 2008. It remains clear though from Figure 2, that most of the variation in HHI is cross-sectional. An ANOVA decomposition of variability shows that 91.4% of the variability is cross-sectional and only 8.6% is due to time-variation around time series averages. The question that we address in the remainder of the paper is how these varying competitive conditions in terms of industry structure affect the pricing strategies of both for-profit and nonprofit MFIs.

4 HYPOTHESES AND MODEL SPECIFICATION

4.1 Hypotheses

Our primary objective is to estimate the effects of concentration on yield spread. To capture the impact of market concentration, we use a Herfindahl Hirschman index (HHI). There is a long tradition in the banking literature of studying the effects of concentration on interest rates within the structure-conduct-performance (SCP) paradigm, see Bain (1956). The SCP contends that in more concentrated environments, banks engage in non-competitive conduct, charging higher loan rates, which leads to higher profits. Increased competition, instead, should have a positive effect from a welfare perspective, as it forces firms to reduce prices, which favors consumer surplus. In general these papers find a positive relation between concentration and loan rates using different specifications, periods and markets (see e.g. Berger and Hannan, 1989; Hannan, 1991; Hannan, 1997; Cyrnak and Hannan, 1999; Sapienza, 2002). Thus, the hypothesis we test is that concentration matters for MFI lending rates, taking into account the diversity of institutional environments, the rapidly changing competitive conditions and the coexistence of for-profit and nonprofit MFIs.

The computation of the HHI assumes that the markets of for-profit and nonprofit MFIs are fully integrated. However, there might be some spillover effects between the two groups, that we capture by adding for-profit share as a control variable which accounts for the relative presence of for-profit MFIs among all MFIs in a given country for a given year. It is often the case that MFIs experiment and develop client relationships under a nonprofit status. Many successful ones subsequently become for-profit and substantially improve their outreach and sustainability. These new performance standards in turn influence the remaining nonprofits. In the case of Bolivia, Gonzalez-Vega and Villafani-Ibarnegaray (2011) document that such externalities can occur through the labor mobility of MFI staff across the two sectors. Such effects are also documented in the nonprofit literature, mainly concerned with the market for hospitals and nursing homes. For instance, Grabowski and Hirth (2003) find that the quality of for-profit nursing homes improves with the share of nonprofits, as does overall quality in the market. Santerre and Vernon (2005) find that the presence of nonprofits improves the quality of for-profits, while the presence of for-profits leads nonprofits to improve efficiency. Hirth (1997; 1999) offer a theoretical model in which competition from nonprofits raises the quality of competing for-profit firms. One stream in the banking literature uses nonprofit share to study spillover effects between credit unions and commercial banks in the US market (see e.g. Feinberg, 2001; Hannan, 2003). Martinez Peria and Mody (2004) use a similar variable (i.e. the share of foreign banks) to study the mutual competitive effects between foreign and domestic banks. Thus, if for-profit share has an impact on loan rates, this will indicate spillover effects from the increasing relative presence of for-profits. Alternatively, if the two markets are fully integrated and there are no spillovers, the for-profit share should have no effect.[13]

Given the general lack of information sharing mechanisms in microcredit markets, proprietary information is likely to be highly valuable.[14] Thus, we further investigate whether the effects of concentration on loan rates are determined by the extent to which MFIs are able to retain and exploit their informational advantage on clients. Given the cross-country nature of our data, there is no direct measure for the amount of information individual MFIs gather about their clients. The best proxy for information acquisition we can get is the size of the pool of borrowers. This is in line with the Marquez (2002) model, where in a first stage banks gather proprietary information about their clients. The lender with a larger pool of clients in the first stage faces a lower degree of asymmetric information when competing for borrowers in the second stage, since she is able to avoid the bad borrowers she learned about in the first stage[15]. In particular, number of borrowers is a better proxy than gross loan portfolio, given that MFIs can hand out loans of very different size. For example, with a lending capacity of USD 1000 a lender will learn about 10 borrowers if her average loan size is USD 100, while she can gather information about 100 borrowers if her average loan size is USD 10. We discuss econometric issues with our proxy for information acquisition further in Section 4.8. MFIs with access to a larger informational base are likely to be in a better position to build screening experience and become better at processing borrower information. Thus, thanks to increased switching costs for borrowers, they might be able to sustain their informational advantage over prospective lenders and extract rents even under competitive pressure (see e.g. Yafeh and Yosha, 2001; Hauswald and Marquez, 2003). However, the value of information on borrowers may not be the same in competitive and concentrated markets in the presence of information spillovers, which level the informational gap between lenders. For instance Gehrig (1998), Hauswald and Marquez (2003) and Schenone (2009) argue that incentives to invest in screening technology may decline in more competitive markets since the profit to be earned on a good borrower decreases relative to the less competitive situation. Also in the model of Marquez (2002), the value of proprietary information is eroded as information becomes more fragmented or dispersed with competition. Thus, by exploiting information on the size of the pool of borrowers, we make an attempt to address the question whether the gap in loan rates across MFIs with differential access to information on borrowers is less pronounced in competitive than in concentrated markets.

4.2 Model

Our base specification explains yield spread from concentration, controlling for market share, for-profit share, cost efficiencies, interest rate ceilings and MFI and country-specific characteristics:

$$\begin{aligned} \text{Yield spread}_{ict} &= \alpha_0 + \alpha_1 \text{HHI}_{ct} + \alpha_2 \text{Market share}_{ict} + \alpha_3 \text{FP share}_{ct} + \alpha_4 \text{X-eff}_{ict} \\ &\quad + \alpha_5 \text{S-eff}_{ict} + \alpha_6 \text{Ceiling}_{ict} + \sum_k \gamma_k X_{k,ict} + \mu_t + \varepsilon_{ict}, \end{aligned} \tag{1}$$

where Yield spread$_{ict}$ is the difference between the loan rate charged by MFI i at time t in country c and the average lending rate prevailing in the same country and period. HHI$_{ct}$ is the Herfindahl Hirschman Index, a measure of gross loan portfolio concentration in country c at time t. Market share$_{ict}$ is the gross loan portfolio market share of MFI i at time t in country c. FP share$_{ct}$ is the share of loans issued by for-profit MFIs and accounts for the relative presence of for-profit MFIs in country c at time t. X-eff$_{ict}$ and S-eff$_{ict}$ are the measures of efficiency of MFI i in country c at time t derived from a cost function. We explain how we derive these two variables later in Section 4.4. Ceiling$_{ict}$ is a dummy variable for the presence of interest ceilings that apply to MFI i in country c at time t. $X_{k,ict}$ is a vector of K MFI and country control variables. The μ_t are time dummies, that capture economy-wide shocks determining differences in lending rates across years, and ε_{ict} is an error term.

As defined above, our dependent variable, yield spread, is calculated from MFI loan rates adjusted for country rates. The loan rate charged by a given MFI is defined as the fraction of interest received on total loan amount outstanding. Note that our measure of rates considers the total of interest and fees, but we are not able to distinguish between the two. We obtain the average loan rate per country per year from the World Bank Development Indicators. While the microfinance literature usually considers unadjusted rates (see e.g. Cull, Demirgüç-Kunt and Morduch, 2007; Ahlin, Lin and Maio, 2011), we follow the practice of cross-country studies in the banking literature such as Corvoisier and Gropp (2002) of adjusting the rates. We want to make sure that we capture differences in interest rates that are related to the microfinance industry and not to other country-specific factors, and we believe that this adjustment is made all the more relevant by the great disparity in macroeconomic conditions of the countries in our sample. We cut the very extremes of the distribution of yield spread at the 1% and 99% to handle outliers.

Descriptive statistics for yield spread appear in Table 1. The average MFI charges a premium of 20% above the average loan rate in a given country and period with a standard deviation of 16.5%. We find no significant difference between nonprofit and for-profit MFIs.[16] Yield spreads vary widely across countries, and may be particularly affected by legislated interest rate ceilings discussed in Section 4.7. They also vary across time for a given MFI, as can be seen from an ANOVA decomposition of variability using only MFI effects, which shows a time series standard deviation of 6%.[17]

4.3 Estimation methodology

We estimate our model for the full sample and also separately for the subsamples of for-profit and nonprofit MFIs, to allow for the possibility that these two categories of MFIs respond differently to competitive conditions. This distinction speaks directly to the debate on financial self-sufficiency vs. subsidized models in microfinance. We pool all observations and use robust standard errors. Since our main interest lies in the effect of country level variables on individual MFI observations, clustering the standard errors by country seems natural, to account for within-country correlation. However, we do not opt for this approach, since we have a relatively small number of clusters, while the use of cluster standard errors relies on large number of clusters asymptotics. Moreover the number of observations per country in our sample is extremely unbalanced and this can lead to misestimating clustered standard errors, particularly as the contribution to the variance of small clusters is likely to be very imprecise.[18] Alternatively, to take into account a possible dependence in the residuals, we check whether our results are robust to the use of autocorrelation-consistent Newey-West standard errors (see Newey and West, 1987). We use a lag length of one, given that the number of observations per country in our sample is extremely unbalanced. Our results, available upon request, are hardly affected.

Our estimation approach takes into account the possibility that loan rates and our main explanatory variable, HHI, might be simultaneously determined by omitted country-level and MFI-level factors and cost efficiencies. We tackle these potential issues in a number of ways:

- First, there is a concern with omitted country-level factors. For instance, countries with a higher level of institutional and infrastructure development are more likely to attract market participants, particularly for-profit MFIs, and thus favor competition. However, these same conditions help banks reduce costs in general, and possibly, the lending rates. A country fixed-effects estimation is not an alternative in our case, since our main variable, HHI, varies mostly in the cross-section but not sufficiently over time, as shown in Section 3. We address the effect of time invariant unobserved country effects that might be correlated with country-level regressors by including a number of country controls, such as institutional development indices, and demand factors such as the share of rural population and rural population growth, that are virtually time-invariant over our sample period. Moreover, our dependent variable is already constructed as a difference between an MFI rate and an average country lending rate. In a sense, this already purges our dependent variable from a number of time invariant and possibly time-varying country-specific effects. We also include time-varying country level factors like GDP growth, the average quality of borrowers, and financial sector outreach, proxied by bank branch penetration.

- Second, there is also some concern with time-invariant unobserved MFI-level effects that could be correlated with our regressors, which would warrant the use of MFI fixed effects. Instead, in order to alleviate potential concerns of endogeneity, we strive to control for as many variables that could possibly affect yield spread, as we can, also at the firm level.

For example, we include controls for MFI legal status, lending methodology, and deposits taking.

- Third, we take into account the possibility that lending rates and our main explanatory variable, HHI, are simultaneously determined by cost efficiencies (see e.g. Berger, 1995). MFIs producing at more efficient scales or with better technologies will enjoy lower costs and higher profits, which may have an effect on loan rates. Meanwhile, these MFIs will be able to capture higher market shares, which could result in higher HHI. Thus to rule out a spurious relation between loan rates and HHI, we follow previous studies (see e.g. Frame and Kamerschen, 1997) and we control for scale efficiencies, X-efficiencies and market shares.

- Fourth, we estimate our model using instrumental variables, which allows us to consistently estimate coefficients even if our main explanatory variable is correlated with the error term. We propose two variables as plausible instruments for the microfinance HHI, the average number of procedures to start a business in a given country, and the average cost to start a business, as a percentage of income per capita. The choice of these two instruments, which correlate negatively with the microfinance HHI, is discussed later. Our IV estimates are obtained using a reduced sample of 38 countries for which the two instruments and critical control variables are available. In particular, our IV estimation includes bank-branch demographic penetration as a control for the potential local competition from main banks, as well as controls for macroeconomic conditions and institutional development. Our results are presented in Section 5.3.

In the remainder of this section, we discuss these issues further and we describe each of our controls.

4.4 Country-specific controls

Following Demirgüç-Kunt et al. (2004), we include measures of institutional development in a country, such as indicators of property rights protection and the degree of economic freedom, which potentially impacts both lending rates and MFI activity or entry simultaneously. We use the Worldwide Governance Indicators (WGI) from the World Bank, constructed by Kaufmann, Kraay and Mastruzzi (2009) (i.e. KKM indicators), and the Heritage Foundation indicators of economic freedom. We only report the results for the most relevant indicators, namely regulatory quality, governance effectiveness, political stability and the Heritage Foundation overall score.[19]

We also account for differences in demand for microcredit across countries, by including the growth and the percentage of rural population per country, obtained from the World Bank. These are proxies for the size and growth of the main target population of microfinance. We further include GDP growth, to capture overall investment opportunities in a country.

One particular factor that may simultaneously affect lending rates and market structure is the quality of borrowers in a country. On the one hand, less risky environments naturally attract more competition among MFIs. On the other hand, in less risky environments, MFIs are likely to charge lower interest rates. To tackle this potential source of endogeneity, we control for the average portfolio quality in each country. Average portfolio quality reflects ex ante riskiness of borrowers in a country, but is also influenced by MFI conduct, since it is essentially an ex post measure of risk. However, MFI conduct is already partly accounted for, since we include a number of MFI level variables, such as lending methodology for instance. Considering the same data set of 1333 MFIs used to construct the concentration index per country, we calculate an aggregate measure of portfolio quality for every country year as a weighted average of the portfolio quality of all MFIs in that country. We capture portfolio quality with a measure of delinquent loans known as portfolio-at-risk (PAR), which is the portion of outstanding loans of an MFI with payments overdue by, typically, 30 days or more.

We find an average country PAR in our sample of 0.02 with a median of 0.01. However, in our estimation, for each MFI-year in our sample, we correct country PAR by excluding the PAR of the MFI under consideration, to avoid potential mutual concurrent effects between lending rates and PAR in a given MFI.

4.5 For-profit share

Besides considering the effects of different institutional environments on competition, we also control for potential competitive pressures arising between nonprofit and profit-motivated MFIs. To capture this effect, we calculate for each country and each period, the share of the total dollar amount of loans issued by profit-motivated institutions relative to the total issued by all MFIs. For this calculation we consider the same sample of MFIs used to construct the concentration index. Constructing for-profit share required a significant amount of manual work in tracking MFI status over time. Relying on the profit-nonprofit status reported by the MIX is not appropriate, as MIX only reports the latest available status. We track changes over time in the profit-nonprofit status for the 1333 MFIs from the MIX that operate in the 67 countries in our 2002-2008 sample period. We expect changes in status to be from nonprofit to for-profit. Thus, for each MFI that was for-profit in 2008 according to MIX, we systematically consult documentation to verify whether it was originally nonprofit. We meticulously check rating reports whenever available, otherwise we search all audited reports, as well as any other documents available from the MIX website. In some instances we found information instead on the web sites of the MFIs or national and regional microfinance networks. Likewise, we examine a random sample of MFIs that were nonprofits in 2008, but, as expected, we found no prior change of status.

We obtain an average for-profit share in our sample of 53%. Put differently, for-profit institutions issue the majority of loans in dollar value, although nonprofit MFIs outnumber those for-profits by almost two times (see previous section). Figure 3 depicts the distribution of for-profit share across countries for 2002 and 2008 and shows variation both across countries and over time. In most countries the for-profit share increases during the sample period, which may represent a growing competitive pressure on nonprofit MFIs. For example, in the Philippines the for-profit share increases from nearly 48% in 2002 to 58% in 2008. In El Salvador it increases from 81% to 90%, in Kenya from 72% to 92%, and in Bolivia from 68% to 82%. There are a few exceptions, like Mexico, Ecuador and Peru, where the for-profit share was 70% or above in 2002, and declines to less than 60% in 2008. Finally, as explained in the previous section, we have a few countries where the for-profit share is constant over time. In one extreme, in countries like Moldova, Cambodia, Montenegro and Mongolia only for-profit MFIs operate over the sample period. At the other extreme, only nonprofit MFIs operate in countries like Egypt, Morocco, Jordan or Benin. Overall, an ANOVA shows that 95.2% of the variability in for-profit share is cross-sectional, leaving only 4.8% of variation around time series averages.

4.6 Market share and efficiency

An alternative theory to the structure-conduct-performance (SCP) is the efficiency-structure hypothesis. The efficiency-structure hypothesis contends that the relation between concentration and prices or profits is spurious because concentration is endogenously determined by firms gaining market shares as a result of their superior efficiency (see e.g. Peltzmann, 1977). A number of studies account for this potential endogeneity in the profit-structure relation by controlling for market share (Smirlock, 1985) and for measures of efficiency (e.g. Berger, 1995; Frame and Kamerschen, 1997). Typically these control variables substantially reduce the effect of concentration on profits, which supports the efficiency hypothesis. Thus we include both market share and measures of efficiency to examine instead the relation between concentration and loan rates, although loan rates and market shares may be endogenously determined if MFIs gain market shares by offering more favorable loan rates (see Berger and Hannan, 1989). However, this would tend to reduce the coefficient of HHI in our loans regressions.

We derive two measures of cost efficiency: X-efficiency, which accounts for an optimal use of factors of production and S-efficiency, an indicator of how close our MFIs are to producing at the cost-effective scale, which corresponds to the level of output that minimizes average cost. We follow the banking literature in estimating a translog specification:

$$\begin{aligned}\log C = \quad & \alpha_0 + \textstyle\sum_i \alpha_i \log(q_i) + \sum_{ij} \alpha_{ij} \log(q_i)\log(q_j) + \sum_i \beta_i \log(p_i) \\ & + \textstyle\sum_{i,j} \beta_{ij} \log(p_i)\log(p_j) + \sum_{ij} \gamma_{i,j} \log(q_i)\log(p_j) + \varepsilon, \end{aligned} \tag{2}$$

where C is total operational cost, q_i are the outputs and the p_i are input prices. The inputs we use are physical capital and labor. We impose homogeneity of degree one of the cost function in prices by subtracting off the log of the price of physical capital for all price variables, including cost. In a recent paper, Caudill, Gropper and Hartarska (2009) estimate a similar cost function for a sample of about one hundred Eastern European MFIs. They find that half the MFIs in their sample are becoming more efficient over time. We estimate a specification with gross loan portfolio (GLP) and the number of loans as outputs, see Table A.1 in the Appendix. Like Berger (1995) we compute X-efficiency as the ratio of the average residual for an MFI, leaving out the current period, to the average residual for all MFIs for that year.

Scale-efficiency can be computed in the (possibly) multi-output case by considering the ratio of the ray average cost function to the actual average cost.[20] It can be computed in closed-form in the case of the translog cost function as S-efficiency $= \exp\left(-(1-\varepsilon(q,p))^2/2\alpha\right)$, where $\varepsilon(q,p) = \sum_i \frac{\partial \log C}{\partial \log(q_i)}$ is the sum of the elasticities of cost with respect to all outputs and $\alpha = \sum_{ij} \alpha_{ij}$ (see Balk, 2001).

Table 1 shows descriptive statistics for X-efficiency and S-efficiency. Nonprofit MFIs exhibit higher scores of X-efficiency than profit-oriented ones by 3%. However, for-profit MFIs exhibit superior S-efficiency, by about 7%.

4.7 Interest rate ceiling

Some countries have imposed interest rate ceilings, that may affect the rates charged by MFIs. They are intended partly to protect borrowers from predatory lenders. They may apply differently to banks, NBFIs, NGOs or cooperatives. In some cases, ceilings are part of specific microfinance laws, as is the case for instance in Honduras, while in other countries, they are specified in usury laws or more general banking laws. To our best knowledge, we are the first to construct a comprehensive variable for the presence of interest rate ceilings, specific to the microfinance sector, across countries and years, which is crucial to understand MFI loan rates. Further, we only account for ceilings that are being enforced, which is not always the case. For instance, in countries like Niger, there is a ceiling on interest rates by law but it has never been applied in practice. Moreover, we take into account exemptions that can apply for specific MFIs in specific periods. To construct this variable we hand-collected information on interest rate ceilings from a variety of data sources, including country reports from rating agencies, rating reports of MFIs, World Bank, CGAP, USAID, mftransparency.org and legal information from different countries available on the internet, among others. Given the maze of different sources we used, we were not able to compile the actual levels of the ceilings for a comprehensive sample. Instead, we construct a dummy variable indicating the presence or not of interest rate ceilings in every country and sector (banks, NGOs, NBFIs, etc.) over time. We include this variable as a control in our yield spread regressions. As a result, we have 444 MFI-year observations that are subjected to an interest rate ceiling, of which a large majority of 393 observations correspond to nonprofit MFIs. The average yield spread of for-profit MFIs subject to an interest rate ceiling is 14%, while for nonprofit MFIs it is 19%. When interest rate ceilings do not apply these averages are 20% and 21% respectively.

4.8 Information acquisition and other MFI characteristics

The size of the customer base, reflected by the number of borrowers, is to some extent indicative of the amount of information an MFI has gathered about the market, which is justified on theoretical grounds as discussed in Section 4.1, see Marquez (2002). In this sense, we interpret this variable as a proxy for information acquisition in Section 5.1. We alleviate concerns that this variable could capture other non-information effects in several ways. For instance, since we are controlling for market share and cost efficiencies, we can rule out the possibility that number of borrowers simply captures market power or a potential reduced efficiency of dealing with a larger client base. It could also be the case that if MFIs with more borrowers are the ones that hand out smaller loans, they would incur higher costs that could get translated into higher rates. To rule out this channel, we also include two dummies for lending technology and we control for average loan size.[21] Finally, we include other MFI-specific characteristics that might potentially affect loan rates, such as size, age, a dummy for deposit-taking institutions, four dummies accounting for different world regions and four dummies accounting for legal status. The latter capture the possibility that MFIs in a particular category experience levels of loan rates that are significantly different from other categories. Some of these variables may present endogeneity concerns. Following Ahlin et al. (2011), we also run the regressions leaving out all MFI-specific variables. Further, whenever there is a possibility of reverse causality, we run the regression both with and without the potentially problematic variable. The results of these alternative estimations are discussed in the robustness section (Section 6.3).

5 EMPIRICAL RESULTS

5.1 Concentration and loan rates

The results of estimating Equation (1) are shown in Tables 4 and 5. We confirm our hypothesis, that lending rates are sensitive to the degree of MFI concentration in a country and that this effect is mostly driven by for-profit MFIs. Table 4, reports different specifications using the entire sample. When country-specific variables are not taken into account, we find evidence that ceteris paribus, MFIs in more concentrated environments charge higher lending rates (Column 1). When we control for different World Bank and Heritage Foundation indicators, the effect reduces, but remains significant in most specifications. The indicator for government effectiveness has the strongest effect (Column 3), since it takes away significance of the coefficient of HHI. This suggests that weaker institutions lead to less concentrated microfinance markets.

In Table 5, we report similar regressions for the subsamples of for-profit and nonprofit MFIs.[22] Remarkably, we find evidence that the concentration index has a significantly higher effect on loan rates of for-profit MFIs, even after controlling for country-specific indicators. For example, let us consider our regression reported in Column 3, where we control for government effectiveness. Moving from a country with an HHI equal to 0.25, which is close to the median HHI in our sample, to a higher-concentration country in the top decile of the distribution, with HHI equal to 0.75, would imply that for-profit MFIs increase the yield spread with respect to the average lending rate in the country by 7.3%. The magnitude of this effect is more than twice the one reported in several studies in the banking sector. For instance, Sapienza (2002) analyzes the Italian market and her results indicate that a similar change in the HHI of 0.5 would increase the loan rate by 2.9%. Similarly, Cyrnak and Hannan (1999) in the US market report a 1% to 2.7% increase. However, the impact of HHI varies widely across studies and its magnitude is often much lower (see e.g. Kim, Kristiansen and Vale, 2005; Degryse and Ongena, 2008). Arguably, these larger shifts in MFI interest rates are made possible by the high rates charged in microfinance. The table also indicates that the impact of concentration on lending rates could be seriously overestimated (by up to 60%) if we do not control for the level of development of institutions and markets in a country (Column 1). Admittedly, both competition and lower interest rates are jointly favored by improved quality of regulation, government effectiveness and the level of economic freedom.

The effect of concentration reduces substantially for nonprofit MFIs. The magnitude of the effect is between 20% and 40% of the effect on for-profits (Columns 6 to 10). It remains significant, except when controlling for regulatory quality and government effectiveness. The fact that lending rates of nonprofit institutions are less sensitive to changes in the concentration index indicates that yields might already be depressed due to donor restrictions, limiting the pressure for further rate reductions. Also, the concentration index may not capture the market structure of nonprofit MFIs well, since these are likely to have a different objective function than their profit-oriented counterparts. Moreover, some nonprofits might engage in non-financial activities, such as financial literacy training, and combine them with financial services, and thus interest rates could also reflect the cost of these services, as part of some cross-subsidization strategy, making the price structure more rigid.[23] Further, weaknesses in governance and greater barriers to access funding limit the ability of nonprofit MFIs to exploit growth opportunities and generate economies of scale, and since they are less regulated, Delgado, Parmeter, Hartarska and Mersland (2015) suggest that nonprofit MFIs are also limited in generating economies of scope. High interest rates may also reflect the higher exposure of nonprofit MFIs to local systemic shocks. Finally, competitive pressures might be reduced if nonprofit MFIs are able to retain their sole ownership of borrowers' information, in spite of decreased concentration, for instance as a result of having more captive borrowers. These arguments, however, suggest that the effects of concentration in the nonprofit sector may depend on the lending technology specific to each MFI. We analyze this possibility later in this section.

Our control variables reveal a number of effects. For-profit share allows for a differential competitive pressure between for-profit and nonprofit MFIs. The null hypothesis is that both for-profit and nonprofit markets are fully integrated, in which case any mutual competitive effects are symmetric, and the for-profit share has no effect. Our regression results in Table 5 indicate that, ceteris paribus, a 10% increase in the relative presence of for-profit MFIs in a country, triggers a reduction in the loan rates charged by these MFIs of 1.5% to 1.9%, depending on our model specification (Columns 1 to 5). We also find some evidence that the loan rates of nonprofit MFIs react to the increased presence of for-profit institutions, but in the opposite direction: they increase by nearly 35 to 44 basis points (Columns 6 to 10), although this effect is only significant when we effectively control for institutional development indicators such as regulatory quality and government effectiveness. This is consistent with the idea stated above that nonprofit MFIs have a limited capacity to compete with further price reductions. Thus, in the presence of increased competition from for-profit MFIs, nonprofits might be forced to concentrate on niche markets, where they have increased flexibility to adjust their prices, while facing a riskier clientele. This ability to shift to other markets and circumvent competitive pressures may also explain why nonprofit institutions are less sensitive to the concentration index. Overall we reject the null hypothesis, as we find significant evidence of spillover effects from the for-profit to the nonprofit sector.

Interest rate ceilings significantly reduce yield spreads by 4.1% to 5% in our estimations for the entire sample (see Table 4). However, the effect is particularly striking for profit-oriented MFIs (Table 5), which reduce their interest rates by about 10% to 13%, when ceilings are imposed. To put this number in perspective, this means that imposing interest rate ceilings has the same effect on profit-oriented MFIs as a change in concentration of 55% to 85% of the way from monopoly to perfect competition, depending on the specification. In contrast, the effect of interest rate ceilings on nonprofits is substantially smaller at about 2%, and only marginally significant.

The coefficient for market share is not significant and thus our results do not support the market power hypothesis stated above. The deposit dummy has a negative impact on loan rates, reflecting the fact that deposits are a low cost source of funding for MFIs, which allows MFIs to leverage their equity and remain self-sustainable with high returns on equity, even when they reduce the interest rates they charge their borrowers, thus adversely impacting their return on assets.[24] Ceteris paribus, deposit-taking institutions in the nonprofit sector charge lending rates that are about 2% lower, compared to lending-only MFIs. We do not find this effect in the for-profit sector. This suggests that nonprofit MFIs that do not take deposits will find it hard to achieve self-sustainability in competitive environments, where loan rates face further downward pressure.

Other control variables in our model are also statistically significant. Large nonprofit MFIs, in terms of total assets, charge lower rates. Both for-profit and nonprofit MFIs specialized in village lending are able to charge substantially higher lending rates, by about 6.5%, compared to MFIs that only lend to individuals. Group lending MFIs also charge somewhat higher rates, by about 2.5%, but this result is only significant when we control for regulatory quality and government effectiveness. This result partly reflects the fact that borrowers face higher switching costs in group or village lending (see Porteous, 2006). Furthermore, group lending MFIs and specially village banking MFIs serve the poorest, they are in general the least profitable and are heavily subsidized (see Cull et al., 2007). Thus high yields partly compensate the large average costs of serving very small loans. In an alternative specification (not reported), we interact lending technology dummies with Herfindahl. The results suggest that village banking is particularly sensitive to competition and that MFIs relying only on this type of lending could be forced to substantially reduce the interest rates they charge. Moving from a country with an HHI equal to 0.25, to a higher-concentration country in the top decile of the distribution, with HHI equal to 0.75, would imply that nonprofit village-lending MFIs increase the yield spread with respect to the average lending rate in the country by about 22%.[25] The fact that interest rates of group and village lending are more responsive to competition compared to individual lending is consistent with the idea that private information matters mostly for individual lending and that individual borrowers are likely to be more captive than group borrowers.[26]

Remarkably, the coefficient for the number of borrowers is positive and highly significant for both nonprofit and for-profit institutions. If an MFI doubles its borrower base, this implies an increase in yield spread by 4.2% to 5.3%[27]. One interpretation is that the relation between number of borrowers and loan rates might result from MFIs with a larger borrower pool handing out smaller loans. This could increase their costs, and they might have to charge higher rates as a result. However, this is not what is driving our result, since we are already controlling for lending technology and loan size. Alternatively, it could be that the number of borrowers is capturing cost inefficiencies associated with the management of a larger pool, or that it is capturing market share, and that our result is actually due to market power. However, we are already controlling for X-efficiencies and S-efficiencies and for market share, which has a correlation of 0.30 with number of borrowers, and is not significant in any of our specifications. Yet, another explanation is that an MFI with a large customer base has an informational advantage over an MFI with few customers. This is because, with a larger pool of borrowers, it faces less asymmetric information, which allows it to extract rents (see e.g. Dell'Ariccia, 2001; Marquez, 2002).

To analyze this further, we estimate Equation (1) by including an interaction term between the number of borrowers and HHI. We estimate our interacted models separately for the subsamples of for-profit and nonprofit MFIs. The results are shown in Table 6. The coefficient of the interaction term is positive in all specifications in the for-profit sector (Columns 1 to 5). The interaction effect indicates that MFIs with a large customer base are able to charge higher rates, particularly in concentrated markets, presumably as a result of an informational advantage. Our evidence in Table 6 is also consistent with a loss of this informational advantage in less concentrated markets, where large MFIs charge lower interest rates compared to concentrated markets. As a result, when HHI approaches zero, interest rates of MFIs with large and small pools of borrowers tend to converge.[28] In the nonprofit sector the interaction coefficient is much weaker in magnitude, though negative.

This indicates that nonprofit MFIs with a large customer base seem to be relatively insensitive to the level of concentration. They apparently succeed in retaining their informational advantage in less concentrated environments. Furthermore, the relation between number of borrowers and loan rates is always positive, irrespective of the level of concentration, suggesting that nonprofit MFIs with large pools of borrowers benefit from an informational monopoly and thus higher switching costs for their clients. This makes borrowers vulnerable to being charged higher rates (see e.g. Schenone, 2009; Santos and Winton, 2008). These results hold even after controlling for other potential non-informational effects of the size of the customer base, like loan size, market share and cost efficiencies. Overall, our results are consistent with an information-based competitive mechanism, particularly in the for-profit sector. Under competitive pressure, for-profit MFIs with a large customer base lose their informational advantage, which results in lower interest rates. The nonprofit sector instead behaves very differently. Our results are consistent with a higher informational gap between lenders, higher switching costs and more captive borrowers in the nonprofit than in the for-profit sector.

5.2 Commercial bank branch penetration

In this Section we address the potential concern that large banks compete for the same clients as MFIs, which exercises some competitive pressure on MFIs. This effect can be captured using measures of market penetration from the Financial Access Survey (see e.g. Cull et al., 2013). More specifically, we use the number of commercial bank branches per 1000 km^2 and per 100000 adults. These indicators of geographic and demographic penetration were constructed by Beck et al. (2007) to measure financial sector outreach across countries. However these variables are only available for a subset of 41 countries of our sample, which reduces the number of observations by more than half, compared to our original sample. Therefore, in an alternative specification, we add these variables to the set of variables accounting for the competitive environment. Our estimations with demographic and geographic bank branch penetration are shown in Table 7.

Given how much our sample reduces, we first reestimate our previous specification for this new sample, without controlling for bank branch penetration (Panel A). This allows us to disentangle the effect of including bank branch penetration measures from the effect of the reduced sample. The effects of HHI and for-profit share appear to be much larger and with a higher level of statistical significance than with our full sample, in spite of the larger standard errors due to the reduced sample. In particular, the coefficient of for-profit share increases up to 4 or 5 times in some specifications, and the effect of Herfindahl is multiplied by up to 2. Our results in Panel B show that demographic penetration has a significant impact on loan rates of MFIs. An increase by 10 bank branches per 100000 adults triggers a reduction of 2% in interest rates of MFIs. In contrast, we find no impact of geographic penetration (Panel C). Controlling for demographic penetration, however, significantly strengthens the effect of HHI in the reduced sample, which increases by 15% to 60% and becomes significant in all specifications (Panel B). The effect of interest rate ceilings is also strongly magnified in the reduced sample, and inclusion of demographic penetration only very slightly attenuates this effect.

5.3 Instrumental variable estimation

One concern, as stated above, is that even though we have included as many country and MFI-level controls as possible, HHI and loan rates might still be simultaneously determined by time invariant unobserved effects. While our results so far are consistent with a causal effect of HHI on loan rates, in this section, we report results using instrumental variable estimation. This procedure allows to consistently estimate coefficients even if our main explanatory variable is correlated with the error term in our base specification.

To identify the causal impact of HHI on yield spreads requires an instrument that predicts cross-sectional changes in HHI (i.e. relevance condition), but is otherwise unrelated to changes in yield spreads, after controlling for other relevant factors (i.e. exogeneity condition). We propose two plausible instruments, the average number of procedures to start a business in a given country, and the average cost to start a business, as a percentage of income per capita. Both variables are obtained from the World Bank's Global Financial Development Database. The reasons why barriers to establish businesses in a country are likely to be predictors of the HHI in the cross section, are twofold. First, they are proxies for the demand of capital in a country and thus reflect the level of development of the main credit sector. Several recent studies find evidence that microfinance institutions develop more profitably and reach more clients where the formal banking sector is less developed (see e.g. Vanroose and D'Espallier, 2013). Second, onerous regulatory burden to start a business likely force small firms into the informal sector, to avoid taxes or legal requirements (see e.g. Johnson, Kaufmann and Zoido-Lobaton, 1998; Friedman, Johnson, Kaufmann and Zoido-Lobaton, 2000). But operating in the informal sector exposes firms to multiple constraints, among which a lack of access to formal financial intermediation. Both the lack of a well-developed credit sector and the presence of an informal economy are conditions that typically motivate donors, development agencies and private investors to fund microfinance institutions. In this sense, barriers to start a business covary with HHI due to higher incentives for MFIs to enter that particular market. Consistent with this argument, a correlation analysis shows that the number of procedures and costs to start a business correlate negatively with microfinance HHI. The correlation coefficients are -25% and -13% respectively, both being statistically significant[29].

The question remains whether our two candidates for instruments may be plausibly excluded from our main specification determining yield spreads. There are two reasons why these two variables could have a direct impact on yield spreads, which would question their exogeneity as instruments. First, it could be argued that large barriers to start a business and the consequent lower development of the formal banking sector not only covary with microfinance HHI, but also have the concomitant effect of reducing competition from main banks in the microfinance sector, thus affecting directly MFIs yield spreads. Therefore, in our instrumental variable estimation it is crucial to control for potential local competition of main banks via bank branch penetration variables, as we did in Section 5.2. Second, it could be that the set of factors that determine the barriers to establish a business affect yield spreads of MFIs directly and that these factors are not properly accounted for in our main specification. These factors are related either to the country's institutional development (e.g. weak rule of law, corruption, inconsistent legal enforcement, etc.) or to macroeconomic variables such as high tax rates, income levels, inflation, etc. Therefore, it is equally crucial that we attempt to control for a variety of such factors in our IV estimations, via KKM indices, Heritage Foundation indices, GDP growth and the quality of borrowers, as we have done in previous sections.

Table 1 provides summary statistics of our two instruments, which are available for a subset of 63 countries of our sample (out of a total of 67). Since we need to control for demographic bank branch penetration, which is itself available only for a subset of 41 countries of our sample, the number of observations we use in our IV estimation reduces to 514 (corresponding to 38 countries). Given how much our sample shrinks, we first reestimate our main specification for this subsample, controlling for demographic bank branch penetration. Table 8, Panel A, reports OLS estimates, which do not control for potential endogeneity of HHI. The effect of HHI across specifications mimics our results in our robustness test in Table 7, although the magnitude of the coefficient is somewhat reduced, ranging between 0.09 and 0.22. As in Table 7, the standard errors are relatively large because the sample size shrinks by 60%. Thus, for this very reduced sample, the HHI coefficient is no longer statistically significant when we control for governance effectiveness, Column 3.

The first stage relation between HHI and barriers to start businesses is estimated as follows:

$$\text{HHI}_{ct} = \gamma_0 + \gamma_1 \text{Procedures}_{ct} + \gamma_2 \text{Start Cost}_{ct} + \sum_k \gamma_k X_{k,ict} + \nu_t + \varepsilon_{ict}, \tag{3}$$

where Procedures_{ct} is the log of number of procedures to start a business in country c at time t, while Start Cost_{ct} is the average cost to start a business, as a percentage of income per capita, in country c at time t. $X_{k,ict}$ is a vector of k MFI and country control variables as in equation 1, including for-profit share, interest rate ceilings, cost efficiencies, lending technology, etc. The ν_t are time dummies, and ε_{ict} is an error term. Panel B, in Table 8, shows estimates of this reduced-form equation using OLS. Our first instrument, the log of the number of procedures to start a business, covaries negatively with microfinance HHI in all specifications. The coefficient is always highly statistically significant and ranges between -0.249 and -0.273. Other regressors also have statistically significant coefficients and appear to be important determinants of HHI, such as interest rate ceilings, demographic branch penetration and all governance controls. The R-squared indicates that our first-stage explains between 66% and 71% of the within-sample variation in HHI depending on the specification. The joint F-test for the two instruments ranges from 23 to 38.78 depending on the specification, which exceeds the critical values for the Stock and Yogo (2005) weak-instrument test, and thus alleviates concerns about our instruments' relevance.

The relationship between HHI and yield spreads is modeled as in Equation (1), but we use the log number of procedures and the cost to start a business as instruments for microfinance HHI. Under the assumption that exclusion of our instruments from the yield spread equation is valid, the two-stage least squares will lead to consistent estimates. We report two-stage least squares estimates in Panel C, Table 8. Notice first that the coefficients of our control variables remain basically unchanged with respect to the OLS estimates in Panel A. Thus, we focus our discussion on the HHI coefficient. While the reduced sample makes it difficult to get entirely conclusive results, our IV estimations suggest a positive causal effect of HHI on yield spreads across specifications and a range of point estimates on HHI in almost all specifications that is consistent with our previous results using our full sample. Across most specifications, the range of point estimates on HHI is nearly of similar order of magnitude than the corresponding OLS estimates in Panel A (between 0.09 and 0.35). The exceptions are Columns 3 and 5, for which the IV estimates are substantially smaller than the OLS ones. This would suggest that OLS might be overestimating the true causal effect of HHI on yield spreads. However, given the very reduced sample size, the instrumental variables are not particularly precise, in spite of the tests supporting our instruments relevance. Thus, the differences between IV estimates and OLS estimates could just be due to sampling error. Further, even though the two-stage least squares estimates are consistent, they are potentially subject to finite sample bias. Finally, while our lower bound point estimate on HHI of 0.016, is much smaller than our estimates for the full sample, it is of the same order of magnitude as the estimates reported in previous studies of bank concentration (i.e. an increase of HHI by 0.5 implies an increase in loan rates by 0.8%), (see e.g. Degryse and Ongena, 2008). Under the assumption that exclusion of barriers to start a business from the yield spread equation is valid, we conduct a regression-based Hausman test by including the residuals of the first stage as regressors in our model of yield spreads (estimated with OLS). The test (not reported) does not reject the exogeneity of HHI in any of our specifications.

6 ROBUSTNESS TESTS

6.1 *For-profit and nonprofit Herfindahl indices*

Our main specification is based on the use of an overall Herfindahl index, controlling in particular for for-profit share. If the nonprofit and for-profit segments were fully integrated, for-profit share should not matter in the regression of loan rates. Our results show that this is not the case. However, at the other end of the spectrum, one could hypothesize that the for-profit and nonprofit sector are actually completely independent one from another. This hypothesis of full market segmentation cannot be tested directly in our main specification. In order to consider this possibility, we also try specifications including a nonprofit and for-profit Herfindahl, denoted HHI_{NP} and HHI_{FP}, and market shares computed on each segment. For-profit share and these two Herfindahls relate to the overall Herfindahl as follows: $HHI = HHI_{FP}.(\text{FP share})^2 + HHI_{NP}.(1 - \text{FP share})^2$. This shows that segment specific concentration indexes are related to the overall Herfindahl and to the for-profit share, which are the variables we include in our main specification. Under the full segmentation hypothesis, each segment should only react to its own Herfindahl but not to the Herfindahl of the other segment. We run the same specifications as in Table 5, but with two Herfindahls instead of one. In a regression where we use market shares computed on each segment, we find that the for-profit sector reacts exclusively to for-profit Herfindahl, the nonprofit sector reacts to for-profit Herfindahl, but not to its own concentration index, while market shares in both sectors become insignificant. When we use instead market shares computed on the joint for-profit and nonprofit market, we find that for-profit Herfindahl affects both segments in most cases, and in a few regressions (when regulatory quality or government effectiveness is included), nonprofit Herfindahl is also significant in the nonprofit sector. Overall these results reject the hypothesis that the two markets are fully segmented and are consistent with our previous findings in Section 5.1, that there is a significant impact of the for-profit on the nonprofit sector.

6.2 Alternative measures of concentration

We check the robustness of our result using an alternative indicator of concentration, the 3-firm concentration (CR3), which is the total market share of the three largest firms in the market.[30] The results with this variable are qualitatively and quantitatively very similar to the ones obtained with HHI, except for the interactions with number of borrowers, that are not significant in the case of the yield spread of nonprofits (Table 6, Panel A, Columns 6 to 10). This again suggests that nonprofits are not that responsive to competitive conditions in their pricing. We also considered using the inverse of the number of players in the market. Arguably, this indicator is less prone to endogeneity problems, as it reflects entry and exit, which are less influenced by changes in market shares. However in our case, it is not feasible to reliably construct such an indicator, since it is impossible to obtain the actual number of MFIs in the market, some of which might be very small.[31]

6.3 Exclusion of MFI-specific controls

As an additional robustness check we also run our basic regressions, whose results appear in Table 4 without any MFI-specific variable to rule out any endogeneity concerns. This is in line with the estimation strategy of Ahlin et al. (2011). The variables we take out are size, age, number of borrowers, loan size, the deposit dummy, the lending methodology dummies (village lending and group lending), as well as market share and the cost-efficiency measures (X-efficiency and S-efficiency). The results for our main variables Herfindahl and for-profit-share remain highly significant and the magnitude of the coefficients is comparable to the one in our main specification.[32]

We also estimated our main specification leaving out each MFI control one at a time (except for the two efficiency measures and the two lending methodology dummies which we leave out pairwise). There is a particular concern with market share, as pointed out by Berger and Hannan (1989), who note that the inclusion of market share in a price regression can be problematic if banks charging lower rates tend to get higher market shares. Our results where we leave out these controls (not reported) are hardly affected.

6.4 Further robustness

Our current specification controls for the type of lending methodology, in the form of group and village lending dummies, with individual lending being the base case. We further test the robustness of our results to the use of the share of individual lending instead of the two dummies. The results (unreported) are consistent with our main results, and the rates consistently decrease with the extent of individual lending. The effect of HHI remains robust to this specification.

In unreported results, we also test the robustness of our results to the inclusion of a strength of legal rights index, a depth of credit information variable, that can affect the cost of finance, and two measures of the costs of contract enforcement, enforcing contracts (time) and enforcing contracts (costs), which could increase interest rates. Our results are robust to these new controls, obtained from the World Bank's Doing Business Indicators.

In our current specification, we rely on the growth and the share of rural population as proxies for the demand for microfinance services. Given that many MFIs do not target exclusively rural populations, we check the robustness of our results to measures of poverty, as alternative demand shifters. Unfortunately, the poverty measures available from the World Bank do not cover all our countries and years. Even poverty headcount ratio at 1.25$ a day (PPP), the poor population variable with the widest coverage, leaves us with a total sample size of only about a third the size of the original sample (420 as opposed to 1234 observations). Our results (unreported) are robust to the new controls, which are significant in the full sample and in the nonprofit sample, but not in the for-profit sample. Besides, we also tried to use Poverty gap at 1.25$ a day (PPP) in percentage, which was not significant in any of our regressions.

7 CONCLUDING REMARKS

In this paper we provide a description of the competitive environment of microcredit markets in 67 countries from 2002 to 2008 and we investigate the effects of competition on loan rates of MFIs. Specifically, we analyze the impact of decreasing overall market concentration resulting from entry into the sector of both for-profit and nonprofit MFIs. We control for differences in institutional environments, for competitive pressures from main banks and for the overall increase in the share of profit-oriented institutions attracted by the success of microfinance lending technologies.

We find remarkable differences in the competitive conditions for nonprofit and profit-oriented MFIs. Loan rates of nonprofit MFIs are mostly insensitive to changes in concentration. In contrast, our results show that with increased competition, for-profit MFIs reduce their loan rates, favoring consumer surplus. According to our most conservative estimate, a change in HHI of 0.5 implies an increase in the yield spread by 7.3% which is more than twice the effect reported in several studies in the banking literature. In particular, we control for interest rate ceilings, which very significantly reduce rates in for-profit MFIs by about 10%. This is equivalent to the effect of a reduction in concentration of 55% to 85% of the way from monopoly to perfect competition, depending on the specification. In contrast, interest rate ceilings have a substantially smaller effect on nonprofits. We also find that for-profit MFIs are more sensitive to competition from other for-profit MFIs. A 10% increase in for-profit share in a country induces a reduction in for-profit loan rates of 1.5% to 1.6%. There is some evidence that loan rates of nonprofit MFIs also react to the increased presence of for-profit institutions, but in the opposite direction: they increase by nearly 35 to 44 basis points. This is consistent with the idea that nonprofit MFIs circumvent competition from for-profits by concentrating on niche markets, where they have increased flexibility to adjust their prices. Our results are robust to the inclusion of indicators of commercial bank branch penetration, to alternative measures of concentration, and to an alternative estimation procedure using instrumental variables. Overall, we conclude that concentration matters in the for-profit sector and that there are significant spillover effects from the for-profit to the nonprofit.[33]

Further, our study suggests an information-based competitive mechanism at work in the microfinance sector. MFIs with large numbers of borrowers in concentrated markets appear to enjoy an information monopoly, which allows them to charge higher rates. In a competitive environment, however, large for-profit MFIs exhibit lower interest rates compared to concentrated markets, while small MFIs are able to charge higher rates. This is consistent with a reduced ability of lenders to exploit their informational advantage under competition, presumably as a result of lower screening incentives, lower switching costs and less captive borrowers. An open question for further research is whether reduced loan rates and information dispersion would make the costly lending model of microfinance institutions unsustainable, forcing for-profit MFIs to drift away from their social mission of targeting the very poor. The nonprofit sector instead behaves very differently. Our results are consistent with high switching costs and more captive borrowers in this sector, which allows yield spreads to remain high. High switching costs coupled with a monopoly of information appear to be a major competitive advantage for nonprofit MFIs with large numbers of borrowers.

8 APPENDIX: COST FUNCTION

In order to compute our cost efficiency measures we estimate the following translog specification:

$$\begin{aligned}\log C = \; & \alpha_0 + \alpha_1 \log(q_1) + \alpha_2 \log(q_2) + \alpha_{11} \log(q_1)^2 + \alpha_{12} \log(q_1) \log(q_2) + \alpha_{22} \log(q_2)^2 \quad (4)\\ & + \beta_1 \log(p_1) + \beta_{11} \log(p_1)^2 + \gamma_{11} \log(q_1) \log(p_1) + \gamma_{21} \log(q_2) \log(p_1) + \varepsilon, \quad (5)\end{aligned}$$

where C is operational cost, outputs are number of loans (q_1) and gross loan portfolio (q_2), and inputs are physical capital and labor with price (p_1). The cost of physical capital is calculated as actual operating expense minus actual personnel expense divided by net fixed assets. The cost of labor is calculated as actual personnel expense divided by the number of employees. As is standard, we impose homogeneity of degree one in all prices by subtracting the log of the price of physical capital from the cost and the price of labor. This variable does therefore not appear explicitly in our equation. The estimation results in Table A.1 reveal that even a simple cost function achieves a surprisingly good fit.

We compute X-efficiency following Berger (1995) from the residuals ε_{it} of the cost function, where i denotes the MFIs and t is time. X-efficiency compares the average residual for MFI i excluding the current year with the smallest residual over all MFIs for that year:

$$\text{X-efficiency}_{it} = \exp\left(\frac{1}{n_s - 1} \sum_{s \neq t} \varepsilon_{is} - \min_j \varepsilon_{jt}\right).$$

The scale efficiency measure compares the actual average cost to the scale-efficient average cost, mentioned in Balk (2001), whose presentation we follow in the remainder of this Appendix. In the case where there is only one output, this corresponds simply to the quantity that minimizes average cost. When there is more than one output, this generalizes to the ray average cost (RAC)

$$RAC(q, p) \equiv \min_\lambda \frac{C(\lambda q, p)}{\lambda} = \min_\lambda C\left(\frac{q}{\lambda}, \frac{p}{\lambda}\right).$$

The optimal scale λ^* satisfies the first order condition, which is equivalent to $\varepsilon(\lambda^* q, p) = 1$, where $\varepsilon(q,p) \equiv \sum_i \frac{\partial \log C}{\partial \log(q_i)}$ is the sum of the elasticities of cost with respect to all outputs.

In the case of the translog, one obtains

$$\varepsilon(\lambda^* q, p) = \varepsilon(q,p) + \alpha \log(\lambda^*),$$

where $\alpha = \sum_{ij} \alpha_{ij}$, and $\varepsilon(\lambda^* q, p) = 1$ is equivalent to $\lambda^* = (1 - \varepsilon(q,p))/\alpha$. Moreover

$$\log\left(RAC(q,p)\right) = \log C(q,p) + \log(\lambda^*)\left[\frac{1}{2}\alpha \log(\lambda^*) + \varepsilon(\lambda^* q, p) - 1\right].$$

Finally S-efficiency is the ratio of the ray average cost to the cost and can be shown in for the translog to be

$$\text{S-efficiency} = \frac{RAC(q,p)}{C(q,p)} = \exp\left(-\frac{(1-\varepsilon(q,p))^2}{2\alpha}\right).$$

Table A.1: Translog cost function for efficiency measures

	Operating expenses
Constant (α_0)	2.236* (0.905)
Number of loans (α_1)	0.319* (0.158)
Gross loan portfolio (α_2)	-0.241 (0.175)
Number of loans^2 (α_{11})	0.035** (0.009)
Number of loansGross loan portfolio (α_{12})	-0.033 (0.018)
Gross loan portfolio^2 (α_{22})	0.026* (0.011)
Labor cost (β_1)	0.854** (0.131)
Labor cost^2 (β_{11})	-0.016* (0.007)
Number of loansLabor cost (γ_{11})	-0.008 (0.012)
Gross loan portfolioLabor cost (γ_{21})	0.015 (0.014)
Obs.	1433
R^2	0.903

Note: Robust standard errors in parentheses: ** p<0.01, * p<0.05.

References

Ahlin, C., Lin, J. and Maio, M. (2011), 'Where does microfinance flourish? Microfinance institution performance in macroeconomic context', *Journal of Development Economics* **95**(2), 105–120.

Assefa, E., Hermes, N. and Meesters, A. (2013), 'Competition and the performance of microfinance institutions', *Applied Financial Economics* **23**(9), 767–782.

Bain, J. (1956), *Barriers to New Competition*, Harvard University Press, Cambridge.

Balk, B. M. (2001), 'Scale efficiency and productivity change', *Journal of Productivity Analysis* **15**(3), 159–183.

Baum, C. F., Nichols, A. and Schaffer, M. E. (2010), Evaluating one-way and two-way cluster-robust covariance matrix estimates, BOS10 Stata Conference 11, Stata Users Group.

Beck, T., Demirgüç-Kunt, A. and Maksimovic, V. (2004), 'Bank competition and access to finance: International evidence', *Journal of Money Credit and Banking* **36**(3), 237–269.

Beck, T., Demirgüç-Kunt, A. and Martinez Peria, M. S. (2007), 'Reaching out: Access to and use of banking services across countries', *Journal of Financial Economics* **85**(1), 234–266.

Berger, A. N. (1995), 'The profit-structure relationship in banking - Tests of market-power and efficient-structure hypotheses', *Journal of Money, Credit and Banking* **27**(2), 404–431.

Berger, A. N., Frame, W. S. and Ioannidou, V. (2011), 'Tests of ex ante versus ex post theories of collateral using private and public information', *Journal of Financial Economics* **100**(1), 85–97.

Berger, A. N. and Hannan, T. H. (1989), 'The price-concentration relationship in banking', *The Review of Economics and Statistics* **71**(2), 291–299.

Berger, A. N., Miller, N. H., Petersen, M. A., Rajan, R. G. and Stein, J. (2005), 'Does function follow organizational form? Evidence from the lending practices of large and small banks', *Journal of Financial Economics* **76**(2), 237–269.

Caudill, S. B., Gropper, D. M. and Hartarska, V. (2009), 'Which microfinance institutions are becoming more cost efficient with time? Evidence for a mixture model', *Journal of Money, Credit and Banking* **41**(4), 651–672.

Claessens, S. and Laeven, L. (2004), 'What drives bank competition? Some international evidence', *Journal of Money, Credit and Banking* **36**(3), 563–583.

Corvoisier, S. and Gropp, R. (2002), 'Bank concentration and retail interest rates', *Journal of Banking and Finance* **26**(1), 2155–2189.

Cull, R., Demirgüç-Kunt, A. and Morduch, J. (2007), 'Financial performance and outreach: A global analysis of leading microbanks', *The Economic Journal* **117**(517), 107–133.

Cull, R., Demirgüç-Kunt, A. and Morduch, J. (2013), 'Banks and microbanks', *Journal of Financial Services Research* **46**(1), 1–53.

Cyrnak, A. and Hannan, T. (1999), 'Is the cluster still valid in defining banking markets? Evidence from a new data source', *Antitrust Bulletin* **44**(2), 313–331.

Degryse, H. and Ongena, S. (2008), Competition and regulation in the banking sector: A review of the empirical evidence on the sources of bank rents, *in* 'Handbook of financial intermediation and banking', Oxford University Press, pp. 483–554.

Delgado, M. S., Parmeter, C. F., Hartarska, V. and Mersland, R. (2015), 'Should all microfinance institutions mobilize microsavings? Evidence from economies of scope', *Empirical Economics* **48**(1), 193–225.

Dell'Ariccia, G. (2001), 'Asymmetric information and the structure of the banking industry', *European Economic Review* **45**(4), 1957–1980.

Demirgüç-Kunt, A., Laeven, L. and Levine, R. (2004), 'Market structure, institutions and the cost of financial intermediation', *Journal of Money, Credit and Banking* **36**(3), 593–622.

Feinberg, R. M. (2001), 'The competitive role of credit unions in small local financial services markets', *Review of Economics and Statistics* **83**(3), 560–563.

Frame, W. S. and Kamerschen, D. R. (1997), 'The profit-structure relationship in legally protected banking markets using efficiency measures', *Review of Industrial Organization* **12**(1), 9–22.

Friedman, E., Johnson, S., Kaufmann, D. and Zoido-Lobaton, P. (2000), 'Dodging the grabbing hand: the determinants of unofficial activity in 69 countries', *Journal of Public Economics* **76**(3), 459–493.

Garmaise, M. J. and Natividad, G. (2010), 'Information, the cost of credit and operational efficiency: An empirical study of microfinance', *Review of Financial Studies* **23**(6), 2560–2589.

Garmaise, M. J. and Natividad, G. (2013), 'Cheap credit, lending operations, and international politics: The case of global microfinance', *Journal of Finance* **68**(4), 1551–1576.

Gehrig, T. (1998), 'Screening, cross border banking and the allocation of credit', *Research in Economics* **52**(4), 387–407.

Gilbert, R. A. and Zaretsky, A. M. (2003), 'Banking antitrust: Are the assumptions still valid?', *Review of the Federal Reserve Bank of St. Louis Review* pp. 29–52.

Gonzalez, A. (2010), Is microfinance growing too fast?, Technical report, MIX Data Brief No. 5.

Gonzalez-Vega, C. and Villafani-Ibarnegaray, M. (2011), Microfinance in Bolivia: Foundataion of the growth, outreach ad stability of the financial system, *in* B. Armendariz and M. Labie, eds, 'Handbook of Microfinance', World Scientific Publishing Ltd, pp. 203–250.

Grabowski, D. C. and Hirth, R. A. (2003), 'Competitive spillovers across non-profit and for-profit nursing homes', *Journal of Health Economics* **22**(1), 1–22.

Hannan, T. (1991), 'Bank commercial loan markets and the role of market structure: Evidence from surveys of commercial lending', *Journal of Banking and Finance* **15**(1), 133–149.

Hannan, T. (1997), 'Market share inequality, the number of competitors and the HHI: An examination of bank pricing', *Review of Industrial Organization* **12**(1), 23–35.

Hannan, T. (2003), The impact of credit unions on the rates offered for retail deposits by banks and thrift institutions, Technical report, Board of Governors of the Federal Reserve System Discussion Paper.

Hartarska, V. and Nadolnyak, D. (2007), 'Do regulated microfinance institutions achieve better sustainability and outreach? Cross-country evidence', *Applied Economics* **39**(10-12), 1207–1222.

Hauswald, R. and Marquez, R. (2003), 'Information technology and financial services competition', *Review of Financial Studies* **16**(3), 921–948.

Hauswald, R. and Marquez, R. (2006), 'Competition and strategic information acquisition in credit markets', *Review of Financial Studies* **19**(3), 967–1000.

Helms, B. and Reille, X. (2004), Interest rate ceilings and microfinance: The story so far, Technical report, CGAP Occasional Paper, No.9.

Hirth, R. A. (1997), 'Competition between for-profit and nonprofit health care providers: Can it help achieve social goals?', *Medical Care Research and Review* **54**(4), 414–438.

Hirth, R. A. (1999), ‘Consumer information and competition between nonprofit and for-profit nursing homes’, *Journal of Health Economics* **18**(2), 219–240.

Johnson, S., Kaufmann, D. and Zoido-Lobaton, P. (1998), ‘Regulatory discretion and the unofficial economy’, *American Economic Review* **88**(2), 387–392.

Kaufmann, D., Kraay, A. and Mastruzzi, M. (2009), Governance matters VIII, Technical report, World Bank Development Research Group Working Paper No. 4978.

Kim, M., Kristiansen, E. and Vale, B. (2005), ‘Endogenous product differentiation in credit markets: What do borrowers pay for?’, *Journal of Banking and Finance* **29**(3), 681–699.

Lyman, T. R., Mahieux, T. and Reille, X. (2005), Report of CGAP multi-donor mission: Microfinance in Yemen, Technical report, Consultative Group to Assist the Poor.

Marquez, R. (2002), ‘Competition, adverse selection and information dispersion in the banking industry’, *Review of Financial Studies* **15**(3), 901–926.

Martinez Peria, M. S. and Mody, A. (2004), ‘How foreign participation and market concentration impact bank spreads: Evidence from Latin America’, *Journal of Money, Credit and Banking* **36**(3), 511–537.

McIntosh, C., de Janvry, A. and Sadoulet, E. (2005), ‘How rising competition among microfinance institutions affects incumbent lenders’, *Economic Journal* **115**(506), 987–1004.

Navajas, S., Conning, J. and Gonzalez-Vega, C. (2003), ‘Lending technologies, competition and consolidation in the market for microfinance in Bolivia’, *Journal of International Development* **15**(4), 747–770.

Newey, W. and West, K. (1987), ‘A simple, positive semi-definite, heteroscedastic and autocorrelation consistent covariance matrix’, *Econometrica* **55**(4), 703–708.

Peltzmann, S. (1977), 'The gains and losses from industrial concentration', *Journal of Law and Economics* **20**(2), 229–263.

Porteous, D. (2006), 'Competition and microcredit interest rates', *CGAP Focus Note* (33).

Rogers, W. (1993), 'Regression standard errors in clustered samples', *Stata Technical Bulletin* **13**, 19–23.

Rosenberg, R., Gonzalez, A. and Narain, S. (2009), 'The new moneylenders: Are the poor being exploited by high microcredit interest rates?'.

CGAP Occasional Paper No. 15.

Santerre, R. E. and Vernon, J. A. (2005), 'Hospital ownership mix efficiency in the US: An exploratory study'.

NBER Working Paper 11192.

Santos, J. a. A. C. and Winton, A. (2008), 'Bank loans, bonds and information monopolies across the business cycle', *Journal of Finance* **63**(3), 1315–1359.

Sapienza, P. (2002), 'The effects of banking mergers on loan contracts', *Journal of Finance* **57**(1), 329–367.

Schenone, C. (2009), 'Lending relationships and information rents: Do banks exploit their informational advantages?', *Review of Financial Studies* **23**(3), 1149–1199.

Smirlock, M. (1985), 'Evidence on the (non) relationship beween concentration and profitability in banking', *Journal of Money, Credit and Banking* **17**(1), 69–83.

Stock, J. and Yogo, M. (2005), Testing for weak instruments in iv regression, *in* 'Identification and Inference for Econometric Models: A Festschrift in Honor of Thomas Rothenberg', Cambridge University Press.

Vanroose, A. and D'Espallier, B. (2013), 'Do microfinance institutions accomplish their mission? evidence from the relationship between traditional financial sector development and microfinance institutions outreach and performance', *Applied Economics* **45**(15), 1965–1982.

Yafeh, Y. and Yosha, O. (2001), 'Industrial organization of financial systems and strategic use of relationship banking', *European Finance Review* **5**(1-2), 63–78.

Notes

[1]This trend continued in more recent years. According to Microfinance Information Exchange (MIX), in 2012, the global loan portfolio reached 81.5 US billion dollars with 91.4 million borrowers served.

[2]In more recent years, there has been increasing evidence of microfinance borrowers taking loans from multiple sources, accompanied by a reduction of interest rates in the (regulated) markets where this takes place and by some overindebtedness, especially in Latin America. Nevertheless, the most successful MFIs seem to have been able to retain the good behavior of their clients, possibly because of the greater credibility of their offer of long-term relationships (see Gonzalez-Vega and Villafani-Ibarnegaray, 2011).

[3]Consultative Group to Assist the Poor (The World Bank)

[4]Note that we use this combined data set only for purposes of constructing market shares and HHI.

[5]According to the World Bank definition, lending rate is the bank rate that usually meets the short- and medium-term financing needs of the private sector.

[6]This result goes against the popular view that nonprofit institutions necessarily favor the poor. This is consistent with evidence from Bolivia, where nonprofits charge higher interest rates, while for-profits reach larger numbers and tend to favor their clients over time, with steadily declining rates for all loan sizes, including the smallest (see Gonzalez-Vega and Villafani-Ibarnegaray, 2011).

[7]Data are obtained from the rating agencies under confidentiality agreements.

[8]For example Hartarska and Nadolnyak (2007) use 114 MFIs from the MIX, while Cull et al. (2007) use data from the Microbanking Bulletin (MBB), a subsample of 124 MFIs of the MIX that has been adjusted by MBB staff or a local partner to help ensure comparability across countries. Cull et al. (2013) uses 342 observations from 238 MFIs in MBB. Garmaise and Natividad (2010) and Garmaise and Natividad (2013) use 825 MFI-year observations from 133 MFIs provided by the rating agency MicroRate.

[9]In their reports, rating agencies document and correct errors they find in the accounts of MFIs. For example, a rating report states: *"The rating team found errors in aging of overdues and portfolio-at-risk during their visits to the branch offices."*. For a few MFIs no rating was given due to suspicious or unreliable data; we eliminate such MFIs from our sample.

[10]Loan size could also reflect the effectiveness of the lending technologies. For instance, village banking MFIs tend to make loans to poorer people, but they also do not sufficiently differentiate, and thus their more creditworthy borrowers get loans that are too small. Further, internal agency dynamics constrain the growth of loan sizes for the best clients. Many among them eventually seek a second, larger loan from another MFI, while keeping their small, precautionary loan with the village bank. For-profit MFIs, in contrast, are better able to generate economies of scale and diversification, which allows them to differentiate loans in

terms of size while keeping costs and interest rates low. We thank an anonymous referee for suggesting this alternative explanation.

[11]These numbers correspond to a download of the MIX of December 2010.

[12]The Herfindahl-Hirschman Index (HHI), is a measure of industry structure defined as the sum of the squares of the market shares of the firms within the industry, where the market shares are expressed as fractions. Thus, it ranges from 0 to 1, where 0 indicates a large number of very small firms and 1 indicates a single monopolistic producer. An increase in the Herfindahl index generally indicates a decrease in competition and an increase of market power.

[13]It could also be the case that the two markets are fully segmented. We rule this possibility out in Section 6.1.

[14]Even in those markets where there are very good information-sharing mechanisms (comprehensive credit bureaus), like Bolivia, proprietary information continues to be very valuable, given the large number of new clients, without credit histories, and the value of information on intangible characteristics of applicants in determining loan sizes (see Gonzalez-Vega and Villafani-Ibarnegaray, 2011).

[15]More precisely, in the first stage of the Marquez (2002) model, banks gather proprietary information about their pool of borrowers, the size of which is determined exogenously by the amount of funds they have available for loans (loan size is fixed to 1). Before the second stage, a fraction λ of these borrowers leave and is replaced by new borrowers from the same type distribution as the original population of borrowers. This λ parameter controls the degree of information asymmetry and determines the value of the information collected in the first stage. Obviously if all borrowers get replaced by new ones in the second stage, collecting information (learning who are the good and bad types) in the first stage is useless. The bad borrowers, that have been identified in the first period and rejected by their bank, join the λ new borrowers in the "free market", and banks compete over these borrowers in the second stage. With more competition, information becomes more disperse, i.e. each bank will know a smaller fraction of the bad borrowers in the free market and, hence will face more adverse selection in the second stage.

[16]This lack of significance remains even after controlling for time and country fixed effects.

[17]A similar variation across time is found for the nominal and real portfolio yields, before adjusting for country-level lending rates. This shows that indeed the average rates charged by MFIs vary over time.

[18]For instance Baum, Nichols and Schaffer (2010) suggest that there should be at least 20 balanced or 50 reasonably balanced clusters and Rogers (1993) advises that no cluster should contain more than 10% of the data. However, we have several countries with only one or two observations (Pakistan, Burundi, Congo), while Peru, the largest country in our sample represents more than 10% of our total observations. In our split sample, we have 36 clusters in the for-profits, with a median cluster size of 6, and the largest cluster

makes up 14% of the observations, while in the nonprofit sample, we have 57 clusters, with a median size of 12, and the largest cluster represents 10% of the sample.

[19]Our regressions that include the remaining indicators from KKM, namely rule of law, voice and accountability, control of corruption, and those from the Heritage Foundation, namely labor freedom, business freedom, freedom from corruption, fiscal freedom, monetary freedom, government spending, property rights, investment freedom, trade freedom and financial freedom are available upon request.

[20]The ray average cost function is the smallest average cost attainable for a given mix of outputs, where the minimum is obtained by varying the scale of production. This assumes that the outputs are kept in the same proportion and only the scale varies.

[21]There is a potential concern that number of borrowers (we use it in log) could simply reflect the size of the market or country population. However the correlation of number of borrowers with proxies of market size such as the fraction of rural population and rural population growth is only -0.055 and 0.032, respectively, while with total and total rural population (both in log), the correlations are only 0.010 and -0.016. Another concern is that MFIs with a larger pool of borrowers face riskier borrowers and thus they have to charge higher rates to compensate for the risks. Yet, the correlation between risk (measured by portfolio-at-risk PAR) and the number of borrowers is negative, about -0.34, which means that it is more plausible that MFIs with a larger client pool actually face less risky borrowers.

[22]We also ran the estimations in Table 4 with a for-profit dummy and its interaction with Herfindahl and for-profit share, where we force the effect of the controls to be similar across for-profit and nonprofit samples. Our results (unreported) remain largely unchanged.

[23]We thank an anonymous referee for suggesting this explanation.

[24]We thank an anonymous referee for suggesting this additional explanation.

[25]One concern could be that village banking is most prevalent in highly concentrated markets, in countries with less developed institutions. However this is not the case. The distribution of village banking across levels of Herfindahl is similar to the distributions of MFIs overall.

[26]We thank two anonymous referees for suggesting this explanation.

[27]The variable is in log, so when the number of borrowers doubles, the variable increases by $log(2) = 0.693$.

[28]One concern could be that MFIs with large pools of borrowers are more prevalent in highly concentrated markets. However this is not the case. Data points are widely dispersed in terms of HHI for any given number of borrowers, but also in terms of number of borrowers for any given level of HHI.

[29]We have tested other potential instruments that proxy for the development of the formal banking sector, like CR3 or the Boone indicator, but they appear to be weak instruments for the microfinance HHI.

[30]These results are not shown due to space constraints, but they are available from the authors upon

request.

[31]We abstain from using alternative measures of competition, such as the H-statistic of the Panzar-Ross approach, the Boone or the Lerner indicator. First of all, the Herfindahl is the classical measure that is used in antitrust cases, and it allows to separate the for-profit and nonprofit segments. The alternative measures are based on underlying assumptions such as long term market equilibrium for the H-statistic or they rely heavily on the cost function, whose estimation is a particulary daunting task in a cross-country sample with extreme heterogeneity of MFIs: for-profits vs non-profits, different types of incorporations, deposit-taking and regulated or not, products offered etc. It is not even clear from a theoretical point of view, whether all MFIs, including non-profits actually attempt to maximize profits, which leads Assefa, Hermes and Meesters (2013) to drop nonprofits from their Lerner index-based study of competition in microfinance. A further difficulty is that interest-rate ceilings can bias some of the price-based measures of competition.

[32]These results are not shown due to space constraints, but they are available from the authors upon request.

[33]It would be interesting to consider the potential influence that innovation in lending technologies and funding has had on lending rates and the nature of competition. Ideally, we would like to account for the increasing variety of savings and insurance products, the development of microfinance investment funds as well as crowd funding and other fintech innovations, or how payments and transfers have been revolutionized by mobile communication and smart cards. Yet, none of these developments are directly observable in our cross-country database.

Table 1: Descriptive statistics

Panel A: MFI-specific variables (MFI/year observations)

Variable	Whole sample N=1452 Mean	Median	For-profit N=405 Mean	Median	Nonprofit N=1047 Mean	Median	Difference (t test) p-value
Yield spread	0.20	0.17	0.20	0.15	0.20	0.18	0.45
N. Borrowers (not in log)	21317	7215	35063	9778	16000	6336	<.01
Loan size	1016	580	1403	808	866	525	<.01
Loan size (% of GNI)	0.33	0.18	0.41	0.19	0.29	0.16	<.01
Market share	0.07	0.02	0.09	0.02	0.06	0.02	<.01
X-efficiency	0.18	0.18	0.16	0.15	0.19	0.18	<.01
S-efficiency	0.64	0.63	0.69	0.70	0.62	0.60	<.01
Size (not in log)	18081	4383	29915	8542	13504	3538	<.01
Age (not in log)	10.26	8.00	8.47	7.00	10.95	9.00	<.01
Individual lending	0.63	0.84	0.70	0.97	0.60	0.70	<.01
Group lending	0.27	0.03	0.23	0.01	0.28	0.03	0.03
Village lending	0.11	0.00	0.07	0.00	0.13	0.00	<.01

Panel B: Country-specific variables (Country/year observations)

Variable	Whole sample N=369 Mean	Median
Herfindahl (HHI)	0.40	0.33
For-profit share (FP share)	0.53	0.61
GDP	0.06	0.06
Rule of law	-0.61	-0.60
Political stability	-0.54	-0.49
Voice and accountability	-0.37	-0.26
Regulatory quality	-0.33	-0.36
Control of corruption	-0.56	-0.61
Government effectiveness	-0.48	-0.52
HF overall score	57.24	56.80
Business freedom	57.30	55.00
Trade freedom	66.12	67.00
Fiscal freedom	77.09	78.55
Government spending	77.68	81.50
Monetary freedom	75.15	77.05
Investment freedom	48.17	50.00
Financial freedom	50.17	50.00
Property rights	35.00	30.00
Freedom from corruption	27.83	27.00
Labor freedom	58.60	59.70
Geographic penetration	5.83	2.07
Demographic penetration	10.55	6.08
Rural pop.(% of total pop.)	51.97	51.55
Rural population growth	0.68	0.73
Country PAR	0.02	0.01
Starting a Business: Procedures (number)	2.46	2.48
Starting a Business: Cost (% of income per capita)	0.81	0.43

Note: Yield spread is adjusted real portfolio yield minus real lending interest rate. N. Borrowers is the number of borrowers. Loan size is the average loan size disbursed by MFIs. Loan size (% of GNI) is average loan size disbursed expressed as a percentage of gross national income (GNI) per capita. Market share is the gross loan portfolio market share of an MFI. S-efficiency is scale efficiency. Size is total assets in thousands of USD. Age is the age of MFIs. Individual, group lending and village lending are lending technologies expressed as percentages of gross loan portfolio (GLP). Herfindahl (HHI) is Herfindahl Hirschman concentration index. For-profit share (FP share) is the share of for-profit MFIs in gross loan portfolio in a given country to total country gross loan portfolio. GDP is the growth rate of gross domestic product. The variables from rule of law to government effectiveness are governance indicators from Kaufmann et al. (2009), also known as KKM indicators. The variables from HF overall score to labor freedom are the Heritage Foundation (HF) economic freedom indicators. Geographic penetration is the number of commercial bank branches per 1000 km2. Demographic penetration is the number of commercial bank branches per 100000 adults. Geographic and demographic penetration are from Financial Access Survey and are available for 162 year/country observations only. Rural population refers to people living in rural areas as defined by national statistical offices. It is calculated as the difference between total population and urban population. Rural pop.(% of total pop.)is rural population as a percentage of total population. Rural population growth is the annual growth rate of rural population. Country PAR is a proxy for country riskiness and is computed as the sum of gross loan portfolio with payments overdue by 30 days or more of all MFIs in a country j at year t to total gross loan portfolio of all MFIs in that country in year t. Starting a Business: Procedures (number) and Starting a Business: Cost (% of income per capita) are from the World Bank doing business data base and are available for 252 year/country observations only.

Table 2: Legal status and lending methodology

Legal status	Individual lending only	Group lending only	Village lending only	Individual & group lending	Individual & village lending	Group & village lending	Individual, groups village lending	Total
NBFI	219	40	19	243	5	4	32	562
NGO	146	65	38	194	52	0	93	588
Cooperative	119	3	0	79	0	0	10	211
Bank	37	0	0	33	0	0	3	73
Other	6	4	0	8	0	0	0	18
Total	527	112	57	557	57	4	138	1452

Note: This table shows the total number of year-MFI observations for each year of the sample. We distinguish between MFIs according to their legal status and to the different lending methodology they use. The different legal status are non-bank financial institution (NBFI), non-governmental organization (NGO), cooperative, bank, or other. The lending methodologies are individual lending, joint liability group lending, or village banking. Note that an MFI can adopt more than one lending methodology.

Table 3: Legal and for-profit vs. nonprofit status per year

Panel A: For-profit vs. nonprofit status from our sample

	Year							Total
Profit status	2002	2003	2004	2005	2006	2007	2008	
For-profit	11	39	53	71	89	91	51	405
Nonprofit	70	160	202	196	200	148	71	1047
Total	81	199	255	267	289	239	122	1452

Panel B: For-profit vs. nonprofit status in the combined data set of market shares (MIX and rating agencies data combined)

	Year							Total
Profit status	2002	2003	2004	2005	2006	2007	2008	
For-profit	181	242	283	338	379	380	369	2172
Nonprofit	595	695	756	794	790	752	681	5063
Total	776	937	1039	1132	1169	1132	1050	7235

Note: Panel A of this table shows the total number of observations per legal status for each year of the sample. Legal status of MFIs are non-bank financial institution (NBFI), non-governmental organization (NGO), cooperative, bank, or other. Panel B shows for-profit vs. nonprofit status from the sample we use in this study. For the sake of comparison, Panel C shows number of observations of for-profit vs. nonprofit status over time from our combined data set of market shares (MIX data and rating agencies combined).

Table 4: The effect of concentration on yield spread

	Yield spread				
Governance controls	(1)	Regulatory quality (2)	Government effectiveness (3)	Political stability (4)	HF overall score (5)
Herfindahl	0.100**	0.056	0.040	0.100**	0.083**
	(0.030)	(0.029)	(0.031)	(0.029)	(0.029)
Market Share GLP	-0.116*	-0.075	-0.078	-0.116*	-0.103*
	(0.052)	(0.050)	(0.046)	(0.052)	(0.052)
For-Profit Share	-0.050*	-0.035	-0.038	-0.050*	-0.054*
	(0.021)	(0.020)	(0.021)	(0.022)	(0.021)
Interest Ceiling	-0.050**	-0.041**	-0.048**	-0.050**	-0.048**
	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)
X-Eff	-0.259*	-0.284**	-0.287**	-0.259*	-0.240*
	(0.108)	(0.105)	(0.104)	(0.109)	(0.107)
S-Eff	-0.262*	-0.294**	-0.311**	-0.263*	-0.247*
	(0.106)	(0.104)	(0.105)	(0.107)	(0.104)
Governance controls		0.068**	0.088**	0.001	0.003**
		(0.011)	(0.017)	(0.010)	(0.001)
Size	-0.038**	-0.038**	-0.035**	-0.038**	-0.037**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Age	-0.012	-0.014	-0.012	-0.012	-0.011
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
Loan Size (% of GNI)	-0.012	-0.006	-0.006	-0.011	-0.014
	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)
N. Borrowers	0.072**	0.073**	0.073**	0.072**	0.069**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Deposit	-0.031*	-0.024	-0.025*	-0.031*	-0.026*
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Group Lending	0.020	0.028*	0.022	0.020	0.025
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Village Lending	0.057**	0.053**	0.053**	0.057**	0.064**
	(0.017)	(0.016)	(0.017)	(0.017)	(0.017)
GDP	-0.353**	-0.359**	-0.344**	-0.353**	-0.357**
	(0.113)	(0.112)	(0.112)	(0.113)	(0.113)
Country PAR	0.496*	0.476*	0.275	0.493*	0.503*
	(0.239)	(0.222)	(0.225)	(0.240)	(0.237)
Rural population growth	-0.019**	-0.026**	-0.019**	-0.019**	-0.026**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Rural pop(% of total pop.)	-0.001*	-0.000	0.000	-0.001*	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Africa	0.060**	0.052**	0.035	0.060**	0.063**
	(0.021)	(0.020)	(0.020)	(0.021)	(0.021)
ECA	0.016	0.029	0.037	0.016	0.032
	(0.022)	(0.021)	(0.021)	(0.023)	(0.022)
LAC	0.022	0.031	0.049	0.022	0.016
	(0.027)	(0.026)	(0.026)	(0.028)	(0.027)
MENA	0.019	0.033	0.013	0.020	0.027
	(0.028)	(0.026)	(0.026)	(0.028)	(0.028)
NBFI	-0.081**	-0.094**	-0.083**	-0.081**	-0.085**
	(0.024)	(0.023)	(0.023)	(0.024)	(0.024)
NGO	-0.083**	-0.091**	-0.081**	-0.083**	-0.086**
	(0.026)	(0.025)	(0.025)	(0.026)	(0.026)
Cooperative	-0.088**	-0.102**	-0.094**	-0.088**	-0.096**
	(0.026)	(0.025)	(0.025)	(0.026)	(0.027)
Other	-0.168**	-0.203**	-0.195**	-0.169**	-0.182**
	(0.051)	(0.049)	(0.049)	(0.052)	(0.051)
Constant	0.477**	0.462**	0.439**	0.476**	0.300*
	(0.135)	(0.133)	(0.133)	(0.136)	(0.143)
Observations	1,234	1,234	1,234	1,234	1,223
R-squared	0.272	0.293	0.292	0.272	0.278

Note: Robust standard errors in parentheses: ** p<0.01, * p<0.05. Yield spread is adjusted real portfolio yield minus real lending interest rate. Herfindahl is Herfindahl Hirschman concentration index. Market share is the gross loan portfolio market share of an MFI. For-profit share is the share of for-profit MFIs in gross loan portfolio in a given country to total country gross loan portfolio. Interest ceiling is a dummy variable which equals one if there are limitations on interest rates and zero otherwise. S-efficiency is scale efficiency. The governance controls are KKM country governance indicators. They are: regulatory quality, government effectiveness, and political stability in Columns (2), (3), (4) respectively. In Column (5) it is the Heritage Foundation (HF) economic freedom overall score. Size is the log of total assets. Age is the log of the age of the MFI. Loan size (% of GNI) is average loan size disbursed, expressed as a percentage of gross national income (GNI) per capita. The variable N. Borrowers is the log of total number of borrowers. Deposit is a dummy for deposit-taking by MFIs. Group and village lending are dummy variables for solidarity groups and village banking lending methodologies, respectively. GDP is the growth rate of gross domestic product. Country PAR is a proxy for country riskiness and is computed as the sum of gross loan portfolio with payments overdue by 30 days or more of all MFIs in a country j at year t to total gross loan portfolio of all MFIs in that country in year t. Rural population refers to people living in rural areas as defined by national statistical offices. It is calculated as the difference between total population and urban population. Rural pop.(% of total pop.)is rural population as a percentage of total population. Rural population growth is the annual growth rate of rural population. Africa, ECA, LAC and MENA are dummy variables for Africa, Eastern Europe and Central Asia, Latin America and the Caribbean and Middle East and North Africa, respectively. Other is a dummy for MFIs, which are neither banks, nor NBFIs, nor NGOs or cooperatives. Time dummies are included but not reported to save space.

Table 5: The effect of concentration on yield spread. For-profit vs. nonprofit MFIs

	For-profit					Nonprofit				
Governance controls	(1)	Regulatory quality (2)	Government effectiveness (3)	Political stability (4)	HF overall score (5)	(6)	Regulatory quality (7)	Government effectiveness (8)	Political stability (9)	HF Overall score (10)
Herfindahl	0.232**	0.148*	0.145*	0.210**	0.157*	0.063	0.041	0.029	0.064	0.061
	(0.061)	(0.062)	(0.057)	(0.067)	(0.062)	(0.034)	(0.034)	(0.036)	(0.033)	(0.034)
Market Share GLP	0.040	0.130	0.070	0.024	0.059	-0.073	-0.053	-0.050	-0.075	-0.071
	(0.085)	(0.098)	(0.090)	(0.086)	(0.093)	(0.062)	(0.060)	(0.056)	(0.062)	(0.062)
For-Profit Share	-0.188**	-0.162*	-0.179**	-0.189**	-0.152*	0.038	0.044	0.043	0.035	0.038
	(0.062)	(0.063)	(0.062)	(0.063)	(0.068)	(0.026)	(0.025)	(0.025)	(0.026)	(0.026)
Interest Ceiling	-0.129**	-0.103**	-0.124**	-0.130**	-0.126**	-0.022	-0.017	-0.021	-0.021	-0.022
	(0.036)	(0.037)	(0.037)	(0.037)	(0.036)	(0.013)	(0.012)	(0.012)	(0.013)	(0.013)
X-Eff	-0.556	-0.612*	-0.620*	-0.566	-0.575	-0.202	-0.221*	-0.217*	-0.204	-0.200
	(0.305)	(0.302)	(0.292)	(0.310)	(0.312)	(0.104)	(0.101)	(0.101)	(0.105)	(0.105)
S-Eff	-0.112	-0.164	-0.117	-0.133	0.029	-0.252*	-0.275*	-0.288*	-0.246	-0.251*
	(0.193)	(0.178)	(0.178)	(0.192)	(0.186)	(0.125)	(0.127)	(0.129)	(0.128)	(0.125)
Governance controls		0.106**	0.159**	0.022	0.009**		0.037**	0.046*	-0.006	0.000
		(0.025)	(0.038)	(0.024)	(0.002)		(0.013)	(0.018)	(0.011)	(0.001)
Size	-0.057*	-0.057**	-0.060**	-0.054*	-0.065**	-0.041**	-0.041**	-0.039**	-0.041**	-0.040**
	(0.022)	(0.021)	(0.020)	(0.022)	(0.021)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Age	0.018	0.003	0.012	0.017	0.016	-0.019	-0.019	-0.019	-0.019	-0.019
	(0.021)	(0.021)	(0.022)	(0.021)	(0.022)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Loan Size (% of GNI)	0.003	0.011	0.014	0.004	0.010	-0.014	-0.005	-0.009	-0.013	-0.015
	(0.023)	(0.021)	(0.019)	(0.023)	(0.024)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
N. Borrowers	0.065**	0.070**	0.070**	0.065**	0.060**	0.076**	0.077**	0.077**	0.075**	0.075**
	(0.022)	(0.021)	(0.019)	(0.022)	(0.023)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Deposit	-0.023	0.010	-0.007	-0.022	-0.004	-0.021	-0.021	-0.020	-0.021	-0.022
	(0.023)	(0.025)	(0.022)	(0.023)	(0.023)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Group Lending	0.044	0.052	0.027	0.048	0.053	0.022	0.026	0.025	0.023	0.022
	(0.036)	(0.035)	(0.034)	(0.037)	(0.035)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Village Lending	0.089*	0.088*	0.062	0.091*	0.111*	0.066**	0.064**	0.064**	0.067**	0.067**
	(0.044)	(0.042)	(0.043)	(0.044)	(0.045)	(0.018)	(0.018)	(0.018)	(0.019)	(0.019)
GDP	-0.566*	-0.752*	-0.704*	-0.550	-0.747*	-0.347**	-0.353**	-0.348**	-0.347**	-0.352**
	(0.283)	(0.293)	(0.287)	(0.283)	(0.293)	(0.122)	(0.122)	(0.123)	(0.122)	(0.122)
Country PAR	0.145	-0.288	-0.291	-0.011	0.299	0.603**	0.610**	0.490*	0.615**	0.601**
	(0.726)	(0.774)	(0.798)	(0.749)	(0.799)	(0.233)	(0.221)	(0.217)	(0.234)	(0.232)
Rural population growth	-0.031	-0.033*	-0.026	-0.029	-0.053**	-0.009	-0.013	-0.010	-0.010	-0.010
	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)
Rural pop(% of total pop.)	-0.001	0.001	0.002	-0.000	0.000	-0.001	-0.000	0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Africa	0.060	0.051	0.003	0.065*	0.100**	-0.006	-0.014	-0.013	-0.003	-0.011
	(0.032)	(0.031)	(0.035)	(0.032)	(0.033)	(0.035)	(0.034)	(0.034)	(0.034)	(0.036)
ECA	0.007	0.020	0.025	0.017	0.034	-0.007	-0.002	0.012	-0.007	-0.010
	(0.035)	(0.036)	(0.035)	(0.038)	(0.036)	(0.038)	(0.037)	(0.036)	(0.038)	(0.038)
LAC	0.072	0.070	0.079*	0.086	0.060	-0.026	-0.022	-0.002	-0.026	-0.031
	(0.042)	(0.039)	(0.040)	(0.046)	(0.041)	(0.040)	(0.039)	(0.039)	(0.040)	(0.041)
MENA						0.017	0.022	0.020	0.017	0.012
						(0.036)	(0.035)	(0.035)	(0.036)	(0.037)
Constant	0.668**	0.657**	0.693**	0.636*	0.232	0.365*	0.356*	0.334*	0.367*	0.348*
	(0.258)	(0.242)	(0.244)	(0.252)	(0.262)	(0.151)	(0.152)	(0.153)	(0.152)	(0.164)
Observations	353	353	353	353	346	881	881	881	881	877
R-squared	0.339	0.375	0.386	0.341	0.382	0.302	0.309	0.308	0.302	0.302

Note: Robust standard errors in parentheses: ** p<0.01, * p<0.05. The dependent variable is the yield spread, which is adjusted real portfolio yield minus real lending interest rate. Herfindahl is Herfindahl Hirschman concentration index. Market share is the gross loan portfolio market share of an MFI. For-profit share is the share of for-profit MFIs in gross loan portfolio in a given country to total country gross loan portfolio. Interest ceiling is a dummy variable which equals one if there are limitations on interest rates and zero otherwise. S-efficiency is scale efficiency. The governance controls are KKM country governance indicators. They are: regulatory quality in Columns (2) and (7), government effectiveness in Columns (3) and (8), and political stability in Columns (4) and (9). In Columns (5) and (10) it is the Heritage Foundation (HF) economic freedom overall score. Size is the log of total assets. Age is the log of the age of the MFI. Loan size (% of GNI) is average loan size disbursed, expressed as a percentage of gross national income (GNI) per capita. The variable N. Borrowers is the log of total number of borrowers. Deposit is a dummy for deposit-taking by MFIs. Group and village lending are dummy variables for solidarity groups and village banking lending methodologies, respectively. GDP is the growth rate of gross domestic product. Country PAR is a proxy for country riskiness and is computed as the sum of gross loan portfolio with payments overdue by 30 days or more of all MFIs in a country j at year t to total gross loan portfolio of all MFIs in that country in year t. Rural population refers to people living in rural areas as defined by national statistical offices. It is calculated as the difference between total population and urban population. Rural pop.(% of total pop.)is rural population as a percentage of total population. Rural population growth is the annual growth rate of rural population. Africa, ECA, LAC and MENA are dummy variables for Africa, Eastern Europe and Central Asia, Latin America and the Caribbean, and Middle East and North Africa, respectively. Time dummies are included but not reported to save space.

Table 6: The effect of concentration on yield spread including interactions of HHI and number of borrowers

	Yield spread									
	For-profit					Nonprofit				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Herfindahl	-0.407	-0.568**	-0.763**	-0.409	-0.626**	0.376*	0.367*	0.365*	0.375*	0.376*
	(0.209)	(0.210)	(0.211)	(0.210)	(0.216)	(0.157)	(0.154)	(0.153)	(0.157)	(0.157)
Market Share GLP	-0.051	0.033	-0.054	-0.062	-0.058	-0.065	-0.044	-0.040	-0.066	-0.062
	(0.092)	(0.105)	(0.098)	(0.092)	(0.099)	(0.062)	(0.059)	(0.056)	(0.062)	(0.061)
For-Profit Share	-0.162**	-0.131*	-0.140*	-0.163**	-0.109	0.033	0.039	0.038	0.030	0.032
	(0.061)	(0.064)	(0.062)	(0.063)	(0.066)	(0.025)	(0.024)	(0.024)	(0.025)	(0.026)
Interest Ceiling	-0.121**	-0.093*	-0.112**	-0.122**	-0.119**	-0.021	-0.016	-0.021	-0.021	-0.022
	(0.036)	(0.036)	(0.037)	(0.036)	(0.036)	(0.013)	(0.013)	(0.012)	(0.013)	(0.013)
X-Eff	-0.567	-0.626*	-0.644*	-0.575	-0.583	-0.209*	-0.229*	-0.225*	-0.211*	-0.207*
	(0.300)	(0.295)	(0.281)	(0.305)	(0.304)	(0.103)	(0.100)	(0.100)	(0.104)	(0.104)
S-Eff	-0.210	-0.276	-0.255	-0.225	-0.077	-0.225	-0.247	-0.261*	-0.220	-0.224
	(0.203)	(0.189)	(0.187)	(0.201)	(0.195)	(0.125)	(0.127)	(0.128)	(0.128)	(0.125)
N. Borrowers	0.035	0.037	0.029	0.036	0.023	0.084**	0.086**	0.086**	0.084**	0.083**
	(0.024)	(0.023)	(0.021)	(0.025)	(0.025)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
N. BorrowersHerfindahl	0.072**	0.080**	0.101**	0.070**	0.088**	-0.035*	-0.037*	-0.038*	-0.035*	-0.035*
	(0.023)	(0.022)	(0.022)	(0.024)	(0.023)	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)
Size	-0.035	-0.033	-0.030	-0.033	-0.040	-0.043**	-0.043**	-0.041**	-0.043**	-0.042**
	(0.024)	(0.023)	(0.023)	(0.024)	(0.023)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Governance controls		0.111**	0.182**	0.018	0.009**		0.038**	0.048**	-0.005	0.000
		(0.025)	(0.039)	(0.024)	(0.002)		(0.013)	(0.018)	(0.010)	(0.001)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	353	353	353	353	346	881	881	881	881	877
R-squared	0.353	0.392	0.413	0.354	0.402	0.306	0.313	0.312	0.306	0.306

Note: Robust standard errors in parentheses: ** p<0.01, * p<0.05. Yield spread is adjusted real portfolio yield minus real lending interest rate. Herfindahl is Herfindahl Hirschman concentration index. Market share is the gross loan portfolio market share of an MFI. For-profit share is the share of for-profit MFIs in gross loan portfolio in a given country to total country gross loan portfolio. Interest ceiling is a dummy variable which equals one if there are limitations on interest rates and zero otherwise. S-efficiency is scale efficiency. N. Borrowers is the log of the number of borrowers. N. BorrowersHerfindahl is an interaction variable. Size is total assets in thousands of USD. The country governance variables are: regulatory quality (in Columns (2) and (7)), government effectiveness (in Columns (3) and (8)), political stability (in Columns (4) and (9)) and Heritage Foundation (HF) overall score (in Columns (5) and (10)). Control variables included but not reported are: (1) log of age; (2) average loan size disbursed, expressed as a percentage of gross national income (GNI) per capita; (3) dummy for deposit-taking MFIs; (4) group and village lending dummies for lending methodologies; (5) growth rate of GDP; (6) Country PAR; (7) Rural population growth; (8) Rural population (in percentage of total population); (9) dummies for geographic regions (Africa, ECA, LAC, MENA); (10) time dummies. A constant is included, but not reported.

Table 7: The effect of concentration on yield spread including demographic and geographic bank branch penetration

Governance controls		Regulatory quality	Government effectiveness	Political stability	HF overall score
	(1)	(2)	(3)	(4)	(5)
Panel A: Without Bank Branch Penetration					
Herfindahl	0.204**	0.078	0.071	0.211**	0.084
	(0.054)	(0.054)	(0.052)	(0.055)	(0.058)
For-Profit Share	-0.115**	-0.188**	-0.167**	-0.114**	-0.178**
	(0.043)	(0.043)	(0.042)	(0.044)	(0.043)
Interest Ceiling	-0.082**	-0.080**	-0.139**	-0.080**	-0.094**
	(0.026)	(0.027)	(0.027)	(0.027)	(0.027)
Governance Controls		0.180**	0.247**	-0.008	0.013**
		(0.026)	(0.029)	(0.017)	(0.002)
Observations	569	569	569	569	558
R-squared	0.331	0.390	0.426	0.332	0.369
Panel B: Demographic Bank Branch Penetration					
Herfindahl	0.246**	0.125*	0.118*	0.245**	0.120
	(0.060)	(0.059)	(0.058)	(0.059)	(0.064)
For-Profit Share	-0.111*	-0.184**	-0.163**	-0.111*	-0.172**
	(0.044)	(0.044)	(0.043)	(0.045)	(0.044)
Interest Ceiling	-0.075**	-0.072**	-0.132**	-0.075**	-0.088**
	(0.026)	(0.027)	(0.027)	(0.026)	(0.027)
Dem. Penetration	-0.002**	-0.002**	-0.002**	-0.002**	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Governance controls		0.185**	0.250**	0.001	0.012**
		(0.026)	(0.029)	(0.018)	(0.002)
Observations	569	569	569	569	558
R-squared	0.338	0.399	0.435	0.338	0.373
Panel C: Geographic Bank Branch Penetration					
Herfindahl	0.195**	0.078	0.071	0.202**	0.072
	(0.055)	(0.055)	(0.053)	(0.055)	(0.059)
For-Profit Share	-0.108*	-0.189**	-0.168**	-0.106*	-0.169**
	(0.044)	(0.046)	(0.044)	(0.045)	(0.043)
Interest Ceiling	-0.087**	-0.079**	-0.139**	-0.085**	-0.101**
	(0.027)	(0.028)	(0.027)	(0.028)	(0.028)
Geo. Penetration	0.002	-0.000	-0.000	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Governance controls		0.181**	0.248**	-0.009	0.013**
		(0.027)	(0.029)	(0.017)	(0.002)
Observations	569	569	569	569	558
R-squared	0.333	0.390	0.426	0.334	0.372

Note: Robust standard errors in parentheses: ** $p<0.01$, *$p<0.05$. The dependent variable is the yield spread, which is adjusted real portfolio yield minus real lending interest rate. Herfindahl is Herfindahl Hirschman concentration index. For-profit share is the share of for-profit MFIs in gross loan portfolio in a given country to total country gross loan portfolio. Dem. penetration is demographic penetration and it is the number of commercial bank branches per 100000 adults in a given country. Geo. penetration is geographic penetration and it is the number of commercial bank branches per 1000 km2 in a given country. Country governance variables are regulatory quality, government effectiveness, political stability and Heritage Foundation (HF) overall score in Columns (2), (3), (4), and (5) respectively. Control variables included but not reported are: (1) market share; (2) X-efficiency; (3) S-efficiency; (4) log of total assets for size; (5) log of age; (6) average loan size disbursed, expressed as a percentage of gross national income (GNI) per capita; (7) log of the number of borrowers; (8) dummy for deposit-taking MFIs; (9) group and village lending dummies for lending methodologies; (10) growth rate of gross domestic product; (11) Country PAR; (12) Rural population growth; (13) Rural population (in percentage of total population); (14) dummies for geographic regions (Africa, ECA, LAC, MENA); (15) dummies for MFI legal status in Panel A; (16) time dummies. A constant is included, but not reported.

Table 8: The effect of concentration on yield spread. Instrumental variable estimation.

Governance controls		Regulatory quality	Government effectiveness	Political stability	HF overall score
	(1)	(2)	(3)	(4)	(5)
Panel A: Reduced sample including Bank Branch Penetration and Doing business variables					
Herfindahl	0.224**	0.124*	0.091	0.254**	0.124
	(0.062)	(0.061)	(0.059)	(0.062)	(0.065)
For-Profit Share	-0.096*	-0.177**	-0.137**	-0.081	-0.155**
	(0.046)	(0.049)	(0.045)	(0.047)	(0.047)
Interest Ceiling	-0.074**	-0.067*	-0.124**	-0.061*	-0.081**
	(0.027)	(0.028)	(0.027)	(0.028)	(0.028)
Dem. Penetration	-0.001*	-0.002**	-0.002**	-0.001	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Governance controls		0.176**	0.264**	-0.055**	0.011**
		(0.032)	(0.031)	(0.021)	(0.003)
Control variables	Yes	Yes	Yes	Yes	Yes
Observations	514	514	514	514	504
R-squared	0.360	0.404	0.461	0.368	0.382
Panel B: First stage estimation including Demographic Bank Branch Penetration and instrumental variables					
For-Profit Share	0.099*	0.021	0.082	0.080	-0.020
	(0.049)	(0.051)	(0.048)	(0.050)	(0.053)
Interest Ceiling	0.132**	0.139**	0.108**	0.112**	0.119**
	(0.026)	(0.025)	(0.025)	(0.027)	(0.028)
Dem. Penetration	0.006**	0.005**	0.005**	0.005**	0.005**
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Governance controls		0.172**	0.152**	0.052*	0.016**
		(0.027)	(0.031)	(0.025)	(0.002)
Starting a Business: Procedures (number)	-0.266**	-0.258**	-0.249**	-0.237**	-0.273**
	(0.037)	(0.032)	(0.033)	(0.035)	(0.038)
Starting a Business: Cost (% of income per capita)	-0.027	0.010	0.021	-0.031	0.007
	(0.018)	(0.018)	(0.020)	(0.018)	(0.021)
Control variables	Yes	Yes	Yes	Yes	Yes
Observations	514	514	514	514	504
R-squared	0.658	0.692	0.681	0.663	0.711
F-test of excluded instruments	25.41	34.51	38.78	23.60	30.91
Panel C: IV estimation					
Herfindahl	0.247	0.092	0.016	0.355*	0.016
	(0.156)	(0.163)	(0.160)	(0.175)	(0.186)
For-Profit Share	-0.102*	-0.171**	-0.151**	-0.090	-0.147**
	(0.046)	(0.046)	(0.043)	(0.047)	(0.043)
Interest Ceiling	-0.090**	-0.068*	-0.105**	-0.083**	-0.076*
	(0.031)	(0.033)	(0.029)	(0.030)	(0.033)
Dem. Penetration	-0.001	-0.002*	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Governance controls		0.178**	0.286**	-0.062*	0.012**
		(0.036)	(0.033)	(0.025)	(0.004)
Control variables	Yes	Yes	Yes	Yes	Yes
Observations	514	514	514	514	504

Note: Robust standard errors in parentheses: ** p<0.01, *p<0.05. The dependent variable is the yield spread, which is adjusted real portfolio yield minus real lending interest rate. Herfindahl is Herfindahl Hirschman concentration index. For-profit share is the share of for-profit MFIs in gross loan portfolio in a given country to total country gross loan portfolio. Dem. penetration is demographic penetration and it is the number of commercial bank branches per 100000 adults in a given country. Country governance variables are regulatory quality, government effectiveness, political stability and Heritage Foundation (HF) overall score in Columns (2), (3), (4), and (5) respectively. Control variables included but not reported are: (1) market share; (2) X-efficiency; (3) S-efficiency; (4) log of total assets for size; (5) log of age; (6) average loan size disbursed, expressed as a percentage of gross national income (GNI) per capita; (7) log of the number of borrowers; (8) dummy for deposit-taking MFIs; (9) group and village lending dummies for lending methodologies; (10) growth rate of gross domestic product; (11) Country PAR; (12) Rural population growth; (13) Rural population (in percentage of total population); (14) dummies for geographic regions (Africa, ECA, LAC, MENA); (15) dummies for MFI legal status; (16) time dummies. A constant is included, but not reported. Instrumental variables are starting a business: procedures (number) and starting a business: cost (% of income per capita).

Figure 1: Total number of MFIs in the combination of our sample with MIX, by country and legal status, in 2002 and 2008.

(a) 2002

(b) 2008

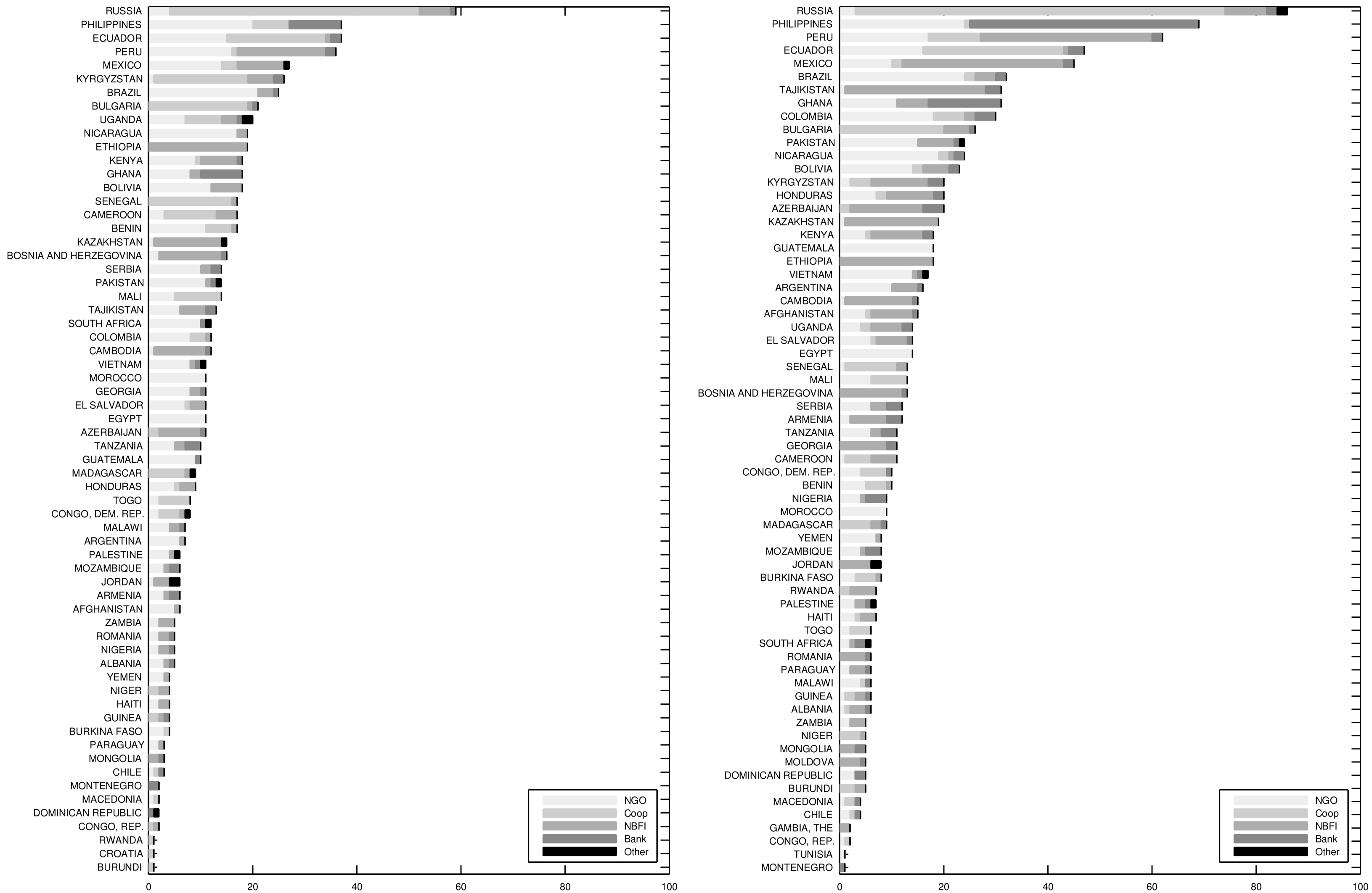

Figure 2: Herfindahl for the countries in our sample in 2002 and 2008.

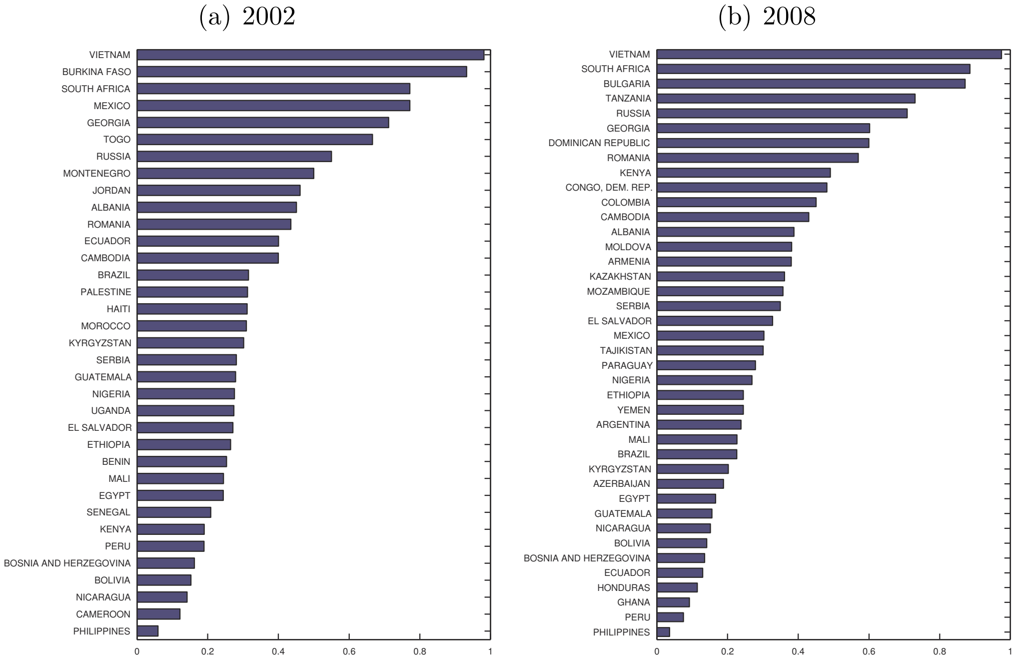

Figure 3: For-profit share for the countries in our sample in 2002 and 2008.