CENTRE FOR FINANCE AND DEVELOPMENT

THE GRADUATE INSTITUTE | GENEVA

CFD Students Working Paper Series

No. 01-2013

# Profits vs. Impact: What can microfinance teach us?

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February, 2013

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Working Paper - February 2013

**Abstract**

How can the private sector work for development? This paper provides answers to this question from the firms' perspective by examining the trade-offs that private firms face between maximizing their profits and achieving a positive social impact. In particular, it considers the experience of microfinance as the best available data source from the point of view of a firm engaged in development issues. The paper studies balance sheet data of microfinance institutions (MFIs) to understand what drives their financial self-sustainability. The analysis focuses on how this variable is affected by firm-level proxies for social impact, such as outreach to women and loan size, using both a quantile regression and an instrumental variable approach. The findings indicate that there is low risk of mission drift as MFIs become more financially sustainable. Indeed, serving women seems to increase financial self-sustainability in all types of institutions due to reduced risk. Moreover, increasing the loan size seems to be less important as firms gain financial self-sustainability. Nevertheless, even if more profitable MFIs tend to cope better with costs, they are also more sensitive to risk and market power. This can limit their role in financing projects with a higher long-term development impact, as well as it can reduce their interest in fostering market mechanisms forward. Therefore there is room for regulation to design risk mitigation mechanisms and promote competition.
JEL: L21 L33 G21.

*I would like to thank Jean Louis Arcand for his continuous support and guidance, and Martina Viarengo and Ugo Panizza for their valuable comments.

# 1 Introduction

Can market driven initiatives generate social change? Is it really possible to do well by doing good? What are the main trade-offs that private firms face when addressing development issues? How could these market-driven initiatives be fostered and promoted? Most of the empirical evidence on market-driven initiatives aimed at addressing development issues while at the same time making profits is based on isolated cases. Even if there are many experiences of various industries that have engaged in new business models to reach the poor[1], there is no common track record that could be used to do cross-sectional comparisons and more precise analyses on these type of innovations.

The experience that microfinance has had, as an innovative business model to reach the poor, constitutes a powerful resource to improve our understanding of the role that the private sector can play in disenfranchised segments of the population that have been for long marginalised from the markets. Indeed, microfinance can be considered as the best case-study for making cross-sectional assessments of the potential success that market-driven initiatives can have in addressing development issues. This paper studies the main trade-offs that microfinance institutions (MFIs) face between making profits and achieving a positive social impact: How and when is it profitable to provide financial services to vulnerable population? What happens as firms become more financially sustainable? Will they move vertically to serve higher income population? Will they be able to assume the risk that is needed in order to finance the missing middle and generate a long-term positive impact on development?

The literature that has studied these trade-offs is relatively limited and has find mixed results. For example, some authors find that more commercialized MFIs will find it convenient to stay in their niche in the future (Cull, Demirgüç-Kunt and Morduch, 2009); while others find that they will leave it and move vertically to serve other markets (Hermes, Lensink and Meestersr, 2011). Such different and contradicting results can be explained by the fact that the specifications proposed so far by the literature may suffer from different sources of bias, as the relationship between MFIs' profitability and their focus on particular income groups is not exogenous. Moreover, this relation-

[1] OECD (2012) presents a report on various inclusive innovation initiatives that have reached the poor by proposing business models that overcome their main limitations that they face for joining the markets. Even if considering different experiences gives a general idea of what works and what does not, as the report does, the evidence is still anecdotical and there are no rigorous results that could be extended to other contexts and cases.

ship is not constant across different types of MFIs, as firms have different constraints, incentives and business objectives as they become more financially self-sustainable. Furthermore, there is a potential risk of sample selection bias, given that the MFIs' balance sheet data analyzed is likely to be reported by the best performing firms.

The main contribution of this paper is that it proposes different strategies to address these potential biases and achieve a better understanding of the trade-offs that MFIs face. Moreover, this paper takes into account the heterogeneity that exists between MFIs and exploits it to better understand the dynamics of the business objectives that these firms have. In particular, this paper contributes to the literature by studying how the financial self-sustainability of MFIs is affected by firm-level proxies of social impact, such as the percentage of female borrowers and the average loan size.

It is important to note that, even if these variables are only imperfect proxies of the social impact that MFIs can have, and that they cannot be used for a proper impact evaluation of the effect that these institutions have on vulnerable population; these variables nonetheless indicate the interest that MFIs have on serving the poor. Given that the purpose of this paper is precisely to understand how these firms set their business objectives and which trade-offs they face, these variables are relevant for the purpose of this study. To reach this purpose, I consider firm-level data of the balance sheets of 1832 MFIs in 110 countries between 1995 -2011 that have been reported to *MIX Market*. The potential biases are addressed by proposing both a quantile regression approach and an instrumental variable approach, as well as by testing for the presence of sample selection bias.

Focusing on social impact has an heterogenous effect across the distribution of MFIs as less or more financially sustainable firms face different limitations, motivations and business objectives. The quantile analysis that this paper proposes takes this into account and exploits this heterogeneity to better understand how the trade-off between profits and impact changes as firms become more financially sustainable and commercialised. Moreover, the instrumental variable approach proposed by this study addresses the potential endogeneity between MFIs' financial self-sustainability and their supply of financial services to clients in which this resources can have a higher social impact.

In particular, the paper proposes an instrument for the percentage of female loans by considering exogenous shocks to fertility, such as the percentage of female and of twin births in a given country-year, which affect women's demand for financial services through their impact on their available time, need of additional resources or bargaining power. These instruments are highly relevant and comply with the exclusion restriction, as they are pure biological shocks with no impact on MFIs' financial self-sustainability. Moreover, the paper considers the potential sample selection bias in the estimation, due to the self-reporting character of the balance sheet data that is used in the estimation, which is more likely to be provided by the best performing firms.

The paper controls for endogeneity also using a quantile regression approach. The results indicate that even after costs and risk are controlled for, lending to women seems to be profitable for all kinds of firms. The drivers of this profitability are related to the fact that lending to women reduces risk. This confirms the finding of Cull, Demirgüç-Kunt and Morduch (2011) that being financially self-sustainable and serving the poor are not incompatible objectives for MFIs.

Once the heterogeneity of firms is considered across different quantiles, it is possible to see that the most profitable firms are less interested in supplying bigger loans, as Gonzales and Rosenberg (2006) predicted. This implies that they will still be interested in serving poor clients and will not necessarily be willing to finance bigger projects, for example of small and medium enterprises which could have a long-term impact on development. Moreover, the most interesting and innovative findings of the paper indicate that even if the most financially self-sustainable firms cope better with higher costs, they are also the most sensitive to risk and to market power.

These findings indicate that more commercialised MFIs will tend to stay in their niche of women and small loans. Nevertheless, even if this can be viewed as a positive result because it suggests that there is low risk of mission drift, the findings also imply that this market-driven initiatives are unlikely to be able to finance projects that could have a higher impact on development outcomes. Indeed, as firms become more commercialised, they are also more sensitive to risk and market power, and therefore less interested in serving riskier projects and in fostering the markets. This implies that there is room for regulation to design mechanisms to mitigate risk and to reduce the importance that these firms attribute to market power. These results may be extendable to other private firms doing business in traditionally neglected segments of the market. Indeed, the amount and quality of data available for MFIs has no parallel for any other similar private initiatives.

## 2 Literature Review

Cull, Demirgüç-Kunt and Morduch (2011) summarizes the research work these authors have done in the last years on the trade-offs that microfinance institutions face and on how regulation, competition and financing affects them. These authors find that higher interest rates increase profits but that after a certain point higher interest rates increase the probability of default, as Stiglitz and Weiss (1981) would predict. Moreover, these authors argue that achieving financial self-sustainability and serving poor costumers are not incompatible objectives, but that serving poor customers decreases profits and makes it more difficult to attract investors. Their findings also suggest that regulation increases costs and pushes MFIs out of the poor customer cluster to serve relatively higher income segments. Competition, on the other hand, increases the tendency of MFIs to serve the poor according to their results.

Most of the existing literature would agree with the findings of Cull, Demirgüç-Kunt and Morduch (2011), except for their result on the impact of competition and commercialisation on MFIs' behavior. Indeed, while Cull, Demirgüç-Kunt and Morduch (2009) find that the competition reflected in higher financial development pushes MIFs to specialise in the niche of women and small loans, other authors reported opposite findings. In particular, Hermes, Lensink and Meesters (2011a) find that MIFs become more "efficient" and less concerned with development outcomes. Crucially, none of these two approaches considers the endogeneity between commercialisation and outreach to poor clients, or the heterogeneity of this relationship across different kinds of institutions. This paper is aimed precisely at filling this gap with the quantile and instrumental variable estimation that is proposed.

The approach proposed by Cull, Demirgüç-Kunt and Morduch (2009a) is to examine the industrial organisation of MFIs and the broader banking sector, analyzing whether the presence of banks affects the profitability and outreach of microfinance institutions. Here they find that bank penetration in the overall economy leads MFIs to operate in poorer markets. Indeed, they find that greater financial deepness is associated with smaller average loans sizes and greater outreach to women. These results hold mostly for MFIs relying on commercial funding and using traditional bilateral lending contracts, rather than for nongovernmental institutions using group lending methods. The authors argue that competition seems to drive MFIs towards niches of poor customers that demand smaller loans.

On the other hand, Hermes, Lensink and Meesters (2011a) find that outreach to vulnerable clients is negatively related to efficiency of MFIs. In particular, the authors find that institutions with lower average loan balance, which may indicate a higher outreach to poor customers, are relatively less efficient. This holds too for MFIs with a higher proportion of women served, measured as the percentage of women borrowers. These findings imply that there is a tradeoff between efficiency and outreach, and the authors argue that as firms become more competitive they will stop serving the poorest potential clients.

Gonzales and Rosenberg (2006) also provide valuable insights. These authors use datasets of MFIs' balance sheets from *The Microbanking Bulletin*, as well as from *MIX Market* and *Microcredit Summit Campaign*. They make a diagnosis of MFIs across the world, analyzing various financial indices. They find that costs, measured as operating expense ratio, are lowered weakly by loan sizes and initially by scale, before the MFI reaches 5,000-10,000 clients. Comparing between for-profit and non-for-profit institutions, they find that for-profit institutions tend to be more efficient than not-for-profit ones. Nevertheless, profitability is interestingly higher in non-for-profit institutions, as they are more likely to be operating under uncompetitive conditions. Furthermore, these authors find that interest rates and spreads drive profitability more than costs or productivity do. Scale or age do not increase profits.

It is also interesting to consider the work by Galema and Lensink (2009). These authors focus on the way in which MFIs attract investors, which is a very important consideration. Using a small sample of institutions, they argue that it is riskier to finance the types of MFIs that serve the poorest borrowers, because they are more subject to subsidy, liquidity and refinancing risks than their larger for-profit counterparts. These authors calculate to what extent social investors are willing to accept a decrease on returns (or an increase in the riskiness of returns) to achieve higher outreach. They show that whereas the trade-off is not large for institutions with average loans of 180 US dollars or more, it is large for institutions with average loans below this level. This outcome suggests that the constraint that institutions face for attracting investors is particularly severe for those that serve the lower end of the population.

None of the papers in the available literature explores the potential biases in the estimations, due to endogeneity, heterogeneity across different MFIs and sample selection. This paper contributes to the literature by directly approaching these problems, as will be explained in the next section.

# 3 Methodology

I propose to estimate the following specification:

$$FSS_{i,t} \;=\; Women_{i,t}\beta_1 \;+ LoanSize_{i,t}\beta_2 \;+\; X_{i,t}^{T}\gamma \;+\; \nu_i \;+\; \upsilon_t +\; u_{i,t} \qquad (1)$$

The dependent variable $FSS_{i,t}$ is the financial self sufficiency ratio of MFI $i$ in year $t$. This index measures an MFI's ability to generate sufficient revenue to cover its costs and operate without subsidies, grants or soft loans. If it takes a value above one, the institution is financially self sufficient, otherwise it is not. This index makes the comparison between institutions easier and is standard in the impact investing industry. It is also more informative than the standard financial ratios such as return on assets or equity. It is constructed after the following formula:

$$FSS_{i,t} \;=\; \frac{fr_{i,t}}{fe_{i,t} \;+\; lip_{i,t} \;+\; oe_{i,t}} \qquad (2)$$

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 $t$.

The variables of interest for examining the trade-offs that MFIs face are the institution-level proxies of social impact, i.e. the *Women* served and the average *Loan Size* of 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, $X_{i,t}$ includes *Real Yield*, which corresponds to the real gross portfolio yield. This variable captures the average interest that MFIs' customers face. The costs that institutions assume are considered by including an index of *Personnel Expenses* over total assets and an index of *Cost per Loan*. In order to capture which MFIs could move to serve the missing middle, it is important to examine the ability that these institutions have to assume risk. For this purpose, I include in the covariate matrix *Portfolio at Risk > 30 days*. 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 the institutions' age, as it may affect their ability to stay in the market. The variable *Age* distinguishes firms between new, young and mature. Size is captured with *Assets*, which may reflect the institution's ability to exploit economies of scale. All the variables in $X_{i,t}$ are considered for MFI $i$ in year $t$.

In order to understand what drives the profitability of lending to women and supplying big loans, I examine how the coefficients of *Women* and *Loan Size* change when key variables such as *Loan Cost* and *Portfolio at Risk* $>$ *30 days* are included or not in the estimation. The logic is the following: If lending to women increases costs, omitting costs in the estimation would lead to a downward biased coefficient for women. Moreover, if lending to women reduces risk (and this is good for financial self-sustainability), then omitting risk would lead to a upward biased coefficient for women.

On the other hand, if bigger loans are less costly, not including costs would bias the loan size coefficient upwards. Furthermore, if bigger loans are riskier (and this is bad for financial self-sustainability), omitting risk would lead to a downward biased coefficient for loan size. All these predictions are easily testable by running different regressions including or not the key variables that have been mentioned. Moreover, other variables such as *Market Power*, *Gender gap*, *GDP growth*, *Education*, *Competition* and *Formal Financial Depth* could play important roles, which I consider in the estimations.

Furthermore, it is very important to consider that there are three possible sources of bias in an OLS estimation of (1): There can be a problem of endogeneity, as *Women* and *Loan Size* may be correlated with the level of financial self-sustainability $FSS_{i,t}$ of a given firm. Moreover, the average firm is very likely not to be representative because key parameters may play different roles according to the MFIs position in the $FSS_{i,t}$ distribution, which is precisely the most interesting research question that this paper aims to explore. Furthermore, there might be an issue of sample selection as financial self-sustainability $FSS_{i,t}$ may be higher for the firms who report to *MIX Market*.

### 3.1 Endogeneity

If there is endogeneity in the specification, then it is the case that $cov(Women_{i,t}, u_{i,t}) \neq 0$ or $cov(LoanSize_{i,t}, u_{i,t}) \neq 0$, which could bias $\beta_{1,OLS}$ and $\beta_{2,OLS}$ in equation (1). This could occur due to missing variables, measurement error or reverse causation problems. If the endogeneity is caused by a problem of omitted variables, then MFI's sustainability could be affected by unobservable variables that could also have an influence on either the supply or on the demand of microfinancial services for women or small/big loans. These unobserved variables could involve concepts such as institutions, the business environment, and culture, which have a contemporaneous influence both on MFIs' sustainability and on the demand that vulnerable population (such as women) have for (big or small) loans.

It is, nevertheless, difficult to determine the direction of the bias originated in this possible problem of unobserved variables, so the best approach is to consider the different possible scenarios: If the unobserved variables have a positive relation with the financial self-sustainability indicator but a negative one with the percentage of women served, $cov(Women_{i,t}, u_{i,t}) < 0$ and $\beta_{1,OLS}$ would be biased downwards. This would hold, for example, when considering unobservables such as institutional quality. Indeed, in a scenario in which MFIs are less sustainable due to a low institutional quality, there could be contemporaneously a high women's demand for microcredit services, as there exist fewer other options available due to the fact that low institutional quality may favour the persistence of gender gaps. The same would hold for *Loan Size* if one argues that less outside options induce people to demand bigger loans.

If these assumptions hold, then the unobservable of institutions would be positively correlated with the dependent variable $FSS_{i,t}$ and negatively correlated with the variables of interest $Women_{i,t}$ and $LoanSize_{i,t}$. Therefore, an OLS estimation that fails to account for institutions would lead to downward biased estimations of $\beta_{1,OLS}$ and $\beta_{2,OLS}$. Nevertheless, since unobservables such as institutions and culture change little over time, this bias could be corrected once fixed effects are performed. Furthermore, if one argues that lower institutions would reduce the demand for bigger loans instead of increasing it, then $cov(LoanSize_{i,t}, u_{i,t}) > 0$ and $\beta_{2,OLS}$ will be biased upwards.

The direction of the bias will be also different when considering unobservables such as business environment. For example, if doing business is not easy in the market in which MFIs operate, they are less likely to be financially self sustainable. In the same way, as women are likely to have the same perception of doing business easiness, they may be more reluctant to engage in debt and their demand for microfinancial services could decrease. In general, people may be less willing to engage in bigger loans.

Since the unobservable of business environment is affecting negatively the dependent variable $FSS_{i,t}$ and the variables of interest $Women_{i,t}$ and $LoanSize_{i,t}$, then $cov(Women_{i,t}, u_{i,t}) > 0$ and $cov(LoanSize_{i,t}, u_{i,t}) > 0$, which implies that $\beta_{1,OLS}$ and $\beta_{2,OLS}$ would be biased upwards. In this case, since business environment is more likely to change dynamically over time, implementing MFI-fixed effects is not likely to sort out the problem. Therefore, year-fixed effects or an instrumental approach are needed in order to identify causality.

Table 1: **Expected Biases**

| | $\beta_{1,ols} < \beta$<br>$\beta_{2,ols} < \beta$ | $\beta_{1,ols} > \beta$<br>$\beta_{2,ols} > \beta$ | $\beta_{1,ols} < \beta$<br>$\beta_{2,ols} > \beta$ | $\beta_{1,ols} > \beta$<br>$\beta_{2,ols} < \beta$ |
|---|---|---|---|---|
| **Omitted Variables** | $\downarrow institut. \rightarrow$ $FSS_{i,t} \downarrow$<br>$w_{i,t} \uparrow$<br>$ls_{i,t} \uparrow$ | $\downarrow db \rightarrow$ $FSS_{i,t} \downarrow$<br>$w_{i,t} \downarrow$<br>$ls_{i,t} \downarrow$ | $\downarrow institut. \rightarrow$ $FSS_{i,t} \downarrow$<br>$w_{i,t} \uparrow$<br>$ls_{i,t} \downarrow$ | |
| **Reverse Causation** | | $\uparrow comm. \rightarrow$ $FSS_{i,t} \uparrow$<br>$w_{i,t}n \uparrow$<br>$ls_{i,t}n \uparrow$ | $\uparrow subsidies \rightarrow$ $FSS_{i,t} \downarrow$<br>$w_{i,t} \uparrow$<br>$ls_{i,t} \downarrow$<br>$\uparrow comm. \rightarrow$ $FSS_{i,t} \uparrow$<br>$w_{i,t} \downarrow$<br>$ls_{i,t} \uparrow$ | $\uparrow comm. \rightarrow$ $FSS_{i,t} \uparrow$<br>$w_{i,t} \uparrow$<br>$ls_{i,t} \downarrow$ |
| **Sample Selection** | $\uparrow w_{i,t} \rightarrow FSS_{i,t} \downarrow$<br>$\uparrow ls_{i,t} \rightarrow FSS_{i,t} \downarrow$ | $\uparrow w_{i,t} \rightarrow FSS_{i,t} \uparrow$<br>$\uparrow ls_{i,t} \rightarrow FSS_{i,t} \uparrow$ | | |

Where w, ls, institut, db and comm. stand for Women, Loan Size, Institutions, Doing Business and Commercialisation.

If the endogeneity is being caused by reverse causality problems, determining the direction of the bias is equally problematic. One could imagine a situation in which MFIs that are less sustainable are so not because they are located in a particular context, but because they are usually heavily subsidised. Since subsidised institutions tend to follow their donors' policy objectives, in which closing the gender gap has played a predominant role in the recent years, then less sustainable institutions would be likely to offer a higher supply of services designed for women than other types of institutions. This would also mean that loans will tend to be smaller.

In this case, $cov(Women_{i,t}, u_{i,t}) < 0$ and $cov(LoanSize_{i,t}, u_{i,t}) > 0$, which implies that $\beta_{1,OLS}$ would be biased downwards and $\beta_{2,OLS}$ would be biased upwards. The result would be the same in the case in which the MFIs that are more sustainable are also likely to be those more financially oriented, which give higher importance to profits than to social impact and, therefore, offer a lower supply of services for women and a higher average loan size.

The key question to answer at this point is the following: Are there firms with high levels of profits and sustainability that are interested in staying in the niche of serving women and small loans? In this case $cov(Women_{i,t}, u_{i,t}) > 0$ and $cov(LoanSize_{i,t}, u_{i,t}) < 0$. Therefore, $\beta_{1,OLS}$ will be biased upwards and $\beta_{1,OLS}$ would be biased downwards. If there is evidence for this and the answer to this question is positive, then the belief that lending to women is unprofitable, as the usually small loans demanded by women imply high transaction costs, would be challenged.

On the contrary, those who believe that lending to women is profitable as it is relatively safe given the high repayment rates of females, would find support. Answering this question entails also a contribution to the discussion regarding up to what extent charging high interest rates is motivated by the need of covering high transaction costs or has become an objective that MFIs follow per se.

As can be seen by this analysis, determining the direction of the endogeneity bias is essential in understanding the complexity of the trade-off between profits and impact that MFI's face. Table 1 sumarizes the main hypothesis and which bias they would imply. In this table I also include the possible bias induced by the sample selection problem, which will be discussed in what follows.

### 3.1.1 Instrumental Variables

As I have discussed, the best way to understand the direction of the potential biases is to use an instrumental variable approach, which would unveil the direction of the bias, and therefore could shed light on the causal mechanisms at stake. I propose instruments for both the proxies of social impact under study, using the following specifications:

$$Women_{i,t} \;=\; Z^T_{1,i,t}\delta_1 \;+\; X^T_{1,i,t}\lambda_1 \;+\; \epsilon_{1,i} \;+\; \xi_{1,t} + \; e_{1,i,t} \tag{3}$$

$$LoanSize_{i,t} \;=\; Z_{2,i,t}\delta_2 \;+\; X^T_{2,i,t}\lambda_2 \;+\; \epsilon_{2,i} \;+\; \xi_{2,t} + \; e_{2,i,t} \tag{4}$$

In the instrumental variable approach, I include $Z_{1,i,t}$ as a matrix of instruments for the percentage of women served. I propose to instrument MFIs' supply of credit for women with exogenous shocks to women's demand for these services. In particular, I use fertility shocks that affect womens demand for microcredit but do not affect MFIs' financial self-sufficiency.

I propose two instrumental variables, i.e. the percentage of female and of twin births in a given country and year, as an exogenous fertility shock that affects women demand for microfinancial services through its impact on women's available time, need of additional resources or bargaining power. It is important to take into account that, even if these variables are computed at the country-year level, the 2SLS estimation predicts women's demand at the MFI-year level.

Moreover, in the vector $Z_{2,i,t}$ I consider remittances as an instrument for the average loan size. In this sense, the supply of small/big loans will be instrumented by exogenous shocks to the demand for small/big loans. Remittances are not a completely exogenous instrument since they are likely to be related to the macroeconomic conditions of the country-year under study, which also affect the MFIs in it. Nevertheless, it is an instrument that has been used in various studies and that I try for the sake of completeness.

## 3.2 Sample selection bias

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

$$FSS_{i,t} = \begin{cases} FSS^*_{i,t} & if \quad FSS^*_{i,t} > FSS^L_{i,t} \\ 0 & if \quad FSS^*_{i,t} < FSS^L_{i,t} \end{cases} \tag{5}$$

MFIs report to *MIX market* according to the value of $FSS^*_{i,t}$, which represents their financial self sustainability that we do not always observe. Indeed, there is a threshold $FSS^L_{i,t}$ below which firms decide not to send their balance sheet information to *MIX Market* or simply do not have the accounting ability to do so.

This could bias our estimation of $\beta_{1,OLS}$. Indeed, if serving women per se has a negative effect on financial self-sustainability, then one could argue that MFIs that serve relatively more women and still present their data to *MIX Market*, would be unfairly compared with MFIs that serve relatively less women (and present their data as well). In the opposite way, if serving women has a positive impact on financial self sufficiency, then the MFIs that serve relatively less women and still report to *MIX Market* 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 OLS estimation of the coefficients. In the first case, the negative impact of serving more women would be underestimated. In the second case, the positive impact of serving more women would be overestimated.

It could also bias our estimation of and $\beta_{2,OLS}$. Indeed, if supplying bigger loans has a positive effect on financial self-sustainability, then it is possible that MFIs that offer bigger loans will be more likely to provide their data to *MIX Market*, which will have an advantange when compared to those firms that offer smaller loans and still report their information to *MIX Market*. If this is the case then the coefficient of *Loan Size* would be overestimated.

Since we do not possess any information regarding the firms that do not report, it is impossible to do a regular Heckman procedure to identify the selection equation. Therefore, I propose to use a censoring procedure in order to make firms that report and serve relatively more women and offer smaller loans comparable with those that report and serve relatively less women offering bigger loans. In this way, once different institutions are comparable, we will be able to estimate the impact of serving women and providing small loans per se.

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 $FSS^*_{i,t}$ index below a certain threshold

$FSS^L_{i,t}$, so it treats the firms with $FSS_{i,t}$ actual indices under that threshold as if they never reported to *MIX Market*. If the model is well specified, then the resulting $\beta_1$ and $\beta_2$ are stable when using different censoring points, i.e. when changing the value of $FSS^L_{i,t}$.

### 3.3 Non linearity of the trade-off

The behavior of this biases is likely to change across the distribution of MFIs. In particular, the nature of the tradeoff between profits and impact is likely to change depending on which firms are taken into account. For example, firms in the lowest quantile of the $FSS_{i,t}$ distribution are likely to present a behaviour that is different from that of firms in the highest quantile of the $FSS_{i,t}$ distribution.

Quantile regression analysis allows to examine if having a higher percentage of women lenders has a variable effect on profits depending on which part of the distribution is consider. It also allows to understand which firms would be more likely to stay in the niche of small loans and women, and which would move up maybe to serve the missing middle and engage in financing SME.

## 4 Data

I use a dataset that is publicly available in the *MIX Market* webpage. It includes balance sheet data of 1832 MFIs in 110 countries between 1995 and 2011. This dataset is an unbalanced panel with 10'023 observations. The summary statistics of the main variables of interest are reported in Table 2 and by quantiles in Table 3

As can be observed in these tables, 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. Figure 1 presents the kernel density of the main resulting variables.

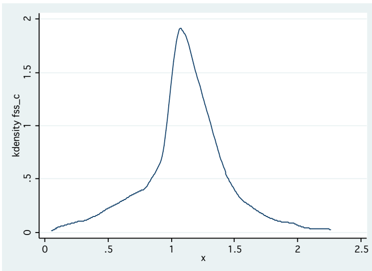
Table 2: **Summary Statistics**

| | FSS | Active Borrowers (thousands) | Women | Number of Loans (thousands) | Gross Loan Portfolio (million $) | Average Loan Balance ( $) | Real Yield | Assets (million $) | Personnel Expenses (million $) | Age (new, young, mature) |
|---|---|---|---|---|---|---|---|---|---|---|
| N | 7567 | 9,459 | 7,757 | 5,662 | 10,059 | 9,399 | 4,893 | 9,810 | 5,383 | 9,853 |
| mean | 1.16 | 57.86 | 66% | 74.22 | 30.40 | 1,353 | 24.4% | 38.90 | 5.50 | 2.4 |
| p50 | 1.12 | 6.87 | 66% | 9.88 | 2.31 | 390 | 20.9% | 3.31 | 0.59 | 3.0 |
| sd | 0.56 | 357.21 | 26% | 415.88 | 296.00 | 14,042 | 17.8% | 307.00 | 184.00 | 0.8 |
| min | -0.68 | 0.00 | 10% | 0.00 | 0.00 | 0 | -24.7% | 0.00 | 0.00 | 1.0 |
| max | 19.39 | 8,362.10 | 100% | 7,536.96 | 18,500.00 | 1,237,916 | 202.4% | 23,700.00 | 13,500.00 | 3.0 |
| p1 | 0.22 | 0.03 | 13% | 0.10 | 0.01 | 25 | -6.2% | 0.02 | 0.01 | 1.0 |
| p5 | 0.50 | 0.17 | 23% | 0.39 | 0.07 | 55 | 2.9% | 0.12 | 0.03 | 1.0 |
| p10 | 0.68 | 0.43 | 31% | 0.85 | 0.18 | 74 | 6.7% | 0.28 | 0.06 | 1.0 |
| p25 | 0.98 | 1.74 | 45% | 2.81 | 0.65 | 138 | 12.9% | 0.95 | 0.18 | 2.0 |
| p50 | 1.12 | 6.87 | 66% | 9.88 | 2.31 | 390 | 20.9% | 3.31 | 0.59 | 3.0 |
| p75 | 1.30 | 23.00 | 93% | 32.57 | 9.72 | 1,158 | 32.1% | 13.30 | 1.94 | 3.0 |
| p90 | 1.55 | 74.11 | 100% | 100.75 | 40.70 | 2,675 | 46.6% | 56.00 | 5.67 | 3.0 |
| p95 | 1.77 | 146.82 | 100% | 202.01 | 100.00 | 4,296 | 58.0% | 139.00 | 12.10 | 3.0 |
| p99 | 2.65 | 852.93 | 100% | 1,142.65 | 464.00 | 10,314 | 83.8% | 596.00 | 46.80 | 3.0 |

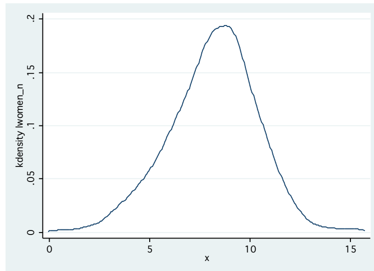
Table 3: **Summary Statistics by Quantile**

| | | FSS | Active Borrowers (thousands) | Women | Number of Loans (thousands) | Gross Loan Portfolio (million \$) | Average Loan Balance ( \$) | Real Yield | Assets (million \$) | Personnel Expenses (million \$) | Age (new, young, mature) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Q1 | mean | 0.49 | 46.27 | 71% | 53.04 | 10.40 | 711 | 23.5% | 13.10 | 1.05 | 2.0 |
| | sd | 0.17 | 401.02 | 25% | 475.56 | 102.00 | 2,218 | 20.4% | 110.00 | 3.82 | 0.9 |
| Q2 | mean | 0.84 | 36.92 | 68% | 52.01 | 18.50 | 991 | 25.7% | 23.70 | 1.73 | 2.4 |
| | sd | 0.07 | 357.27 | 25% | 456.83 | 178.00 | 2,477 | 18.8% | 188.00 | 5.99 | 0.8 |
| Q3 | mean | 1.00 | 52.86 | 68% | 62.91 | 23.00 | 1,109 | 24.1% | 30.40 | 2.28 | 2.5 |
| | sd | 0.02 | 344.94 | 26% | 377.25 | 96.90 | 2,002 | 18.0% | 115.00 | 6.50 | 0.7 |
| Q4 | mean | 1.06 | 53.35 | 65% | 65.99 | 62.00 | 1,849 | 25.1% | 83.70 | 24.90 | 2.5 |
| | sd | 0.02 | 337.49 | 25% | 390.31 | 648.00 | 14,595 | 17.0% | 846.00 | 538.00 | 0.7 |
| Q5 | mean | 1.12 | 53.14 | 64% | 66.52 | 36.90 | 1,336 | 24.9% | 49.80 | 3.63 | 2.6 |
| | sd | 0.02 | 246.06 | 24% | 289.69 | 127.00 | 2,594 | 18.9% | 170.00 | 10.60 | 0.6 |
| Q6 | mean | 1.19 | 58.54 | 63% | 75.50 | 34.80 | 1,383 | 25.0% | 46.70 | 3.30 | 2.7 |
| | sd | 0.02 | 323.18 | 25% | 381.90 | 110.00 | 3,372 | 16.2% | 142.00 | 8.89 | 0.6 |
| Q7 | mean | 1.27 | 81.45 | 64% | 91.95 | 46.10 | 1,276 | 24.2% | 69.20 | 4.42 | 2.7 |
| | sd | 0.03 | 397.42 | 25% | 437.79 | 158.00 | 2,554 | 16.5% | 284.00 | 14.10 | 0.6 |
| Q8 | mean | 1.41 | 82.38 | 65% | 92.91 | 38.70 | 1,446 | 24.7% | 59.50 | 3.44 | 2.6 |
| | sd | 0.05 | 442.96 | 26% | 477.25 | 176.00 | 6,771 | 14.6% | 328.00 | 13.80 | 0.7 |
| Q9 | mean | 1.74 | 103.10 | 64% | 146.25 | 26.20 | 1,235 | 22.7% | 36.40 | 3.08 | 2.4 |
| | sd | 0.19 | 472.44 | 27% | 586.90 | 88.20 | 3,634 | 18.6% | 132.00 | 11.50 | 0.8 |

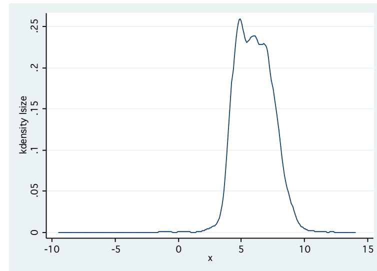
Figure 1: **Distribution of Main Variables**



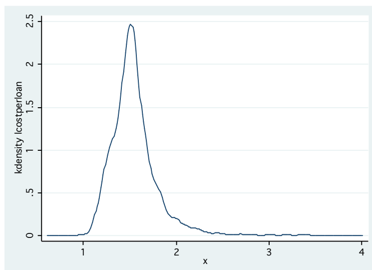

(a) FSS (cleaned)



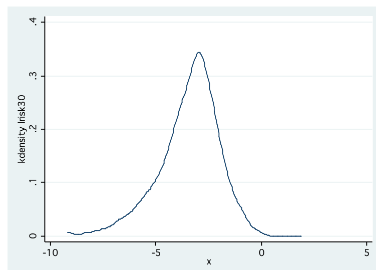

(b) Women (log)




(c) Avg. Loan Size (log)




(d) Cost per Loan (log)

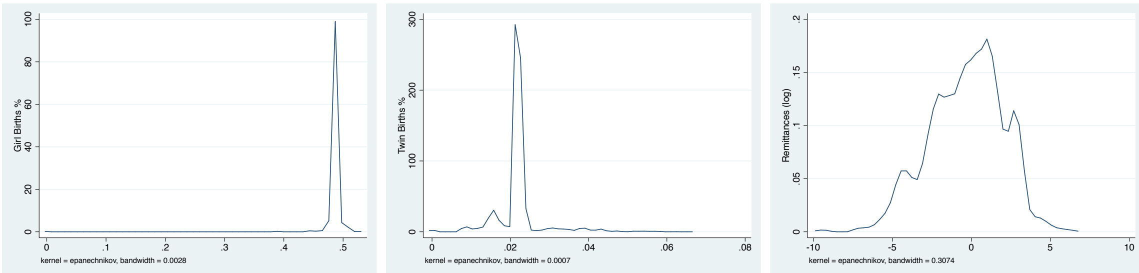



(e) Portfolio at Risk 30 days (log)

For constructing my instruments for *Women*, I use data coming from *Measure DHS* on births at the household level. I possess 197 surveys for 81 countries between 1985-2010. The year of the survey is not constant across countries. Therefore, I use the following methodology: I open each of these surveys and get the number of babies that were born in all country's households in a given year. I classify them by sex and by twin/non twin and first/non first baby. Taking these characteristics into account, I obtain yearly data on births at the household level using a cohort approach. In particular, in each survey, I use the year of birth of the children in the household as an indicator for the number of births that took place in that particular year. Once this is computed for each survey, I sum the resulting values for each year using all the disposable surveys for a given country.

The resulting country-year ratios of girls and twins births over total births had little variation at the MFI level. In order to increase it I reduce my observations: For each MFI, I divide the observations into initial and later years. I do the mean of all fertility variables for those two periods by MFI. Then I calculate new rates.

Figure 2: **Distribution of Instruments**




(a) Girls' Births (b) Twins' Births (c) Remittances (log)

The instrument that I propose for *Loan Size* comes from the Beck and Demirg-Kunt (2009) dataset on financial depth, which gives information across countries for 1960-2007. I consider the remittances per country and year. Since these variable has low variation I take the same approach as with the other instruments, i.e. I reduce my observations by considering the mean of the first and second group of available years per country. I then consider the logarithm of the resulting variable.

I explore how relevant are these variables for explaining the potentially endogenous variables. The most relevant variables for explaining the logarithm of women are the ratio of girl's and twins' births over total births. Their densities are reported in Figure 2 together with that of the logarithm of the remittances.

For the controls that I include and for the robustness checks, I use the following sources: Macroeconomic variables are taken from the United States Department of Agriculture, which contains data for 190 countries since 1969. Financial depth information is taken from Beck and Demirg-Kunt (2009), which gives information across countries for 1960-2007. The data on education is taken from Barro and Lee (2010), which provides data on education attainment for population aged 15 and over in 146 countries for 1950 - 2010.

# 5 Results

## 5.1 OLS

As it was mentioned in the methodology section, the first exercise that I propose is to estimate equation (1) with an OLS approach and play with the key variables to try to understand if targeting women and supplying small loans is profitable, and which are the main drivers of such profitability. As it can be seen in column 4 of Table 4, serving 1000 additional women (the median number of women by MFI is 4000) increases FSS by 0.47%. Moreover, increasing the average loan size by 100 USD (the median size of loans by MFI is 400) increases FSS by 0.14%. This indicates that serving women is profitable even if diminishing the average loan size is not. What are the drivers of these results?

If lending to women increases costs, omitting costs would lead to a downward biased coefficient for women. Nevertheless, as it can be seen in Table 4, the coefficient is lower once costs are included. Therefore, lending to women appears to be not so costly. In the same way, if lending to women reduces risk (and this is good for financial self-sustainability), omitting risk would lead to a upward biased coefficient for women. In fact, the coefficient is lower once costs are included. Therefore, according to these results, lending to women is not very costly for MFIs and it is profitable because it reduces risk.

On the other hand, if bigger loans are less costly, not including costs would bias the loan size coefficient upwards. Nevertheless the coefficient is higher once costs are included. This indicates that bigger loans are not necessarily cheaper. Moreover, if bigger loans are riskier (and this is bad for financial self-sustainability), omitting risk would lead to a downward biased coefficient for loan size. Nevertheless, the coefficient is lower once risk is included, which indicates that bigger loans are not necessarily riskier. Therefore, the belief that bigger loans are cheaper and less risky does not appear to be true according to these results.

Table 4: **OLS estimation**

| | Financial Self-Sustainability | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Women Borrowers (log) | 0.0986*** | 0.0673*** | 0.0762*** | 0.0468*** |
| | (0.0170) | (0.0158) | (0.0157) | (0.0138) |
| Avg. Loan Size (log) | 0.107*** | 0.160*** | 0.0871*** | 0.149*** |
| | (0.0234) | (0.0308) | (0.0225) | (0.0317) |
| Real Yield | 0.493*** | 0.509*** | 0.505*** | 0.553*** |
| | (0.0661) | (0.0662) | (0.0615) | (0.0618) |
| Age (log) | 0.0522* | 0.0490* | 0.0778*** | 0.0738** |
| | (0.0275) | (0.0285) | (0.0284) | (0.0295) |
| Assets (log) | 0.132*** | 0.0916*** | 0.155*** | 0.115*** |
| | (0.0260) | (0.0295) | (0.0271) | (0.0309) |
| Personnel Expenses (log) | -0.158*** | -0.122*** | -0.180*** | -0.146*** |
| | (0.0211) | (0.0230) | (0.0240) | (0.0258) |
| Cost per Loan (log) | | -0.550*** | | -0.580*** |
| | | (0.152) | | (0.170) |
| Portfolio at risk, 30 days (logs) | | | -0.0484*** | -0.0490*** |
| | | | (0.00486) | (0.00490) |
| Constant | -0.629** | 0.323 | -0.551** | 0.515 |
| | (0.248) | (0.343) | (0.242) | (0.325) |
| Observations | 4,160 | 4,095 | 3,876 | 3,826 |
| $R^2$ | 0.132 | 0.144 | 0.173 | 0.193 |
| Number of MFIs | 1,280 | 1,275 | 1,216 | 1,213 |
| MFI and Year FE | Yes | Yes | Yes | Yes |

Robust standard errors clustered at the MFI level in parentheses

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

Table 5: **OLS estimation with additional variables - first part**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Women Borrowers (log) | 0.0468*** | 0.0482*** | 0.0468*** | 0.0460*** | 0.0328*** | 0.0480*** | 0.0443*** | 0.0501*** |
| | (0.0138) | (0.0173) | (0.0173) | (0.0138) | (0.0125) | (0.0138) | (0.0135) | (0.0143) |
| Avg. Loan Size (log) | 0.149*** | 0.128*** | 0.129*** | 0.129*** | 0.113*** | 0.153*** | 0.156*** | 0.131*** |
| | (0.0317) | (0.0338) | (0.0345) | (0.0331) | (0.0365) | (0.0327) | (0.0320) | (0.0342) |
| Gender gap | | 0.638 | | | | | | |
| | | (0.395) | | | | | | |
| Years of Schooling | | | 0.0352 | | | | | |
| | | | (0.0550) | | | | | |
| Real GDP growth | | | | 0.00422*** | | | | |
| | | | | (0.00160) | | | | |
| Avg. Deposit Size (log) | | | | | 0.0103 | | | |
| | | | | | (0.0305) | | | |
| Competition | | | | | | 0.460*** | | |
| | | | | | | (0.0897) | | |
| Mkt Power | | | | | | | 0.0214* | |
| | | | | | | | (0.0116) | |
| Priv.Credit | | | | | | | | -0.173 |
| | | | | | | | | (0.105) |
| Constant | 0.515 | 0.819* | 0.227 | 0.363 | -0.0125 | 0.682** | 0.568* | 0.411 |
| | (0.325) | (0.427) | (0.524) | (0.352) | (0.447) | (0.335) | (0.324) | (0.378) |
| Observations | 3,826 | 2,551 | 2,551 | 3,497 | 1,940 | 3,826 | 3,826 | 2,913 |
| $R^2$ | 0.193 | 0.192 | 0.187 | 0.184 | 0.191 | 0.205 | 0.194 | 0.210 |
| Number of MFI | 1,213 | 705 | 705 | 1,131 | 734 | 1,213 | 1,213 | 917 |
| Year and MFI FE | 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: **OLS estimation with additional variables - second part**

| | Financial Self-Sustainability | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Real Yield | 0.553*** | 0.516*** | 0.521*** | 0.536*** | 0.504*** | 0.333*** | 0.551*** | 0.597*** |
| | (0.0618) | (0.0753) | (0.0762) | (0.0660) | (0.0803) | (0.0684) | (0.0615) | (0.0719) |
| Age (log) | 0.0738** | 0.0984*** | 0.0994*** | 0.0856*** | 0.102*** | 0.0694** | 0.0745** | 0.0752** |
| | (0.0295) | (0.0348) | (0.0352) | (0.0318) | (0.0338) | (0.0294) | (0.0294) | (0.0376) |
| Assets (log) | 0.115*** | 0.133*** | 0.137*** | 0.121*** | 0.169*** | 0.113*** | 0.108*** | 0.138*** |
| | (0.0309) | (0.0368) | (0.0370) | (0.0320) | (0.0364) | (0.0310) | (0.0316) | (0.0342) |
| Personnel Exp. (log) | -0.146*** | -0.172*** | -0.171*** | -0.143*** | -0.160*** | -0.151*** | -0.148*** | -0.171*** |
| | (0.0258) | (0.0340) | (0.0341) | (0.0263) | (0.0340) | (0.0255) | (0.0256) | (0.0296) |
| Cost per Loan (log) | -0.580*** | -0.432** | -0.446** | -0.558*** | -0.426* | -0.597*** | -0.541*** | -0.524*** |
| | (0.170) | (0.197) | (0.203) | (0.170) | (0.233) | (0.178) | (0.170) | (0.193) |
| Risk 30 days (logs) | -0.0490*** | -0.0452*** | -0.0459*** | -0.0421*** | -0.0288*** | -0.0479*** | -0.0491*** | -0.0422*** |
| | (0.00490) | (0.00547) | (0.00558) | (0.00526) | (0.00571) | (0.00490) | (0.00489) | (0.00524) |

Robust standard errors clustered at the MFI level in parentheses

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

Other variables besides costs and risks may be helpful to explain the effect that *Women* and *Loan Size* have on financial self-sustainability. For example, gender gaps could play an important role. Indeed, if we consider that lending to women is profitable because it reduces the risk, we could also argue that this reduced risk is due to the fact that women have less outside options and tend to be less mobile. Therefore, the gender gap between women and men measured in terms of years of schooling per country-year could be a variable of interest. However, once this variable is included in the estimation, it does not yield significant effects also leaving the coefficients of *Women* and *Loan Size* almost unchanged, as can be seen in column 2 of Table 5.

On the other hand, it is also possible to think that better macroeconomic conditions could help MFIs to reach poor clients. For example, it could be argued that being located in countries with higher levels of education could facilitate institutions to lend to poor clients. Indeed these target population could become relatively less risky, as it will be able to invest their loans more wisely and will be likely to have a higher financial literacy. Therefore, the years of schooling at the country level in a given year is also a variable of interest that I consider. Nevertheless, as can be seen in column 3 of Table 5, this variable is non-significant and does not have any effect on the coefficients of *Women* and *Loan Size*.

It is also possible to argue that being located in countries with higher GDP growth would facilitate the operation of MFIs and help them reach low income clients. This is indeed the case, as can be seen in column 4 of Table 5, which shows a positive and significant coefficient for GDP growth. Nevertheless, once again, the coefficients of *Women* and *Loan Size* remain almost unchanged.

Another relevant question is to examine wether offering deposit services also plays a role in determining MFIs financial self-sustainability. Nevertheless, as it can be seen in column 5 of Table 5, the logarithm of the average deposit size does not have a significant coefficient and does not have any impact on the impact proxies under study.

Furthermore, variables such as competition with respect to other MFIs could also have an impact in the way that institutions set their target population and their objectives. I propose a measure of competition as the own price minus the average in the same country-year, with price in this case being the real yield. Interestingly, this variable is positive and significant, as can be seen in column 6 of Table 5.

Having market power could also make it easier for an MFI to reach clients traditionally considered to be less profitable, such as women with small loans. In order to capture this I propose a measure of market power as the number of own borrowers minus the average in the same country-year. Indeed, this variable is significant and positive in the estimation, as can be seen in column 7 of Table 5. Nevertheless, the coefficients for *Women* and *Loan Size* remain almost unchanged with the inclusion of the variable measuring market power.

Moreover, the depth of the formal financial system could also play an important role. To examine it, I include as a measure of it the private credit by deposit money banks over GDP by country-year. Nevertheless this variable does not have any impact as can be seen in column 8 of Table 5.

In summary, GDP growth, market power and competition do all have a positive impact on MFIs' financial self-sustainability. It is interesting to see that both market power and competition go in the same direction. This could mean that even if having market power increases financial self-sustainability in the sense that customers have less choice and it is easier to attract them; on the other hand, price competition increases efficiency which is also positive for sustainability. Moreover, it is also important to note that none of these variables is able to change the coefficient of *Women* and *Loan Size*, which means that only costs and risk are behind the motivations that MFIs have to serve this type of clients and offer this type of products.

### 5.2 Sample Selection Test

As we have argued before, this estimation has various sources of bias. Therefore, the results should be revised once the techniques offering solutions for these biases are performed. I start by considering the potential sample selection bias.

In order to control for the possible sample selection bias, I use a Tobit model and I apply a Mundlak procedure to take into account MFI specific means. As can be seen in Table 7, the coefficients of of *Women* and *Avg. Loan Size* do not change much with respect to the OLS ones and remain constant when different censoring points are taken into account. This seems to indicate that there is not a considerable sample selection bias.

Table 7: **Tobit**

| | Tobit | | | | |
|---|---|---|---|---|---|
| | y: Financial Self Sustainability | | | | |
| Lower Bound | 0 | 0.25 | 0.5 | 0.75 | 1 |
| Women Borrowers (log) | 0.0407*** | 0.0413*** | 0.0404*** | 0.0397*** | 0.0352*** |
| | (0.00733) | (0.00738) | (0.00744) | (0.00751) | (0.00796) |
| Avg. Loan Size (log) | 0.0940*** | 0.0958*** | 0.103*** | 0.0984*** | 0.0879*** |
| | (0.0121) | (0.0122) | (0.0125) | (0.0127) | (0.0135) |
| Real Yield | 0.464*** | 0.468*** | 0.473*** | 0.438*** | 0.368*** |
| | (0.0414) | (0.0417) | (0.0422) | (0.0432) | (0.0461) |
| Age (log) | 0.0581*** | 0.0597*** | 0.0536*** | 0.0464*** | 0.0339* |
| | (0.0169) | (0.0170) | (0.0171) | (0.0173) | (0.0183) |
| Assets (log) | 0.0299*** | 0.0293*** | 0.0245** | 0.0217** | 0.0191* |
| | (0.00993) | (0.00998) | (0.0101) | (0.0102) | (0.0107) |
| Personnel Expenses (log) | -0.0719*** | -0.0724*** | -0.0680*** | -0.0667*** | -0.0588*** |
| | (0.00936) | (0.00941) | (0.00950) | (0.00960) | (0.0101) |
| Cost per Loan (log) | -0.557*** | -0.568*** | -0.636*** | -0.592*** | -0.591*** |
| | (0.0565) | (0.0569) | (0.0623) | (0.0650) | (0.0739) |
| Portfolio at risk, 30 days (logs) | -0.0451*** | -0.0450*** | -0.0453*** | -0.0442*** | -0.0421*** |
| | (0.00307) | (0.00309) | (0.00310) | (0.00312) | (0.00324) |
| Constant | 0.0833 | 0.0810 | 0.123* | 0.180** | 0.0833 |
| | (0.0638) | (0.0642) | (0.0655) | (0.0715) | (0.0638) |
| sigma u | 0 | 0 | 0 | 0 | 0 |
| | (0.00609) | (0.00615) | (0.00636) | (0.0112) | (0.00610) |
| sigma e | 0.163*** | 0.164*** | 0.163*** | 0.159*** | 0.163*** |
| | (0.00186) | (0.00188) | (0.00190) | (0.00210) | (0.00186) |
| Censored Observations | 0 | 32 | 133 | 381 | 928 |
| Uncensored Observations | 3,826 | 3,794 | 3,693 | 3,445 | 2,898 |
| Observations | 3,826 | 3,826 | 3,826 | 3,826 | 3,826 |
| Number of MFIs | 1,213 | 1,213 | 1,213 | 1,213 | 1,213 |

Standard errors in parentheses

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

### 5.3 Instrumental Variables Approach

#### 5.3.1 Considering only *Women* as endogenous

Having solved this initial concern, I now consider the instrumental variable approach by taking first only *Women* as potentially endogenous. Both instruments are significant once costs are included in the regressions. Since costs is such an important variable, it makes sense to consider these specifications. In particular, I consider the specification with both costs and risks. Table 8 shows the first stage regression in the first column. *Girl births* has a negative and significant coefficient, while *Twin Births* presents a positive and significant coefficient. This would mean that girl births reduce the exogenous demand that women have for microfinancial services, while having twins increases it.

Using these two instruments I perform the second stage estimation which is presented in column 2 of Table 8. The IV approach diminishes the reverse causality problem and, together with the MFI and year-fixed effecs, also the omitted variables problem is reduced. As can be seen in column 2, *Women* is positive and significant. Moreover, its coefficient is higher with respect to the one estimated in the OLS regression reported in Table 2. Therefore, since the resulting 2SLS estimator is bigger than the OLS estimator, $\beta_{1,OLS}$ is biased downwards and $cov(Women_{i,t}, u_{i,t}) < 0$.

As it is summarized in Table 1, this gives support to the hypothesis that the omitted variables may be affecting $FSS^{*}_{i,t}$ and $Women^{*}_{i,t}$ in opposite directions. An example that could lead to this behaviour could be a scenario in which institutions are important and unobserved, as we discussed earlier. Also, this supports the hypotheses that 1) less sustainable MFIs are both those more subsidised and those institutions more likely to be interested in offering microfinance services to women, and that 2) more sustainable MFIs are both those institutions that are more commercially oriented and those less likely to be interested in impact indicators such as women outreach. In order to define which of the two cases is taking place the quantile regression approach is the most appropriate. But before considering that, it is also important to consider the endogeneity of *Loan Size*, which is done in the next subsection.

Table 8: **Instrumental Variable Approach - Women**

| | (1) Women Borrowers (log) | (2) FSS |
|---|---|---|
| Women Borrowers (log) | | 0.250* |
| | | (0.147) |
| Girl Births % | -1.532** | |
| | (0.604) | |
| Twin Births % | 5.679** | |
| | (2.658) | |
| Avg. Loan Size (log) | -0.500*** | 0.244*** |
| | (0.0991) | (0.0835) |
| Real Yield | -0.0674 | 0.590*** |
| | (0.162) | (0.0888) |
| Age (log) | 0.206* | 0.0994* |
| | (0.120) | (0.0508) |
| Assets (log) | 0.467*** | 0.0401 |
| | (0.0952) | (0.0766) |
| Personnel Expenses (log) | 0.298*** | -0.262*** |
| | (0.0912) | (0.0507) |
| Cost per Loan (log) | -2.558*** | -0.0490 |
| | (0.504) | (0.382) |
| Portfolio at risk, 30 days (logs) | -0.0200 | -0.0483*** |
| | (0.0125) | (0.00656) |
| Constant | 4.825*** | -0.109 |
| | (1.065) | (0.729) |
| Observations | 1,622 | 1,622 |
| $R^2$ | 0.711 | |
| Number of MFI | 522 | 522 |
| Year and MFI FE | Yes | Yes |

Robust standard errors clustered at the MFI level in parentheses

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

### 5.3.2 Considering also *Avg. Loan Size* as endogenous

The instrument that I propose for *Loan Size* does not work as well as those that I use for *Women*. Indeed, as can be seen in column 1 of Table 9, it is only weakly significant. Once the second stage estimation is performed in column 2, it can be seen that the coefficient for *Loan Size* changes sign with respect to the one that was estimated in the OLS procedure. This would indicate that the OLS estimator is biased upwards. Nevertheless, since the instrument is only weakly significant, this is difficult to sustain.

Moreover, the exogeneity of remittances presents some doubts. Therefore, it is hard to say anything about the bias of *Loan Size* at this stage. Nevertheless, it is interesting to observe that when both *Women* and *Loan Size* are taken as endogenous, the magnitude of the *Women* coefficient remains higher than the one of the OLS estimator and close to the IV estimator when taking only women as endogenous . The results are reported in Table 10.

Table 9: **Instrumental Variable Approach - Loan Size**

| | (1) Avg. Loan Size (log) | (2) FSS |
|---|---|---|
| Avg. Loan Size (log) | | -0.184 |
| | | (0.416) |
| Remittances (log) | 0.0675* | |
| | (0.0349) | |
| Women Borrowers (log) | -0.206*** | -0.0203 |
| | (0.0382) | (0.0868) |
| Real Yield | -0.448*** | 0.402** |
| | (0.0756) | (0.197) |
| Age (log) | -0.00712 | 0.0739*** |
| | (0.0444) | (0.0274) |
| Assets (log) | 0.516*** | 0.290 |
| | (0.0325) | (0.215) |
| Personnel Expenses (log) | -0.109*** | -0.182*** |
| | (0.0396) | (0.0478) |
| Cost per Loan (log) | 1.583*** | -0.0438 |
| | (0.479) | (0.664) |
| Portfolio at risk, 30 days (logs) | -0.00720 | -0.0502*** |
| | (0.00544) | (0.00524) |
| Constant | -1.064 | -0.0445 |
| | (0.799) | (0.489) |
| Observations | 3,111 | 3,111 |
| $R^2$ | 0.679 | |
| Number of MFI | 973 | 973 |
| Year and MFI FE | Yes | Yes |

Robust standard errors clustered at the MFI level in parentheses

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

Table 10: **Instrumental Variable Approach - Women and Loan Size**

| | (1) Women Borrowers (log) | (2) Avg. Loan Size (log) | (3) FSS |
|---|---|---|---|
| Women Borrowers (log) | | | 0.274 |
| | | | (0.301) |
| Avg. Loan Size (log) | | | 0.200 |
| | | | (0.457) |
| Girl Births % | -2.056** | 0.848 | |
| | (0.869) | (0.587) | |
| Twin Births % | 10.64*** | -8.450*** | |
| | (3.428) | (1.961) | |
| Remittances (log) | -0.0845 | 0.0331 | |
| | (0.0700) | (0.0534) | |
| Real Yield | 0.0875 | -0.411*** | 0.693*** |
| | (0.202) | (0.116) | (0.190) |
| Age (log) | 0.176 | -0.103 | 0.0377 |
| | (0.174) | (0.0947) | (0.0508) |
| Assets (log) | 0.230** | 0.436*** | 0.0709 |
| | (0.0960) | (0.0537) | (0.271) |
| Personnel Expenses (log) | 0.401*** | -0.172*** | -0.294*** |
| | (0.104) | (0.0558) | (0.0581) |
| Cost per Loan (log) | -3.471*** | 2.030** | 0.159 |
| | (0.814) | (0.846) | (0.337) |
| Portfolio at risk, 30 days (logs) | -0.0159 | -0.00300 | -0.0518*** |
| | (0.0161) | (0.00828) | (0.00885) |
| Constant | 5.774*** | -1.753 | -0.416 |
| | (1.612) | (1.455) | (0.916) |
| Observations | 1,451 | 1,451 | 1,451 |
| $R^2$ | 0.640 | 0.594 | |
| Number of MFI | 485 | 485 | 485 |
| Year and MFI FE | Yes | Yes | Yes |

Robust standard errors in parentheses

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

### 5.4 Quantile Regressions

Table 11: **Quantile Regression**

| | Quantile regression | | | | |
|---|---|---|---|---|---|
| | y: Financial Self Sustainability | | | | |
| | q(0.10) | q(0.25) | q(0.50) | q(0.75) | q(0.90) |
| Women Borrowers (log) | 0.0399 ** | 0.038 ** | 0.030 ** | 0.029 ** | 0.033 * |
| Avg. Loan Size (log) | 0.2249 *** | 0.190 *** | 0.148 *** | 0.113 *** | 0.122 *** |
| Real Yield | 0.7170 *** | 0.632 *** | 0.556 *** | 0.540 *** | 0.561 *** |
| Personnel Expenses (log) | -0.1281 *** | -0.122 *** | -0.144 *** | -0.200 *** | -0.264 *** |
| Age (log) | 0.1563 *** | 0.139 *** | 0.100 *** | 0.055 ** | 0.035 |
| Assets (log) | 0.0471 ** | 0.046 ** | 0.079 *** | 0.135 *** | 0.187 *** |
| Cost per Loan (log) | -0.9293 *** | -0.725 *** | -0.558 *** | -0.355 ** | -0.408 ** |
| Portfolio at Risk - 30 days (log) | -0.0504 *** | -0.054 *** | -0.060 *** | -0.070 *** | -0.079 *** |
| Costant | 0.9928 *** | 1.021 *** | 1.043 *** | 0.981 *** | 1.147 *** |
| MFI FE | Yes | Yes | Yes | Yes | Yes |

Standard errors in parentheses

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

The quantile regression approach allows to observe how the trade-off changes according to MFI's distribution. Moreover, it helps to better consider outliers. Indeed, the distribution of the variables is very skewed and the predicted errors after the OLS, IV and Tobit procedures are not normal. The quantile approach allows to control for this, giving estimators that are not driven by outliers.

Table 11 reports the results of a quantile regression with MFI-fixed effects. The results indicate that serving more women has always a positive effect on MFIs' financial self-sustainability. This effect is always significant and positive. Indeed, the size of the *Women* coefficient is relatively constant across different quantiles.

It is also possible to see that the average size of loans is more important for less financially self-sustainable institutions, since the coefficient of *Avg. Loan Size* is bigger in the lower quantiles.

Table 12: **Quantile Regression with IV**

| | **First Stage - y: Women Borrowers (log)** | | | | |
|---|---|---|---|---|---|
| | q(0.10) | q(0.25) | q(0.50) | q(0.75) | q(0.90) |
| | (1) | (2) | (3) | (4) | (5) |
| Girl Births % | 3.84265 ** | 2.84027 ** | 1.11793 | 0.37624 | -0.0761 |
| Twin Births % | -9.84652 *** | -8.39318 *** | -5.303 ** | -2.01773 | 0.01011 |
| Avg Loan Size (log) | -0.33257 *** | -0.47202 *** | -0.65022 *** | -0.71896 *** | -0.8557 *** |
| Real Yield | 0.61868 ** | 0.20378 | -0.07741 | 0.00878 | -0.01133 |
| Personnel Expenses (log) | 0.74883 *** | 0.59751 *** | 0.428 *** | 0.30773 *** | 0.17581 *** |
| Age (log) | 0.23333 * | 0.0898 | 0.01184 | -0.02006 | -0.02465 |
| Assets (log) | 0.0162 | 0.1944 ** | 0.41006 *** | 0.54791 *** | 0.72732 *** |
| Cost per Loan (log) | -6.00832 *** | -4.97972 *** | -3.76214 *** | -3.25728 *** | -2.18203 *** |
| Portfolio at Risk 30d (log) | -0.03123 | -0.03897 *** | -0.03313 *** | -0.02974 *** | -0.0249 ** |
| Constant | 7.01865 *** | 6.49307 *** | 5.80555 *** | 5.3934 *** | 3.88737 *** |
| | **Second Stage - y: Financial Self Sustainability** | | | | |
| | q(0.10) | q(0.25) | q(0.50) | q(0.75) | q(0.90) |
| | (1) | (2) | (3) | (4) | (5) |
| Women Borrowers (log) | 0.08768 | 0.04234 | -0.07252 | -0.63044 | -1.46631 |
| Avg. Loan Size (log) | 0.30367 *** | 0.24161 *** | 0.13458 * | -0.32583 | -1.16626 |
| Real Yield | 0.9048 *** | 0.86786 *** | 0.77504 *** | 0.73807 *** | 0.57447 ** |
| Personnel Expenses (log) | -0.15042 ** | -0.14447 ** | -0.1248 ** | -0.04105 | -0.05264 |
| Age (log) | 0.11361 ** | 0.09823 ** | 0.07026 ** | 0.02947 | -0.02874 |
| Assets (log) | 0.02334 | 0.06087 * | 0.13453 ** | 0.53982 ** | 1.33948 |
| Cost per Loan (log) | -1.10255 ** | -1.16531 ** | -1.42052 ** | -2.85198 * | -3.62606 |
| Portfolio at Risk 30d (log) | -0.05453 *** | -0.04795 *** | -0.05389 *** | -0.07885 *** | -0.10368 |
| CFA (predicted 1SLS error) | -0.14383 | -0.03216 | 0.44126 | 1.43338 | 2.31817 |
| Constant | 1.01407 | 1.37648 * | 2.17633 ** | 4.7981 * | 6.62058 |
| MFI FE | Yes | Yes | Yes | Yes | Yes |

Standard errors in parentheses

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

Indeed, lower financially self-sustainable firms are more sensitive to costs, as they present bigger negative coefficients for *Cost per Loan*.

Nevertheless, it is interesting to observe that it is the institutions in the highest quantiles for financial self-sustainability the ones that seem to be more sensitive to risk. Indeed the coefficient for *Portfolio at Risk* increases in magniture (becomes more negative) as firms become more sustainable.

Performing a quantile regression with IV allows to better see how the biases behave. The first panel of Table 12 presents the first stage quantile regression, considering only the supply of loans to women as endogenous. The instruments are significant for the lowest quantiles of the distribution (up to the median). Therefore, one would expect that endogeneity is best addressed there and that the bias with respect to the quantile regression without IV will be noticeable for those quantiles.

It is interesting to see in the second panel of Table 12 that the IV coefficient for the first two quantiles (q(0.10) and q(0.25)) is higher than the one without IV, while the opposite happens for the coefficient in the median (q(0.50)). This would indicate that in the lowest quantiles of the FSS distribution, there is a downward bias of the coefficient with no IV. As it is explained in Table 1, this would correspond to a missing variable such as institutions, which affects FSS and *Women* in opposite ways. Moreover, this could also correspond to a reverse causation problem in which MFIs with the lowest FSS are also likely to receive more subsidies (which lower efficiency and sustainability) and therefore more likely to be interested in serving women. Both scenarios are very likely and it is interesting to observe that this considerations are more pertinent for the lowest quantile (q(0.10)), as the bias is bigger there.

On the other hand, in the median level of financial sustainability, the bias is upwards. According to Table 1 this would correspond to the case in which there is an omitted variable such as doing business, that affects both FSS and *Women* in the same way. This confirms the intuition that more commercialised firms respond more to market signals that are common to the consumers than to political incentives, which can work in the opposite direction for consumers. Moreover, according to Table 1, this could also correspond to a problem of reverse causation in which the firms that are more commercialised are also those more interested in serving women.

Unfortunately we cannot identify if there is a bias in the highest quantiles of the FSS distribution, since the instruments are not relevant for these quantiles. Anyway, the fact that the instruments are not relevant in those quantiles could indicate that the supply to women of those

Table 13: **Quantile Regression with other variables of interest**

| | q(0.10) (1) | q(0.25) (2) | q(0.50) (3) | q(0.75) (4) | q(0.90) (5) |
|---|---|---|---|---|---|
| Women Borrowers (log) | 0.0399 | 0.0344 ** | 0.0290 ** | 0.0323 * | 0.0325 |
| Avg. Loan Size (log) | 0.2276 *** | 0.1949 *** | 0.1641 *** | 0.1278 *** | 0.1267 *** |
| Real Yield | 0.7659 *** | 0.6038 *** | 0.6394 *** | 0.5872 *** | 0.6567 *** |
| Personnel Expenses (log) | -0.1323 *** | -0.1106 *** | -0.1463 *** | -0.2125 *** | -0.2605 *** |
| Age (log) | 0.1905 *** | 0.1449 ** | 0.1150 *** | 0.1009 ** | 0.1085 ** |
| Assets (log) | 0.0463 | 0.0295 | 0.0699 ** | 0.1264 *** | 0.1667 *** |
| Cost per Loan (log) | -0.9908 *** | -0.8373 *** | -0.6286 ** | -0.3819 ** | -0.3439 ** |
| Portfolio at Risk 30d (log) | -0.0441 *** | -0.0465 *** | -0.0543 *** | -0.0714 *** | -0.0883 *** |
| Market Power | 0.0117 | 0.0125 | 0.0192 ** | 0.0298 ** | 0.0416 ** |
| Gender Gap | 0.0847 *** | 0.0832 *** | 0.0435 ** | 0.0426 ** | 0.0524 ** |
| Real GDP Growth | 0.0070 ** | 0.0044 ** | 0.0052 *** | 0.0063 ** | 0.0070 |
| Constant | 1.1013 ** | 1.3225 *** | 1.1825 *** | 1.0958 *** | 1.1181 ** |
| MFI FE | Yes | Yes | Yes | Yes | Yes |

Standard errors in parentheses

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

MFIs is not affected by shocks to demand, but is well defined by the firms' business objectives, which can also be an interesting consideration, that will be consistent with what we observe in the median of the FSS distribution.

Exploring other variables of interest in Table 13, it is possible to see that market power becomes more important as firms become more financially self-sustainable. This is an interesting finding that should be considered in the design of regulatory policies. Indeed, even if the market forces are making firms like MFIs serve vulnerable population, the same market forces can play a detrimental role.

One would expect that, as firms become more financially sustainable, then having market power will be less important for them. Indeed, achieving financial self-sustainability should help them to become more efficient and have lower prices. In this way these firms should be able to attract customers without being concerned with how big is their market power. Therefore, if market power is playing a role, this could be an indicator that even if firms become more sustainable, they do not necessarily become more efficient or they do not translate that efficiency into lower prices. Therefore, market power keeps playing an important role for these firms.

Another interesting finding is that GDP growth has a constant effect across different quantiles. This indicates that MFIs have the same capacity to take advantage of positive market conditions, irrespective of their financial self-sustainability. This means that somehow becoming more sustainable does not create the incentives for MFIs to be more interested in responding to growth tendencies, and could indicate that MFIs would not be interested to finance the missing middle even if they become more and more commercialised.

It is also interesting to observe that gender gap is less important for more sustainable firms. This is an indicator that the potential perverse incentives of making women stay in a disadvantaged position to reduce the riskiness of serving them is not very likely to persist as firms become more commercialised.

## 6 Conclusions

This paper considers the experience of microfinance to examine which are the main trade-offs faced by private firms engaged in development issues. Which are the main drivers of their profits? What are the main challenges that they face? What happens as they become more commercialised? How could this private initiatives be fostered and promoted? Due to data availability, the experience of microfinance is highly relevant and informative on these questions.

Proposing a quantile and instrumental variable approach, this paper is able to disentangle the incentives that MFIs face for achieving a positive social impact, and how these incentives change as firms become more commercialised. More in details, this approach allows to gather a clear insight on the dynamics inside MFIs as they become more financially self-sustainable. In this sense, this paper studies the whole process of commercialisation that thousands of MFIs have experienced around the world, trying to identify the key lessons one can learn from it. The results could be relevant also to other industries and could shed light on how to make the private sector work better in solving development issues.

The findings indicate that there is low risk of mission drift as MFIs become more financially self-sustainable. Indeed, serving women seems to increase financial-self sustainability in all types of institutions due to reduced risk. Moreover, increasing the loan size seems to be less important as firms gain financial self-sustainability. These results are robust to the possible endogeneity between MFIs' financial self-sustainability and the supply that these institutions offer of financial services to low income targets, such as women with small loans. The results indicate that profit-driven institutions such as MFIs have an incentive to stay serving the poor.

Nonetheless, the quantile approach is able to show that even if more profitable MFIs tend to cope better with costs, they are also more sensitive to risk. This indicates that even if there exist incentives making these profit-driven institutions be interested in serving the poor, it is also very likely that these firms will not be able to generate a substantial long-term effect on development. Indeed, since the most financially self-sustainable MFIs are more sensitive to risk, they will not be willing to finance bigger projects. Therefore, these institutions will not have the incentives needed to finance SMEs. In sum, the missing middle will still remain too big for MFIs and too small for formal banks.

Furthermore, the findings of this paper also show that more financially self-sustainable MFIs become more interested in market power. This indicates that these institutions are not translating their financial sustainability into more efficient processes that could lead to lower prices (and thus make them care less about the share of the market in which they have power). This also means that even if these institutions are taking the markets closer to disenfranchised and marginalised population, they do not necessarily have clear incentives to let market mechanisms work transparently or to make also other markets come closer to the poor.

According to the results presented in this paper, there is room for regulation to design risk mitigation mechanisms that could make it easier for MFIs to cope with risk. Regulation should also focus on reducing the interest that MFIs have on keeping their market power. Further studies could focus on how these results compare with other kinds of firms that have reached the poor using traditional business models, such as multinationals with broad networks of distribution that reach the poor everyday in every corner of the world. This could shed light on how regulation could better manage the incentives that new business models face and on how policy makers could better teach industries around the world to do well by really doing good.

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