Doing Well by Doing Good? Empirical Evidence from Microfinance

Catalina Martinez

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Centre for Finance and Development, Graduate Institute of International and Development Studies,
Maison de la Paix, Chemin Eugène-Rigot 2, 1211 Geneva 21, Switzerland

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Catalina Martínez*

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Abstract

This paper proposes novel identification techniques to examine the trade-offs that microfinance institutions face between increasing their profits and their social impact. It uses a quantile regression approach to examine how these trade-offs evolve as institutions become more commercialized. The identification strategy is based on an instrumental variable approach, and also leverages the heteroskedasticity in the sample. The findings indicate that increasing outreach to women, a common proxy for social impact, has a positive effect on the financial performance of all institutions across different stages of commercialization. This suggests that there is no trade-off between doing well and doing good. However, the price differential that microfinance institutions can maintain with respect to their competitors becomes more important for them as they become more commercialized. If this price differential is not explained by a better quality of the services provided, this result questions whether microfinance institutions that have reached a high level of commercialization can still do well and do good. The results are robust to potential sample selection biases, and are consistent for different measures of financial performance.

Key words: microfinance, gender, quantile regression, instrumental variable.

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*Center for Finance and Development, The Graduate Institute, Geneva and Center for Microfinance, Department of Banking and Finance, University of Zurich. I would like to thank Jean Louis Arcand for his continuous support and guidance, and Annette Krauss, Ugo Panizza, and Martina Viarengo for their valuable comments. Contact: catalina.martinez@iheid.ch, catalina.martinez@bf.uzh.ch.

1 Introduction

Is it really possible to do well by doing good? It is hard to provide a clear answer to this question based on empirical evidence: There is not much comparable data to be examined, both objectives are likely to be endogeneous, and the trade-offs among them may be significantly different across heterogeneous firms. This paper proposes an answer to this question using historical information reported by microfinance institutions (MFIs) to the *Microfinance Information Exchange* (MIX)[1] across the world in the last decade. It provides two novel identification techniques to solve potential endogeneity concerns between indicators of financial performance and proxies for social impact. It also proposes a quantile approach to explore how the trade-offs between doing well and doing good evolve as MFIs become more commercialized. The findings suggest that more commercialized institutions are still interested in serving vulnerable populations. However, proxies for market power and rent extraction become increasingly important for these institutions. These mixed findings indicate that, even if MFIs do not seem to face a mission drift, their positive social impact may be hindered as they become more commercialized.

Outreach to women is a common proxy for social impact in the microfinance industry[2]. Identifying the impact of increasing outreach to women on MFIs' financial performance is difficult because of potential endogeneity problems: More subsidized MFIs (less self-sufficient) may be influenced by their donors to have a higher outreach to women. In addition, operational self-sufficiency, a common measure of MFIs performance, may be easier to achieve in countries with higher development levels, where women may demand less microfinance loans. In both cases, the potential positive effect of serving more women could be underestimated. This paper proposes an instrumental variable (IV) approach to address this potential endogeneity problem and measure MFIs' trade-offs with a higher precision. In particular, supply of microfinance loans to women is instrumented with shocks to the female demand for such services.

Fertility shocks can impact female demand for microfinance loans through various channels, such as available time and need for additional resources, or intra-household bargaining power.

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

[2]*MIX* has started to collect more specific measures of social performance in recent years. However, the sample of MFIs for which these statistics are available is still small.

This paper considers as fertility shocks the share of girls, first babies, and twins born in a given country-year, by looking at 220 *Demographic and Health Surveys* (DHS) at the household level in 74 countries since 1985. Women's demand for microfinance loans is modelled based on such fertility shocks and a set of relevant macroeconomic variables. The heteroskedasticity of the exogenous variables in this simplified model of female demand for microfinance services is also used in the identification strategy. The results indicate that increasing outreach to women has a positive effect on operational self-sufficiency across all levels of commercialization. This effect becomes bigger once the potential endogeneity is addressed with the proposed instrumental variables (See Figure 1). This result holds also when considering returns on assets instead of operational self-sufficiency.

Since outreach to women is an imperfect proxy for social impact, other variables need to be considered to assess the trade-offs between doing well and doing good faced by MFIs. The price differential between a given MFI and the market average in its same country year (in terms of real yield) is a good proxy for rent extraction. If high for a particular MFI, this ratio indicates that this institution is able to maintain high prices due to competitive advantages, and extract rents from its clients. The results indicate that this proxy for rent extraction has a positive effect on the operational self-sufficiency and the returns on assets for the average MFI, and that this positive effect is higher the more commercialized MFIs are (See Figure 2). This is in line with recent theoretical models indicating that as microfinance markets become more competitive, institutions face high incentives for keeping a high market share, due to asymmetric information problems. Whether the price differentials reflect a better service quality for the client cannot be assessed with this study's data, and is an interesting question for future research.

The quantile regression approach that this study proposes allows to examine the heterogeneities of the trade-offs between doing well and doing good across different levels of MFIs' commercialization. This heterogeneity can drive a considerable variation. Indeed, the trade-offs of small institutions, which have not yet been able to scale-up and are struggling to reach self-sufficiency, cannot be the same trade-offs of firms with years of experience, millions of dollars in their loan portfolios, and very attractive return rates. The results of this paper help to understand this heterogeneity and help firms, investors and regulators better identify which are the best business paths to encourage and foster.

Doing well by doing good is increasingly becoming a mainstream business idea. A growing variety of inclusive business models are reaching disenfranchised populations and including them along the value chain as consumers, producers, employees and entrepreneurs. These business models are also increasingly attracting impact investing capital. However, there is no robust empirical evidence on which are the trade-offs and incentives that these businesses face as they become more commercialized, mainly due to the lack of comparable data. The results of this paper, based on widely available and comparable microfinance panel data, can contribute to a better understanding of which are the potential trade-offs of inclusive businesses also in other industries with less available data.

2 Related Literature

The empirical literature that studies MFIs' trade-offs is relatively limited and has found mixed results. Such different and contradicting results can be explained by the fact that the specifications proposed so far may suffer from different sources of bias. Indeed, the relationship between MFIs' profitability and their focus on particular income groups is not exogenous. Moreover, this relationship is not constant across different types of MFIs and there is a potential risk of sample selection bias. This paper contributes to the literature by proposing different strategies to address these potential biases and achieve a better understanding of the trade-offs that MFIs face.

This is the first paper to address both the endogeneity of the trade-offs, and study their evolution as firms become more self-sufficient. Indeed, most of the existing literature focuses on the average firm overlooking potential endogeneity concerns (Cull, Demirgüç-Kunt and Morduch, 2006 and 2009; Hermes et al., 2011; Salim, 2013). Just a few papers propose methods that could solve the potential endogeneity issues (Quayes, 2012; Mersland and Strom, 2010), but they do not consider the behavior of the trade-offs across heterogeneous firms. Louis et al. (2013) propose an interesting technique for considering this heterogeneity, but the role of competition and market power is not addressed.

Assefa et al. (2012) find that competition negatively affects various measures of MFIs' performance. This paper relates to those findings and explores more in detail which are the incentives that MFIs face in competitive markets and how they evolve as institutions become more commercialized. The findings of this paper confirm theoretical predictions on the importance of competitive advantages for MFIs facing increasing competition. For example, De Quidt et al. (2013) show that in a competitive equilibrium with free entry and asymmetric information, borrowers face lower incentives to repay their debt because they can default and go to the new providers, who will not have access to their credit history. In a competitive market structure with asymmetric information, MFIs foresee this problem and would be interested in keeping a high market share. Otherwise, they would have to undertake credit rationing practices (Shapiro and Stiglitz, 1984) to keep the best customers and protect their profit margins.

The findings of this paper are also consistent with the model proposed by McIntosh and Wydick (2005). These authors argue that if MFIs support their business by cross-subsidizing their poor clients with their most profitable ones, a competitive equilibrium puts pressure on the rents received from this last group of borrowers. Thus, MFIs anticipate this and will be interested in keeping their market power in such a situation. Otherwise, they will be likely to disproportionally diminish their outreach to the poor. If institutions do not share information on the borrowers, the most impatient borrowers would then apply for multiple loans across different institutions. This creates a negative externality, as it diminishes the repayment rate, further reducing the incentives that MFIs face for serving the poorest borrowers.

3 Methodology

This paper considers the following specification, which has been already used in the few papers addressing MFIs tradeoffs:

$$OSS_{i,t} \; = \; \beta Women_{supply,i,t} \; + \; \gamma X_{i,t} \; + \; u_{i,t} \tag{1}$$

The dependent variable $OSS_{i,t}$ is the operational self-sufficiency ratio of MFI i in year t. This indicator measures a MFI's ability to generate sufficient revenue to cover its costs. If it takes a value above 100%, then the institution is self-sufficient, otherwise it is not. This indicator makes the comparison between institutions easier and is standard in the microfinance industry. It is also more informative than the standard financial ratios such as return on assets or equity (Cull, Demirgüç-Kunt and Morduch, 2006). It is constructed after the following formula:

$$OSS_{i,t} \; = \; \frac{fr_{i,t}}{fe_{i,t} \; + \; lip_{i,t} \; + \; oe_{i,t}} \tag{2}$$

where $fr_{i,t}$ is financial revenue, $fe_{i,t}$ is financial expenses, $lip_{i,t}$ is loan impairment provision, $oe_{i,t}$ is operational expenses and all the variables apply for MFI i in year t[3]. However, equation (1) is also considered with *Returns on Assets* on the left hand side to test the robustness of this paper's results.

Measuring the social impact of microfinance is very difficult. It is also complex to find comparable measures across different institutions. Outreach to women is a widely accepted institutional-level proxy of social impact. It is measured as the share of *Women* borrowers served by MFI i in year t.

The matrix of covariates $X_{i,t}$ contains variables that are usually included in the literature examining MFI's performance and outreach. In particular, it includes *Loan Size*, which has an important influence on the costs that a MFI faces. It also contains *Real Yield*, which corresponds to the real gross portfolio yield, and captures the average interest rate that MFIs' customers face and thus the average prices that MFIs charge for their services. The *Price Differential* is calculated as the ratio of the *Real Yield* for a given MFI and the average in its same country-year. If high, this variable indicates that a given institution is able to maintain high prices thanks to competitive advantages that allow it to extract rents from its clients. Competitive advantages could arise due to high market share, but also to product differentiation, marketing, and services quality, as will be discussed in the following sections.

Unfortunately, the market share of MFIs and measures of competition such as the Herfindahl Index of market concentration are not very useful for the microfinance industry. Indeed, according to the level of development of microfinance in a given country-year, these variables may give misleading messages. For example, in a context in which microfinance is only starting, the Herfindahl Index of market concentration will be very high. However, this is not only due to the market power of the MFIs in that given context, but also because the industry is just beginning to develop. Nevertheless, this paper presents summary statistics of these variables across different quantiles of *OSS*.

The costs that institutions assume are considered by including an indicator of *Personnel Expenses* over total assets and an indicator of *Cost per Loan*. These two variables are proxies for the efficiency of a given institution. Productivity is measured with *Loans per Staff*, which is also

[3]It would be ideal to consider the adjusted values of these indicators, after considering subsidies, grants, and discounts on different goods or services received by MFIs. However, these adjustments are not currently available for all the sample in *MIX* data.

an important measure of how close a MFI is to its clientele, and thus able to mitigate potential information asymmetry problems.

The ability that MFIs have to assume risk is also an important control variable. For this purpose, *Portfolio at Risk > 30 days* is included in the covariate matrix. This variable is a ratio of all the outstanding loans that have one or more instalments of principal overdue for more than 30 days over the gross loan portfolio. This variable includes the entire unpaid principal, the past and future instalments, and restructured or rescheduled loans, but it does not include accrued interest.

It is also important to consider MFIs' age, as it may affect their ability to stay in the market. *Age* is a dummy variable that distinguishes firms between new, young and mature. Size, on the other hand, is captured with *Assets*, which may reflect the institution's ability to exploit economies of scale.

Macroeconomic variables are also considered to control for factors that may influence the female demand for microfinance services, and the supply in equilibrium of microfinance loans to women. Women's income in country i and year t is included using *World Development Indicators* (WDI) data on *GDP per capita*. The level of formal financial development in the given country-year is also considered, as formal financial development may be an important substitute or complement of the microfinance industry in each particular context. For this purpose, WDI data on *Domestic Credit to the Private Sector (% of GDP)* is taken into account.

Female demand for microfinance services can also be influenced by the level of empowerment of women in each given market. For this purpose, the years of schooling of female adults over age 15 reported by Barro and Lee (2013) is included in the specification with *Female Education*. The difference in years of schooling between men and women is considered from the same source, resulting in the variable *Gender Gap in Education*.

3.1 Endogeneity

Identifying the impact of increasing outreach to women on MFIs' financial performance is difficult because of potential endogeneity problems. For example, more subsidized and thus less self-sufficient MFIs may be influenced by their donors to have a higher outreach to women. On the other hand, self-sufficiency may be easier to achieve in countries with higher development levels, where women may demand less MFI loans. In the first case, endogeneity would be caused by reverse causation.

In the second one, omitted variables would be the main concern. In both cases, it is expected that $cov(Women_{i,t}, u_{i,t}) < 0$, which implies that the coefficient for *Women* from an OLS estimation β_{OLS} would be biased downwards with respect to the "true" coefficient.

The omitted variables problem can be mitigated using panel data techniques. In particular, time-fixed effects can help to control for unobservables that are time-specific and do not vary across MFIs. For example, the recent global crisis would be one of the unobservables that would be controlled once year-fixed effects are included. MFI-fixed effects, on the other hand, can help to control for unobservables that are MFI-specific and do not vary over time. For example, if country-level institutions do not vary much over time, then the MFI-fixed effects would control for those MFI characteristics related to the country of operation. MFI-fixed effects would also control for variables that present a very low variation over time, such as MFIs' regulatory status, or for-profit status.

However, there are important unobservables that are likely to vary across MFIs and time. For example, the ease of doing business for a particular MFI or its ability to influence regulations are important determinants of its self-sufficiency that depend both on MFIs' unobserved characteristics and on time. The best solution to control for these unobservables is to include MFI-specific time trends, as this paper proposes in all the specifications[4].

3.2 Instrumental variables

Even if using MFI-specific time trends can mitigate the potential endogeneity problems, the best solution to address this problem is to use an instrumental variable approach. This paper proposes to instrument MFIs' supply of loans for women with exogenous shocks to women's demand for these services. The supply of microfinance services for women that institutions choose is instrumented by looking at exogenous determinants of women's demand for these services. In particular, the paper considers exogenous fertility shocks, such as the percentage of *Girls*, *First Babies*, and *Twins* born in a given country-year. These instruments are built using data from *Demographic Health Surveys* on births at the household level in 220 surveys for 74 countries since 1985, as will be described in

[4]MFI specific trends are defined as the interactions between MFI dummy variables and the fiscal year.

the Data section.

$$Women_{demand,i,t} \;=\; \delta Z_{i,t} \;+\; \lambda X_{i,t} \;+\; e_{i,t} \tag{3}$$

The variables in matrix $Z_{i,t}$, i.e. *Girls*, *First Babies* and *Twins*, are relevant instruments. Indeed, they affect women's demand for microfinance services through various channels. The most intuitive one is that fertility shocks affect women's need for additional resources. For example, it is reasonable to expect that an increase in *Twins* in a given country-year would increase women's demand for microfinance services in that specific context. However, such an exogenous shock will also reduce women's available time for investing these resources in productive activities. Thus, even if *Twins* should have an important effect on women's demand for microfinance, the sign of this effect is not clear a priori.

It has been also documented that the birth order and gender of children are important determinants of the intra-household allocation of resources and the dynamics of household members' bargaining power (Duncan, 1994; Udry, 1996, among others). In particular, a rich literature on missing women shows evidence of selective abortion of girls in different developing contexts (Deaton, 1989; Eliana, 1999; Foster and Rosenzweig, 1999; Eliana, 2000; Quian, 2008). Therefore, *Girls* and *First Babies* are important exogenous shocks to women's intra-household bargaining power that could have an effect on their demand for microfinance services. Since we are pooling many different countries and different cultural backgrounds together in our specification, it is again difficult to predict a priory the sign of these effects.

Besides from being relevant, these instrumental variables are also valid. Indeed, they affect women's demand for microfinance services at the MFI level, but have no impact on MFIs' operational self-sufficiency. Thus, these variables are relevant and valid instruments to identify β in equation (1). It is also important to note that, even if the instrumental variables are defined at the country-year level, their effect on MFI's supply of women loans is predicted at the MFI-year level.

The use of fertility shocks as instrumental variables is widespread in the development economics literature. For example, Rosenzweig and Wolpin (1980) use multiple births to instrument fertility, Angrist and Evans (1998) use the sibling-sex composition to instrument fertility, and Angrist et al. (2010) use the sibling-sex composition to estimate the quantity and quality of children.

3.3 Identifying with Heteroskedasticity

In addition to this instrumental variable approach, this paper also uses the heteroskedasticity in the sample to better identify the trade-offs that MFIs face between doing well and doing good. Rigobon (2003) shows that in a system of simultaneous equations, heteroskedasticity introduces an additional equation that can help to solve for the identification problem. Following this idea, it is possible to identify causal relationships through heteroskedasticity. Lewbel (2012) generalizes this approach. This author demonstrates that relevant and valid IVs can be built as a function of exogenous heteroskedastic covariates.

For this paper's particular case, the potential endogeneity problem can be characterized as follows:

$$OSS_{i,t} \;=\; \beta_1\, Women_{i,t} \;+\; \gamma_1 X \;+\; \epsilon_1 \tag{4}$$

$$Women_{i,t} \;=\; \beta_2\, OSS_{i,t} \;+\; \gamma_2 X \;+\; \epsilon_2 \tag{5}$$

where X denotes the exogenous covariates in the estimation, *Women* is the suspected endogenous variable, and $cov(\epsilon_1, \epsilon_2) \neq 0$. Lewbel (2012) demonstrates that if the usual exogeneity assumptions for X hold, such as $E[X\epsilon_1] = E[X\epsilon_2] = cov(X, \epsilon_1\epsilon_2) = 0$ and, in addition, X is heteroskedastic with respect to the error in equation (5), i.e. $cov(X, \epsilon_2^2) \neq 0$, then a good instrument for the endogenous variable is $X\epsilon_2$.

The residuals ϵ_2 reflect the factors other than the covariates that play a role in defining female demand for MFIs' loans. The variance of these residuals captures the model inaccuracy in explaining the endogeneous variable *Women*. The higher this variance, the more likely there will be problems of omitted variables or reverse causation, and thus the more severe the endogeneity would be. If the covariates X are heteroskedastic with respect to this residual, then they contain information about the model's imprecision. Lewbel's IV is a function that leverages this information to identify those observations where the model works best and worse. In this way, it is possible to identify in which countries the endogeneity is stronger and correct for the possible endogeneity bias precisely there.

The macroeconomic variables included in equation (1) can be considered as exogenous in the specification after MFI-specific time trend fixed effects are included. Indeed, it is hard to argue that there is a simultaneity problem, given that the operational self-sufficiency of a single MFIs is unlikely to have an effect on these macroeconomic indicators. In addition, these macroeconomic variables should not be related to the omitted variables in the error term. For example, while unobservables such as institutions, regulatory environment or doing business may affect both *OSS* and *GDPpc*, or *Domestic Credit*; there are strong reasons to believe that once MFI-specific time trends are included, this omitted variable problem is diminished, and the effect that *GDPpc* or *Domestic Credit* have on *OSS* is captured only by these variables, and not by their correlation with the error term. Therefore, it is possible to use these macroeconomic variables in X to apply the Lewbel technique for assessing the robustness of the fertility shocks as instrumental variables.

3.4 Non linearity of the trade-off

Firms in the lowest quantile of the *OSS* distribution are likely to present a behavior that is structurally different from that of firms in the highest quantile of the *OSS* distribution. A quantile regression analysis allows to examine how the trade-offs that MFIs face between doing well and doing good evolve as they increase their operational self-sufficiency. The quantile approach also helps to go beyond the behavior of the average firm and examine the specific difficulties that firms face at different stages of their scaling-up process.

This is particularly important in the case of microfinance, as it is an industry that has achieved very different levels of complexity across different markets in the world. Some markets have developed very high levels of concentration, with important over-indebtedness, multiple and cross-borrowing. At the same time, other markets are still relatively unexplored (Martínez and Krauss, 2015; Krauss et al, 2012). While pooling all these different experiences in a panel dataset can be problematic, using a quantile approach allows to acknowledge these heterogeneities and to explore them in detail, so that valuable lessons can be learnt from them. This paper proposes a quantile regression approach with MFI fixed effects and MFI-specific time trends, with and without the IV discussed above.

3.5 Sample selection bias

Since reporting to *MIX* is voluntary, the data is likely to be biased towards the best performing MFIs, which are usually the more transparent institutions. This sample selection problem can be understood using the following latent variable model:

$$OSS_{i,t} = \begin{cases} OSS^*_{i,t} & if \quad OSS^*_{i,t} > OSS^L_{i,t} \\ 0 & if \quad OSS^*_{i,t} < OSS^L_{i,t} \end{cases} \tag{6}$$

MFIs report to *MIX market* according to the unobserved value of $OSS^*_{i,t}$, which represents their operational self-sufficiency that only they observe and is not always reported to *MIX*. There can be a threshold $OSS^L_{i,t}$ below which firms decide not to send their balance sheet information to *MIX* or simply do not have the accounting ability to do so. There is no information on *MIX* regarding these firms. This could bias our estimation of the coefficient for *Women*. Indeed, if serving women has a positive impact on operational self-sufficiency, then the MFIs that serve relatively less women and still report to *MIX* are likely to be unfairly compared with those that serve relatively more women (and present their data as well). Either way this would imply a sample selection bias in the estimation of the relevant coefficient.

Since we do not possess any information regarding the firms that do not report to *MIX*, it is impossible to do a regular Heckman procedure to identify the selection equation. Therefore, this paper proposes to use a censoring procedure. The main purpose of the censoring technique is to select a fraction of firms that report that is comparable with firms that do not report. This is done by assuming that any non-reporting firm (serving relatively more or less women) would have an $OSS^*_{i,t}$ unobserved index below a certain threshold $OSS^L_{i,t}$, so it treats the firms with $OSS_{i,t}$ observed indices under that threshold as if they never reported to *MIX*. If the model is well specified, then the resulting β_1 are stable when using different censoring points, i.e. when changing the value of $OSS^L_{i,t}$ across different Tobit estimations.

4 Data

This paper uses historical *MIX* data of 415 microfinance institutions (MFIs) between 2003 and 2012 to answer these questions. Even if *MIX*'s publicly available dataset covers more institutions and years, the sample is restricted for those countries in which *DHS* surveys are available for the construction of the instrumental variables, which is synthesized in Table 1. Moreover, the quality of *MIX* data is better for these years than for the previous ones. Indeed, by 2003 *MIX* was a well known platform to which MFI were interested to report in order to increase their visibility, attract capital, and improve their reputation. The same number of observations is kept in all the estimations in order to keep all them comparable.

The summary statistics of the main variables of interest are reported in the Appendix in Table 2 and by quantiles of MFIs' operational self-sufficiency in Table 3. Many of the most important variables are ratios, which makes the analysis difficult. Moreover, outliers play an important role and should not be disregarded. Therefore, the analysis considers logs and, when this is not possible, the variables are cleaned by taking out the values lower or higher than two standard deviations.

In order to construct the instruments for *Women*, this paper considers data coming from *Measure DHS* on births at the household level. In particular, 220 household surveys are considered for 74 countries between 1985 and 2013, which are listed in Table 1. The year of the survey is not constant across countries. Therefore, the following methodology is used: First, for all the 220 country surveys the number of babies that were born in all households in a given country-year is calculated. Second, these births are classified by sex, by twin/non twin and by first/non first baby. Taking these characteristics into account, data on births at the country-year level can be obtained from various surveys for the same country using a cohort approach. The summary statistics of these instrumental variables are reported in Table 4 and their distributions are plotted in Figure 3.

5 Results

The OLS estimation of equation (1) is presented in the first column of Table 5. Serving women has a positive and significant effect on operational self-sufficiency for the average MFI. Increasing outreach to women by 10 percentage points increases operational self-sufficiency by 2.5 percentage points for the average institution, ceteris paribus. As was discussed above, this coefficient is likely to be biased due to the potential endogeneity concerns. The instrumental variable approach presented in this table explores whether this hypothesis is true for the average firm.

The second column of Table 5 presents the first stage results of the IV estimation. The fertility shock represented by a higher share of *Girls* born in a given country-year affects the share of *Women* borrowers significantly and positively. This implies that this instrumental variable is relevant in explaining female demand for microfinance loans. For the average MFI, the resulting IV estimator for the coefficient of *Women* is positive and bigger than the OLS estimator.

In addition, the Limited Information Maximum Likelihood (LIML) estimator helps to correct for possible biases introduced by the IV procedure. For the average MFI, the coefficient for *Women* with this procedure is still positive and bigger than in the OLS case, as can be seen in column 4 of Table 5. The Lewbel approach allows to control further for possible weak instrument problems by using the heteroskedasticity in the sample to identify the causal relationship between *Women* and *OSS*.

It is possible to apply this technique given the heteroskedasticity of some of the macroeconomic exogenous variables in equation (1). As can be seen in Figure 4, the simple model for female demand for microfinance services works worse in countries with low *GDP pc*, and formal financial development proxied by *Domestic Credit*. The errors of this model are also heteroskedastic with respect to the level of *Female Education* and *Gender Gap*.

The Lewbel IV approach uses this information to identify the causal relationship between increasing outreach to *Women* and achieving a higher *OSS*. For the average MFI, this estimator results in a coefficient very close to the OLS one, as can be seen in columns 6 and 8 of Table 5. In this case, the instrumental variables are jointly significant at a very high level, as is reported by the Cragg-Donald Wald F statistic, which increases the consistency of the coefficient.

The results of Table 5 show that the best approach to address the potential endogeneity in equation (1) for the average MFI is using both the external IV generated with the fertility shocks, and the internal Lewbel IV generated with the macroeconomic variables that are exogenous with respect to *OSS*. It also shows that for the average MFI, there is no trade-off between increasing outreach to women and operational self-sufficiency. This result holds also once the potential endogeneity between these two objectives is addressed.

Table 5 also shows that for the average MFI, having a high average loan size, real yield and price differential is significantly associated with higher operational self-sufficiency. On the contrary, costs per loan and risk are significantly associated with lower operational self-sufficiency. Increasing the number of loans per staff also has a significant positive association on operational self-sufficiency.

The quantile regression approach is particularly interesting to better understand these results. Table 6 shows the results for a quantile regression approach with no instrumental variables. In this table it is possible to see that for firms in the 10th percentile of operational self-sufficiency, i.e. firms with an average OSS ratio of 56.5%, outreach to women is negatively associated with operational self-sufficiency. This can be explained with the hypothesis presented above, by which the most subsidized firms, and thus the least self-sufficient ones, may be pushed by their donors to reach more women. Thus, for these firms there is a negative relationship between *OSS* and *Women*.

This negative association between *Women* and *OSS* does not constitute however a causal relationship. Indeed, as can be seen in the first column of Table 8, once endogeneity is addressed, serving women has a positive effect on the *OSS* ratio of the firms in the lowest 10th percentile of *OSS*. This is also true for all the other percentiles, as can be seen in Figure 1. These results confirm the hypothesis of a negative bias of the OLS coefficient. It was not possible to see this when pooling all different kinds of MFI in the specification of Table 5. Thus, the quantile regression approach allows to better understand the dynamics of MFI tradeoffs. These results hold also when considering *Returns on Assets* instead of *Operational Self-Sufficiency*.

Other variables of interest also show interesting patterns in Table 8. In particular, the coefficient of *Price differential* shows a sharp jump between percentile 75th and percentile 90th. While increasing the *Price differential* by 10 percentage points increases *OSS* by 0.9 percentage points for firms in the 75th percentile, this effect is of 1.4 percentage points for firms in the 90th percentile and highly significant. This indicates that MFIs in the highest degrees of commercialization care more about keeping a high price differential with respect to other firms in their market. These results hold also when considering *Returns on Assets* instead of *Operational Self-Sufficiency*.

This last result shows that firms in the higher percentiles of operational self-sufficiency have competitive advantages that allow them to keep high prices with respect to their competitors. Firms may pursue many different strategies to achieve this result. Basic microeconomic theory dictates that market power has a direct influence on the mark-up that firms can charge for their products. Other alternatives include product differentiation or product quality. Indeed, by increasing the quality of their products or attaching value added services to them, firms can maintain competitive advantages in a specific market.

Unfortunately, the dataset used in this study does not allow exploring which of these alternatives drives the competitive advantages pursued by MFIs at the highest levels of financial performance. If these institutions' competitive advantages are associated with market share, then the ability of microfinance to foster market mechanisms forward and boost development outcomes through market forces may be put into question. In the same way, the positive social impact that microfinance institutions may be able to achieve as they become more commercialized may be hindered by their interest in anti-competitive practices that may not be in the best interest of their clientele, extracting rents from them beyond the market fair price. Exploring this issue further is an interesting question for future research.

The results are also robust to the possible sample selection bias due to the self-reporting nature of *MIX* data. Indeed, in order to control for the possible sample selection bias, a Tobit model is used with a Mundlak procedure to take into account MFI-specific means. As can be seen in Table 9, the coefficients of *Women* do not change much when different censoring points are taken into account. This indicates that there is not a considerable sample selection bias that could impact the estimation in relevant ways.

6 Conclusions

This paper shows that increasing outreach to women has a positive impact on the operational self-sufficiency and the returns on assets of microfinance institutions. The positive effect of reaching more women increases once potential endogeneity problems are addressed with a novel instrumental variable approach that uses metadata from household surveys, and the heteroskedasticity in the sample. This result holds for different percentiles of operational self-sustainability, suggesting that microfinance institutions do not face an important risk of mission drift as they become more commercialized.

However, outreach to women is an imperfect proxy for social impact. Thus, other variables need to be considered to assess the trade-offs between doing well and doing good faced by microfinance institutions. The price differential in terms of real yield between a given institution and the market average in its same country-year is a good proxy for rent extraction. If high, this ratio indicates that the firm is able to maintain high prices due to competitive advantages. The results of this paper indicate that this proxy for rent extraction has a positive effect on the operational self-sufficiency and the returns on assets of microfinance institutions, especially in the case of the most commercialized firms.

If these institutions' competitive advantages are associated with market share rather than with an increased quality of the services offered to the bottom of the pyramid, then the ability of microfinance to foster market mechanisms forward and boost development outcomes through market forces may be put into question. Unfortunately this issue cannot be solved using this study's data, and it constitutes an interesting question for future research.

This paper uses microfinance data to understand up to what extent it is possible to reach the poor with goods, services and opportunities in commercially viable ways, doing well by doing good at the same time. For the case of microfinance, the results indicate that even if there is no trade-off between different measures of financial performance and the best comparable proxies for social impact, the most commercialized institutions tend to be more interested in keeping a high price differential. If this differential is not justified by a higher quality of the services provided, this could hinder the positive impact of the most commercialized microfinance institutions. Further studies could explore whether this is also true for inclusive businesses in other industries, and which could be the best measures that investors and policy makers should take in order to make sure that these market-driven initiatives reach their full social potential.

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7 Figures and Tables

Figure 1: **Effect of increasing outreach to *Women* by 10 pp on *Operational Self-Sufficiency* (in pp) across different percentiles**

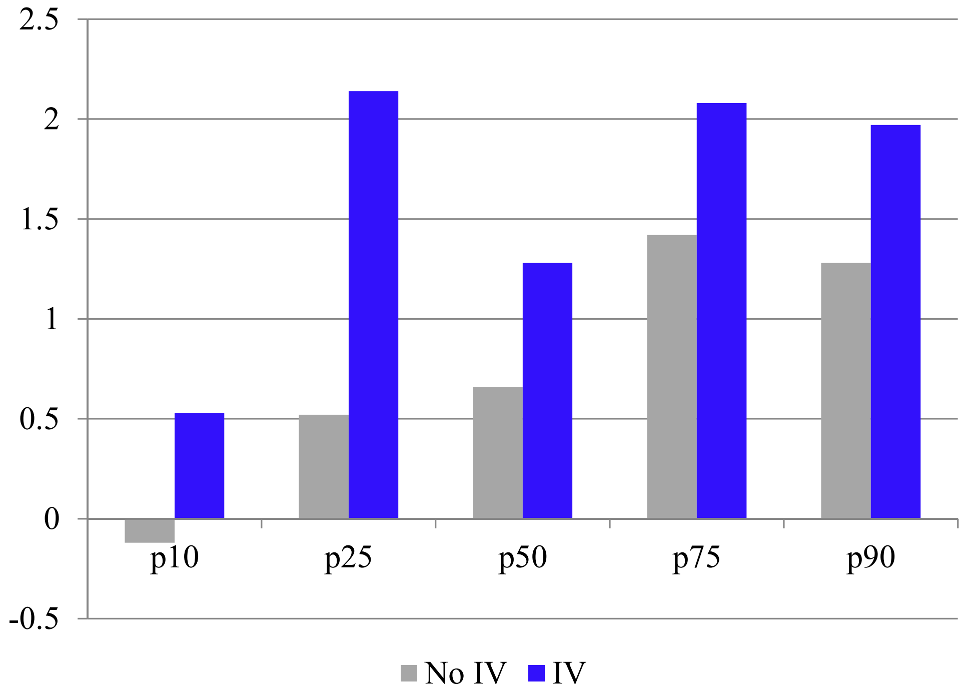

Figure 2: **Effect of increasing *Price Differential* by 10 pp on *Operational Self-Sufficiency* (in pp) across different percentiles**

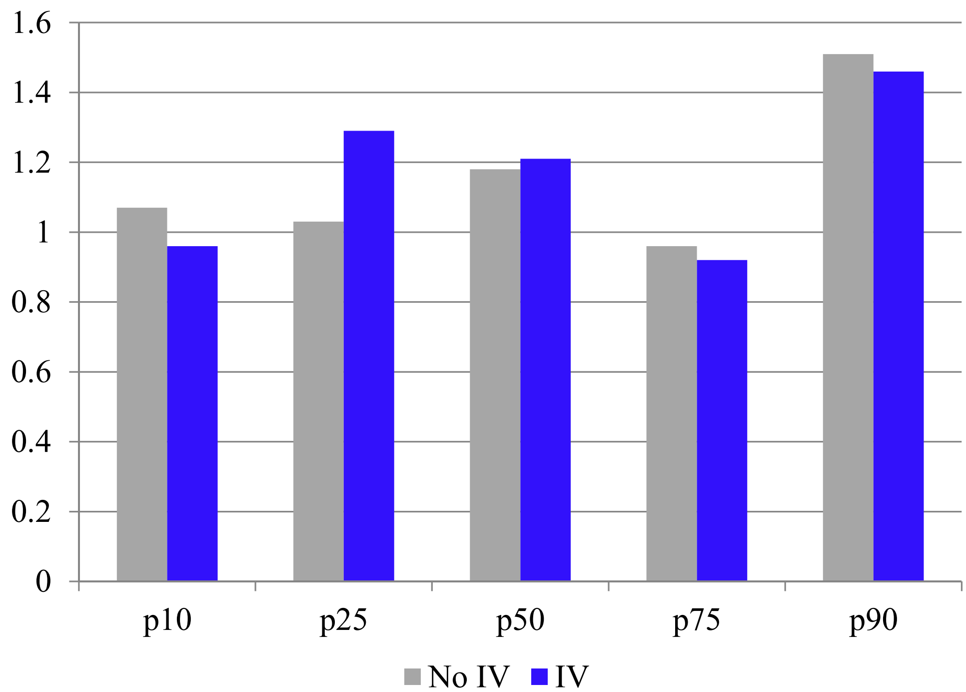

Table 1: **DHS data availability for the construction of instrumental variables**

Country	DHS surveys	Country	DHS surveys	Country	DHS surveys
India	3	Benin	4	Niger	4
Philippines	4	Uganda	5	Burundi	2
Peru	5	Sri Lanka	1	Yemen	1
Ecuador	1	Rwanda	5	Sierra Leone	1
Bangladesh	6	El Salvador	1	Zambia	4
Mexico	1	Tanzania	6	Guinea	3
Indonesia	7	Cameroon	4	Moldova	1
Nepal	4	Togo	2	Congo, Rep.	2
Colombia	6	Uzbekistan	1	Zimbabwe	5
Bolivia	5	Egypt	7	Ukraine	1
Nicaragua	2	Mali	4	East Timor	1
Ghana	5	Armenia	3	Chad	2
Pakistan	3	Madagascar	4	Liberia	2
Nigeria	5	Morocco	4	Tunisia	1
Kenya	5	Burkina Faso	4	Turkey	3
Azerbaijan	1	Congo, Dem. Rep.	1	Thailand	1
Kyrgyzstan	2	Ivory Coast	2	Trinidad and Tobago	1
Brazil	3	Dominican Reb.	6	Namibia	3
Honduras	2	Jordan	6	Sudan	1
Kazakhstan	2	Mozambique	4	Swaziland	1
Ethiopia	3	Haiti	4	Central African Rep.	1
Cambodia	3	South Africa	1	Comoros	2
Guatemala	3	Paraguay	1	Gabon	2
Senegal	5	Albania	1	Guyana	2
Vietnam	2	Malawi	4	Totals	
				74	220

Table 2: **Summary statistics**

	N	Mean	Sd	p10	p25	p50	p75	p90	Min	Max
Operational Self-Sufficiency	1221	112.7%	29.7%	75.1%	100.6%	112.4%	128.7%	146.1%	16.3%	232.8%
Women Borrowers	1221	68.8%	23.3%	37.0%	51.9%	69.0%	91.5%	99.7%	10.6%	100.0%
Avg Loan Size (USD)	1221	630.1	850.4	89.0	134.1	336.3	842.8	1’475.3	12.5	9’744.0
Real Yield	1221	24.7%	13.3%	10.0%	14.9%	23.0%	32.0%	43.6%	-11.2%	62.4%
Price Differential	1221	101.3%	43.2%	59.3%	80.3%	99.1%	117.3%	143.5%	-90.9%	603.6%
Market Share	1221	8.1%	12.0%	0.4%	1.1%	3.5%	10.3%	21.2%	0.0%	100.0%
Herfindahl Index	1221	15.9%	11.6%	5.7%	7.7%	14.2%	20.2%	27.7%	4.4%	100.0%
Borrowers (thousands)	1221	54.4	88.4	2.6	7.7	19.4	63.1	137.0	0.1	577.1
Gross Loan Portfolio (USD m)	1221	22.4	48.4	0.9	2.3	7.1	22.1	52.7	0.0	538.2
Assets (USD m)	1221	30.7	70.1	1.3	3.4	9.6	28.6	73.2	0.1	987.6
Personnel Expenses (USD m)	1221	2.1	4.1	0.1	0.3	0.9	2.3	4.8	0.0	44.9
Cost per Loan (USD)	1221	117.5	119.4	17.0	36.0	90.0	158.0	247.0	3.0	1440.0
Loans per Staff	1221	150.1	114.2	55.0	87.0	131.0	178.0	252.0	2.0	1438.0
Portfolio at Risk 30 days	1221	7.3%	9.5%	0.5%	2.0%	4.6%	8.6%	17.0%	0.0%	100.0%
Age	1221	2.7	0.5	2.0	3.0	3.0	3.0	3.0	1.0	3.0

Table 3: **Summary statistics by percentiles**

		Operational Self-Sufficiency	Women Borrowers	Average Loan Size (USD)	Real Yield	Price Differential	Market Share	Herfindahl
p10	Mean	56.5%	69.5%	235.2	23.4%	98.9%	9.3%	21.1%
	Std Dev	16.1%	27.7%	282.5	16.2%	66.4%	18.7%	16.9%
p20	Mean	89.3%	70.9%	370.4	26.5%	108.1%	7.9%	17.5%
	Std Dev	6.1%	21.6%	465.7	15.9%	57.1%	12.2%	13.1%
p30	Mean	102.0%	71.1%	623.0	24.8%	101.5%	9.0%	14.0%
	Std Dev	1.8%	24.8%	1’035.1	14.2%	33.0%	13.7%	10.6%
p40	Mean	107.6%	70.8%	592.5	26.3%	108.0%	6.8%	14.3%
	Std Dev	1.6%	22.3%	833.3	12.9%	35.9%	9.5%	10.6%
p50	Mean	112.6%	65.4%	910.6	25.2%	99.5%	6.2%	14.3%
	Std Dev	1.3%	21.1%	1’105.9	13.0%	31.7%	7.6%	9.0%
p60	Mean	119.0%	68.8%	740.6	26.2%	100.2%	7.4%	14.3%
	Std Dev	2.3%	21.8%	1’202.9	12.5%	32.8%	9.8%	8.2%
p70	Mean	126.8%	67.2%	670.4	24.5%	97.9%	8.6%	14.5%
	Std Dev	2.2%	22.4%	584.1	11.7%	37.1%	11.2%	11.1%
p80	Mean	136.7%	68.1%	641.0	23.5%	102.8%	9.3%	16.0%
	Std Dev	3.8%	23.3%	586.7	10.4%	34.4%	11.1%	8.8%
p90	Mean	163.8%	67.6%	890.0	21.8%	94.6%	8.5%	16.7%
	Std Dev	18.9%	24.2%	868.5	11.7%	45.7%	10.5%	11.6%
All	Mean	112.7%	68.8%	630.1	24.7%	101.3%	8.1%	15.9%
	Std Dev	29.7%	23.3%	850.4	13.3%	43.2%	12.0%	11.6%

		Borrowers (thousands)	Gross Loan Portfolio (USD m)	Assets (USD m)	Personnel Expenses (USD m)	Cost per Loan (USD)	Loans per Staff	Portfolio at Risk, 30 days	Age
p10	Mean	22.1	4.4	9.1	0.9	129.9	116.0	12.6%	2.4
	Std Dev	39.1	9.2	22.4	1.3	169.6	74.6	15.2%	0.8
p20	Mean	37.5	8.8	16.3	1.2	116.0	135.8	9.2%	2.7
	Std Dev	59.1	12.0	24.5	1.4	104.2	67.8	10.8%	0.6
p30	Mean	67.1	21.4	28.5	2.3	107.5	165.7	7.9%	2.8
	Std Dev	106.9	46.2	56.9	5.0	109.0	152.1	7.4%	0.5
p40	Mean	61.9	15.4	20.9	1.7	132.5	137.2	6.6%	2.8
	Std Dev	110.3	21.5	30.6	1.9	172.1	69.5	6.3%	0.5
p50	Mean	50.3	30.6	41.2	3.0	146.3	130.3	6.7%	2.8
	Std Dev	82.2	66.9	98.3	6.0	123.5	110.5	6.2%	0.5
p60	Mean	58.3	19.5	24.9	1.9	118.1	151.2	7.0%	2.8
	Std Dev	102.5	30.7	37.3	2.4	107.5	141.9	11.6%	0.4
p70	Mean	64.0	31.8	40.6	2.9	107.5	155.2	5.7%	2.9
	Std Dev	86.3	61.9	75.7	5.4	77.6	122.5	6.5%	0.4
p80	Mean	64.3	32.1	41.8	2.8	96.9	167.6	4.9%	2.8
	Std Dev	81.5	56.3	78.3	4.6	85.7	89.8	8.0%	0.4
p90	Mean	64.1	38.0	53.0	2.5	102.0	192.5	4.7%	2.8
	Std Dev	94.8	69.9	121.4	5.1	88.1	143.3	6.6%	0.4
All	Mean	54.4	22.4	30.7	2.1	117.5	150.1	7.3%	2.7
	Std Dev	88.4	48.4	70.1	4.1	119.4	114.2	9.5%	0.5

Table 4: **Summary statistics of instrumental variables**

	N	Mean	Sd
Girls	1,221	48.72%	1.22%
First Babies	1,221	29.18%	6.45%
Twins	1,221	2.26%	1.05%

Figure 3: **Distribution of instruments**

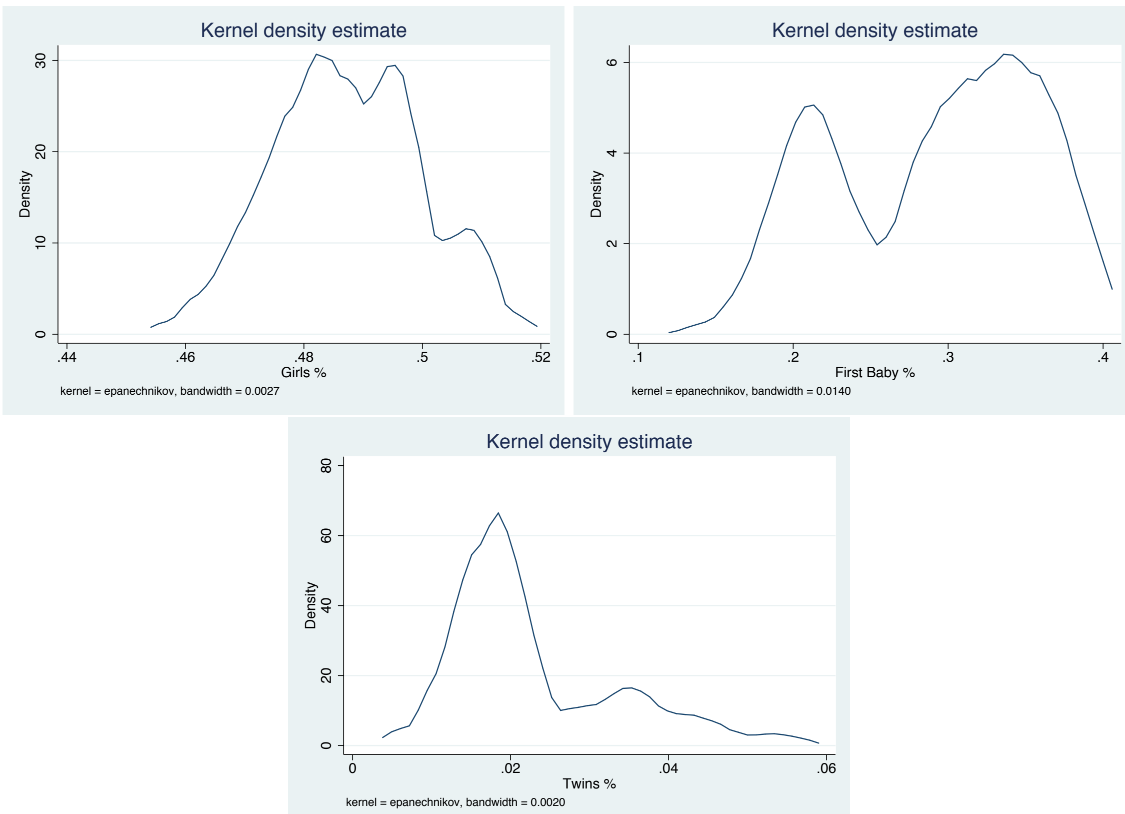

Figure 4: **Heteroskedasticity for Lewbel approach**

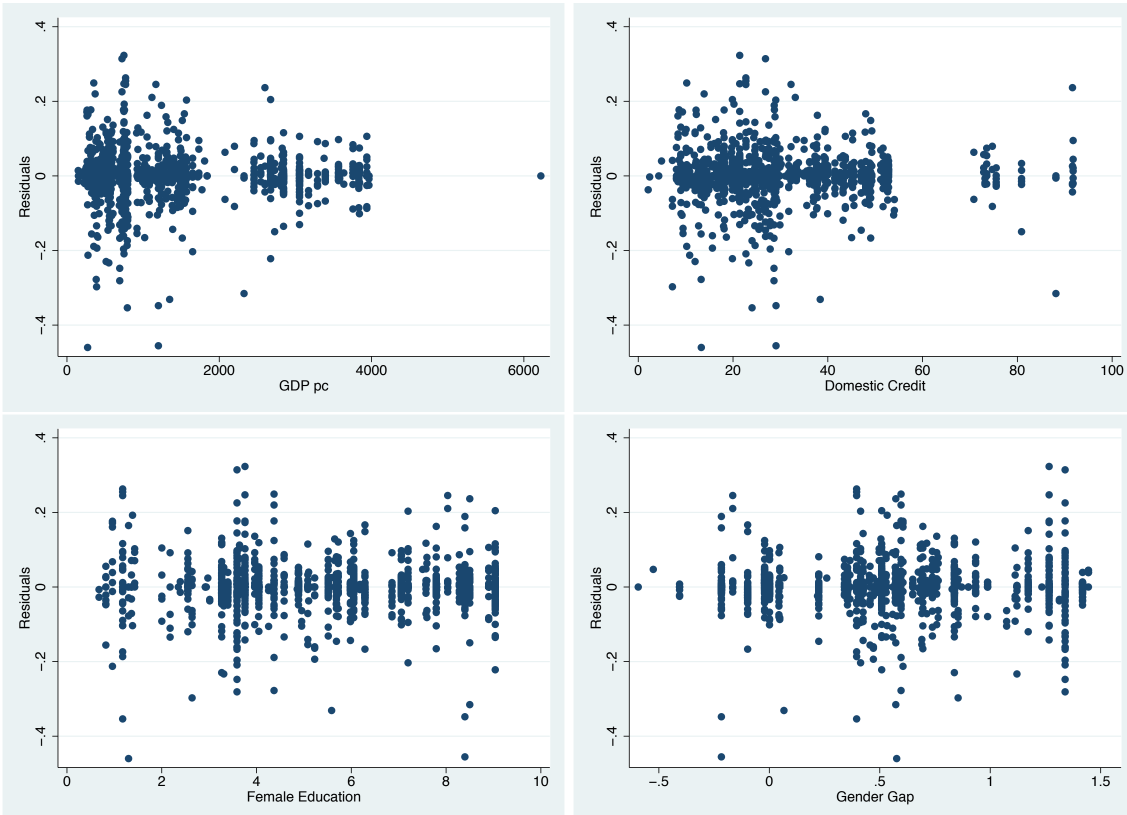

Table 5: **Identification strategy**

	OLS	IV	IV	IV	Lewbel	Lewbel	IV & Lewbel	IV & Lewbel
		1SLS	2SLS	LIML	1SLS	2SLS	1SLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Women Borrowers	0.253**		0.677	0.848		0.197		0.222
	(0.108)		(0.919)	(1.286)		(0.175)		(0.181)
Girls		0.529*					0.418	
		(0.273)					(0.256)	
First Baby		-0.0192					-0.178	
		(0.200)					(0.188)	
Twins		-0.642					-0.532	
		(0.745)					(0.702)	
IV Domestic Credit					-0.160*		-0.154*	
					(0.0911)		(0.0914)	
IV Gender Gap					-0.105		-0.104	
					(0.0785)		(0.0785)	
IV GDP pc					-0.0657		-0.0748	
					(0.0935)		(0.0936)	
IV Female Education					-0.106***		-0.105***	
					(0.0210)		(0.0211)	
Cragg-Donald Wald F		1.47			28.92		17.05	
Stock-Yogo 10% bias		13.91			24.58		31.50	
Stock-Yogo 15% bias		9.08			13.96		17.38	
Stock-Yogo 20% bias		6.46			10.26		12.48	
Stock-Yogo 25% bias		5.39			8.31		9.93	
Observations	1,221	1,221	1,221	1,221	1,221	1,221	1,221	1,221
MFIs	415	415	415	415	415	415	415	415
Years	10	10	10	10	10	10	10	10
MFI-specific time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors clustered at the MFI level in parentheses

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

	OLS	IV 1SLS	IV 2SLS	IV LIML	Lewbel 1SLS	Lewbel 2SLS	IV & Lewbel 1SLS	IV & Lewbel 2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Avg. Loan Size (log)	0.0836*	-0.0672***	0.113	0.124	-0.0636***	0.0798*	-0.0614***	0.0815**
	(0.0496)	(0.0164)	(0.0763)	(0.0993)	(0.0154)	(0.0412)	(0.0154)	(0.0411)
Real Yield	0.451***	0.0288	0.437***	0.431***	0.0462	0.453***	0.0522	0.452***
	(0.136)	(0.0638)	(0.121)	(0.129)	(0.0587)	(0.109)	(0.0598)	(0.109)
Price Differential	0.106**	0.0386**	0.0894*	0.0828	0.0376***	0.108***	0.0368**	0.107***
	(0.0487)	(0.0152)	(0.0515)	(0.0623)	(0.0143)	(0.0394)	(0.0143)	(0.0392)
Age	0.0523	0.00641	0.0494*	0.0479	0.0135	0.0524*	0.0128	0.0528*
	(0.0356)	(0.0120)	(0.0296)	(0.0310)	(0.0113)	(0.0290)	(0.0113)	(0.0289)
Assets (log)	-0.0668	0.0818***	-0.101	-0.115	0.0794***	-0.0626	0.0799***	-0.0640
	(0.0701)	(0.0220)	(0.0963)	(0.122)	(0.0206)	(0.0590)	(0.0207)	(0.0591)
Personnel Exp. (log)	0.0477	-0.0809***	0.0822	0.0960	-0.0866***	0.0430	-0.0865***	0.0453
	(0.0806)	(0.0232)	(0.0967)	(0.121)	(0.0218)	(0.0681)	(0.0218)	(0.0680)
Cost per Loan (log)	-2.782***	0.130	-2.827***	-2.844***	0.260	-2.775***	0.262	-2.779***
	(0.586)	(0.212)	(0.500)	(0.527)	(0.197)	(0.474)	(0.199)	(0.474)
Loans per Staff (log)	0.164***	-0.00467	0.166***	0.167***	-0.00686	0.163***	-0.00564	0.163***
	(0.0510)	(0.0151)	(0.0383)	(0.0379)	(0.0141)	(0.0414)	(0.0141)	(0.0412)
Risk, 30d (log)	-0.0635***	-0.00117	-0.0631***	-0.0629***	-0.00147	-0.0636***	-0.00160	-0.0635***
	(0.0103)	(0.00362)	(0.00821)	(0.00835)	(0.00339)	(0.00832)	(0.00339)	(0.00837)
GDP pc (log)	0.367	0.333***	0.228	0.169	0.278***	0.383*	0.298***	0.380*
	(0.265)	(0.0979)	(0.357)	(0.462)	(0.0892)	(0.227)	(0.0921)	(0.231)
Dom. Credit (log)	-0.0831	-0.0650***	-0.0551	-0.0434	-0.0555***	-0.0864*	-0.0550***	-0.0857*
	(0.0613)	(0.0225)	(0.0850)	(0.107)	(0.0209)	(0.0518)	(0.0212)	(0.0520)
Gender Gap	-0.0803	-0.0428	-0.0671	-0.0610	-0.0432	-0.0812	-0.0515	-0.0822
	(0.163)	(0.0590)	(0.137)	(0.142)	(0.0552)	(0.132)	(0.0555)	(0.132)
Female Education	-0.00559	-0.00689	-0.00110	0.000420	-0.00932	-0.00646	-0.00860	-0.00560
	(0.0370)	(0.0122)	(0.0287)	(0.0294)	(0.0111)	(0.0300)	(0.0115)	(0.0303)
Constant	12.94	5.602	11.26	10.02	1.909	12.63	0.881	13.67
	(24.93)	(6.861)	(18.84)	(19.58)	(6.220)	(18.91)	(6.525)	(21.36)
Observations	1,221	1,221	1,221	1,221	1,221	1,221	1,221	1,221
MFIs	415	415	415	415	415	415	415	415
Years	10	10	10	10	10	10	10	10
MFI-specific time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors clustered at the MFI level in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: **Quantile regression**

	p(0.10)		p(0.25)		p(0.50)		p(0.75)		p(0.90)	
	(1)		(2)		(3)		(4)		(5)	
Women Borrowers	-0.012		0.052		0.066		0.142	*	0.128	
Loan Size (log)	0.053		0.06		0.098	**	0.085	*	0.086	
Real Yield	0.355	**	0.414	***	0.292	**	0.201		0.07	
Price Differential	0.107	*	0.103	*	0.118	***	0.096	*	0.151	**
Personnel Expenses (log)	-0.016		0.037		-0.034		-0.027		-0.024	
Age	0.048		0.045	*	0.044	*	0.047	*	0.04	
Assets (log)	-0.045		-0.075		-0.036		-0.012		-0.027	
Cost per Loan (log)	-1.955	***	-2.569	***	-2.371	***	-2.616	***	-2.83	***
Loans per Staff (log)	0.145	***	0.155	***	0.194	***	0.142	***	0.138	***
Risk 30d (log)	-0.057	***	-0.052	***	-0.047	***	-0.049	***	-0.043	***
GDP pc	0.505	*	0.488	*	0.253		0.161		0.29	
Domestic Credit	-0.049		-0.03		-0.021		-0.061		-0.072	
Gender Gap	-0.128		-0.123		0.039		0.075		0.025	
Female Education	-0.027		-0.001		0.013		0.05	*	0.046	
Observations	1,221		1,221		1,221		1,221		1,221	
MFIs	415		415		415		415		415	
Years	10		10		10		10		10	
MFI-specific time trends	Yes		Yes		Yes		Yes		Yes	

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

Table 7: **Quantile regression with instrumental variables - 1st stage**

	p(0.10)		p(0.25)		p(0.50)		p(0.75)		p(0.90)	
	(1)		(2)		(3)		(4)		(5)	
Girls	0.241	*	0.174		0.131		0.21	**	0.338	***
First Babies	-0.123		-0.183	*	-0.068		-0.107		-0.085	
Twins	-0.336		-0.456		-0.099		-0.141		-0.123	
IV Dom Credit	-0.186		-0.201		-0.179		-0.334		-0.213	
IV GDP	0.609		0.574		0.517		0.504		0.541	
IV Gender Gap	0.174		0.179		0.157		0.406		0.678	
IV Edu Female	-0.25	**	-0.246	***	-0.244	***	-0.255	***	-0.276	***
Loan Size (log)	-0.07	***	-0.065	***	-0.063	***	-0.054	***	-0.047	***
Real Yield	0.021		0.015		0.022		0.022		0.042	
Price Differential	0.037	***	0.033	***	0.031	***	0.026	***	0.017	*
Personnel Expenses (log)	-0.079	***	-0.076	***	-0.071	***	-0.067	***	-0.068	***
Age	0.01		0.006		0		-0.003		-0.006	
Assets (log)	0.083	***	0.075	***	0.072	***	0.067	***	0.059	***
Cost per Loan (log)	0.194		0.192		0.119		0.099		0.158	
Loans per Staff (log)	-0.003		-0.005		-0.006		-0.007		-0.008	
Risk 30d (log)	0.001		0		0		0.001		0	
GDP pc	0.292	***	0.301	***	0.23	***	0.163	**	0.131	
Domestic Credit	-0.048	***	-0.05	***	-0.043	***	-0.034	**	-0.021	
Gender Gap	-0.048		-0.041		-0.029		-0.024		-0.01	
Female Education	-0.018	*	-0.018	**	-0.005		-0.001		0	
Intercept	175.984		115.701		115.686		114.709		171.175	
Observations	1,221		1,221		1,221		1,221		1,221	
MFIs	415		415		415		415		415	
Years	10		10		10		10		10	
MFI-specific time trends	Yes		Yes		Yes		Yes		Yes	

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

Table 8: **Quantile regression with instrumental variables - 2nd stage**

	p(0.10)		p(0.25)		p(0.50)		p(0.75)		p(0.90)	
	(1)		(2)		(3)		(4)		(5)	
Women Borrowers	0.053		0.214		0.128		0.208		0.197	
Loan Size (log)	0.055		0.077		0.101	**	0.102	**	0.103	*
Real Yield	0.351	**	0.359	**	0.285	**	0.192		0.104	
Price Differential	0.096		0.129	***	0.121	***	0.092	*	0.146	***
Personnel Expenses (log)	-0.012		0.036		-0.033		-0.031		-0.016	
Age	0.051		0.053	**	0.042		0.048		0.038	
Assets (log)	-0.05		-0.082		-0.037		-0.016		-0.034	
Cost per Loan (log)	-2.036	***	-2.423	***	-2.334	***	-2.419	***	-2.808	***
Loans per Staff (log)	0.139	***	0.153	***	0.197	***	0.151	***	0.149	***
Risk 30d (log)	-0.056	***	-0.053	***	-0.048	***	-0.048	***	-0.043	***
GDP pc	0.441		0.513	*	0.25		0.08		0.272	
Domestic Credit	-0.038		-0.042		-0.033		-0.044		-0.057	
Gender Gap	-0.114		-0.132		0.025		0.097		0.019	
Female Education	-0.019		-0.01		0.012		0.056	**	0.045	*
Error 1SLS	-0.145		-0.757		-0.187		-0.186		-0.133	
Observations	1,221		1,221		1,221		1,221		1,221	
MFIs	415		415		415		415		415	
Years	10		10		10		10		10	
MFI-specific time trends	Yes		Yes		Yes		Yes		Yes	

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

Table 9: **Tobit approach**

	Tobit				
	y: Operational Self Sufficiency				
Lower Bound	0	0.25	0.5	0.75	1
Women Borrowers	0.253***	0.253***	0.224***	0.167**	0.115*
	(0.0872)	(0.0886)	(0.0808)	(0.0730)	(0.0649)
Avg. Loan Size (log)	0.0836**	0.0840**	0.0691	0.0729*	0.0473
	(0.0400)	(0.0408)	(0.0440)	(0.0416)	(0.0413)
Real Yield	0.451***	0.451***	0.425***	0.409***	0.388***
	(0.109)	(0.110)	(0.108)	(0.0994)	(0.103)
Price Differential	0.106***	0.107***	0.102***	0.0862**	0.0822**
	(0.0392)	(0.0395)	(0.0387)	(0.0354)	(0.0374)
Age	0.0523*	0.0521*	0.0542*	0.0424	0.0452
	(0.0287)	(0.0287)	(0.0282)	(0.0274)	(0.0276)
Assets (log)	-0.0668	-0.0670	-0.0710	-0.0743	-0.0682
	(0.0564)	(0.0565)	(0.0515)	(0.0484)	(0.0468)
Personnel Expenses (log)	0.0477	0.0483	0.0589	0.0562	0.0319
	(0.0649)	(0.0648)	(0.0573)	(0.0521)	(0.0487)
Cost per Loan (log)	-2.782***	-2.814***	-3.058***	-2.909***	-2.917***
	(0.472)	(0.488)	(0.552)	(0.509)	(0.531)
Loans per Staff (log)	0.164***	0.164***	0.150***	0.154***	0.138***
	(0.0410)	(0.0410)	(0.0445)	(0.0412)	(0.0418)
Portfolio at risk, 30 days (log)	-0.0635***	-0.0633***	-0.0634***	-0.0611***	-0.0591***
	(0.00832)	(0.00831)	(0.00805)	(0.00781)	(0.00793)
GDP pc (log)	0.367*	0.363*	0.358*	0.386*	0.433**
	(0.213)	(0.213)	(0.211)	(0.205)	(0.194)
Domestic Credit (log)	-0.0831*	-0.0843*	-0.0837*	-0.0807*	-0.0499
	(0.0493)	(0.0492)	(0.0481)	(0.0455)	(0.0440)
Gender Gap	-0.0803	-0.0781	-0.0708	-0.0512	0.000229
	(0.131)	(0.131)	(0.128)	(0.135)	(0.146)
Female Education	-0.00559	-0.00382	0.00270	0.0107	0.0328
	(0.0298)	(0.0291)	(0.0262)	(0.0250)	(0.0237)
Constant	12.94	13.06	15.36	19.04	24.36
	(20.07)	(20.30)	(19.34)	(17.74)	(16.94)
Observations	1,221	1,221	1,221	1,221	1,221
Censored observations	0	7	48	128	310
MFIs	415	415	415	415	415
Years	10	10	10	10	10
MFI-specific time trends	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses clustered at the MFI level

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