The Ethical Dilemma in Hybrid Organizations: A Production Function Approach to Credit Expansion in Microfinance.

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Abstract

We derive and estimate a production function for microfinance institutions to provide empirical evidence of the ethical dilemma of balancing social and financial logics in hybrid organizations. A worldwide panel dataset of microfinance institutions is utilized and a production function augmented by average loan size is estimated using the control function approach. We show how this framework can be used to quantify the tradeoff between social outreach and financial sustainability in relation to the expansion of microfinance institutions' credit operations. The study reveals that expanding the extensive margin (increasing the number of loan clients) requires on average more than twice as many inputs as expanding the intensive margin (increasing the average loan size) to achieve the same growth in assets. Beyond the case of microfinance our production function illustrates that as hybrid organizations expand, they will inevitably face an ethical dilemma as the laws of economic efficiency exert pressure on their social missions.

1. Introduction and conceptual frame

In this paper we estimate a production function which enable us to quantify the primary ethical dilemma faced by hybrid organizations: balancing their dual logics of pursuing social and financial goals simultaneously. Although the literature describes well the ethical dilemmas of balancing different institutional logics in hybrid organizations from a conceptual viewpoint (Davies and Doherty, 2019; Bull and Ridley-Duff, 2019), there is little empirical research aiming to quantify the ethical challenges that hybrid organizations face[1].

We use data from Microfinance Institutions (MFIs), which are typical examples of hybrid organizations (Battilana and Dorado, 2010) to estimate the parameters of a production function in order to quantify how different strategic choices for expanding the business of an MFI lead to different outcomes. We argue that these strategic expansion strategies represent a core ethical dilemma for MFIs and serve as examples for other hybrid organizations when planning their growth strategies.

MFIs, offering small-scale financial services to vulnerable clients, have two main options when it comes to expanding the credit supply to their clients. They can issue additional loans to new clients or provide larger loans to their existing client base. While it's generally assumed that the latter strategy is more cost-efficient because larger loans are less costly (Xu et al., 2016; Armendariz and Szafarz, 2011) the development outcome of either strategy might also be different (Schreiner, 2002). It is generally accepted that expanding credit to new clients is

[1] In regular businesses, the core ethical consideration is distinguishing between ethical and unethical business practices (Islam and Greenwood, 2021). Due to their inherent social logic alongside financial sustainability objectives, one may argue that hybrid organizations are inherently ethical. Greenwood and Freeman (2017) argue that this view is narrow as business practices in hybrid organizations can differ greatly. In line with this, we take the position that hybrid organizations, even though they have an inherent social bottom-line, encounter ethical challenges in their business operations.

advisable from a development perspective since most development policies are aimed at delivering financial inclusion to as many underserved clients as possible, thereby increasing the *breadth* of outreach[2].

As an alternative to serving more clients, providing larger average loans to existing clients also increases the MFI's credit portfolio (Hartarska et al., 2013), but is generally perceived as *mission drift* (Mersland and Strøm, 2010) since it may result in serving less-poor clients over time, thereby reducing the *depth* of outreach[3]. MFIs, being hybrid organizations with a need to balance out financial and social objectives, thus face a difficult decision when it comes to expansion of their credit operations (Davies and Doherty, 2019; Van der Auwera et al., 2023): Should they pursue new clients to enhance their social goals in line with existing development agendas at a higher cost, or should they extend less costly additional credit to the existing client base and risk mission drift?

In this paper, we estimate an augmented production function for a large sample of MFIs in order to pin down the magnitude of the tradeoff between both expansion strategies. While the cost advantage of expanding the existing client base via higher average loans compared to attracting new clients has long been recognized (Hermes et al., 2011; Xu et al., 2016), conceptualized (Morduch, 2000) and discussed in the microfinance literature from several angles[4], the efficiency benefit of either strategy has not been formally modelled nor estimated or quantified.

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[2] See for instance the UN Sustainable Development Goals (SDGs) where SDG1.4 and SDG8.3 mention the role of MFIs in increasing access to financial services (https://sdgs.un.org/goals); CGAP-reports that describe financial inclusion as a tool to combat climate change (https://www.cgap.org/blog/inclusive-finance-can-help-world-achieve-cop26-goals-heres-how); or World Bank policies that view financial inclusion as a "key enabler to reducing poverty and boosting prosperity" (https://www.worldbank.org/en/topic/financialinclusion/overview).

[3] "Mission drift" is generally defined as the situation where the social mission becomes secondary to financial and commercial considerations (Wry and Zhao, 2018; Armendàriz and Szafarz, 2011).

[4] See, e.g., Aubert et al. (2009) on credit officer incentives; Salim (2013) on branch location and Ault (2016) on the institutional context.

As we will show, a production function estimation allows for an elegant quantification of the efficiency-benefit of expanding via increased average loans (intensive margin) versus attracting new clients (extensive margin).

We argue that as microfinance markets mature and institutions expand, MFIs are increasingly faced with challenging ethical dilemmas related to their operational activities. McIntosh and Wydick (2005) demonstrate how increased competition between MFIs can put poor borrowers at risk of becoming even poorer. Similarly, Hossain et al. (2020) argue that increased competition between MFIs will lead to greater challenges in balancing the MFIs' hybrid institutional logics. In light of these ethical concerns, it is important to gain a better understanding of the economics of MFIs' expansion strategies.

We utilize a large panel dataset of MFIs from the MIX Market dataset, which comprises financial and market information on financial service providers targeting developing market throughout the world. The unbalanced sample comprises yearly data for the period 2004-2018 on 1 139 MFIs. Our starting point is that the output from a bank's lending activities can be measured by the number of loan clients, when the attributes of the loan portfolio are appropriately accounted for. Since many MFIs finance their lending operations from other sources than deposits (e.g., grants or loans from donors, international organizations, and investors) our data offers a research opportunity to explore the relation between input use and lending output given the attributes of the loan portfolio.

The key attribute we focus on is average loan size. Building on this, we derive an augmented production function and convert it into an econometric specification that can be estimated using the control function approach pioneered by Olley and Pakes (1996) and refined by Levinsohn and Petrin (2003) and Ackerberg et al. (2015).

A main result of this exercise is the estimate of the coefficient on average loan size in the augmented production function. Our point estimate centers around -0.4 in various specifications and the precision is very high. These estimates confirm the longstanding belief that it is less cost efficient to increase the balance sheet by increasing the number of loan clients than by providing larger loans to existing clients (Abate et al., 2014; Cull et al., 2007). Specifically, our estimations allow for the following quantification: by increasing the number of clients *only*, an MFI can achieve a 10% increase in total assets with a 10% proportional increase in its inputs. However, by increasing average loan size *only,* an MFI can achieve a 10% increase in total assets with only a 4% proportional increase in its inputs. Thus, from a banking standpoint, it is more than twice as cost efficient for an expanding MFI to provide larger loans to existing clientele (thereby increasing its intensive margin) than to attract new clients (thereby increasing its extensive margin).

As a byproduct of our production function estimation, we obtain a number of interesting additional industry-level insights. First, we find that over the sample period the number of clients has roughly doubled while the average loan size remained stable and overall productivity growth has been low. This suggests that, while for the individual MFI the cost-benefit of expanding the intensive margin is substantial, the industry as a whole has not been operating under the most efficient path of expansion. While this can be seen as encouraging news in terms of mission drift, indicating that the industry continues to serve low-income families, the persistent lack of productivity gains is worrying at the same time. Low productivity in the sector contributes to unusually high interest rates, which often prevent clients from fully realizing the long-term benefits of their borrowing (Cull et al., 2009). Next, we cannot reject that the industry, on average, is subject to constant returns to scale which is in line with recent MFI cost function studies that use both gross outstanding loans and the number of loan clients to measure output (e.g., Hartarska and Nadolnyak, 2019), but not with earlier such studies that use only one of these variables (e.g., Hartarska et al. 2013).

Our exercise does not only add to the microfinance tradeoff literature and the ethics literature on hybrid organizations. We also contribute to the banking productivity literature pioneered by Colwell and Davis (1992) and Berger and Humphrey (1992), which deals with the appropriate measurement of "output" in financial institutions. One controversy in this regard centers on the role of deposits. According to the *production approach*, a traditional bank uses labor, capital, and intermediate inputs to produce services related to loans and deposits. Following this line of reasoning, deposits are output. According to the *intermediation approach*, however, banks are intermediaries of financial services, and deposits therefore serve as input in the production of loans. The *user cost approach* attempts to resolve the issue by classifying a financial product as an output or input according to its net contribution to revenues[5].

Wang (2003) and Wang et al. (2008) dismiss all of the above approaches. They argue that the core bank function is to screen and monitor borrowers in order to reduce asymmetric information problems in the provision of loans, and to provide payment and safekeeping services to deposit holders at a fee[6]. Their conclusion is that the output of a bank can be measured by netting out the risk-based returns from assets and liabilities[7]. In our exercise, we

[5] Berger and Humphrey (1992, p. 248) describe this precisely: "If the financial return on an asset exceeds the opportunity cost of funds or if the financial costs of a liability are less than the opportunity cost, then the instrument is considered to be a financial output. Otherwise, it is considered to be a financial input."

[6] A problem with measuring bank output in this regard is that financial institutions typically do not charge explicitly for the services they provide. Instead, the implicit service fees in banking are embedded in the interest structure on loans and deposits. Thus, we cannot compute a measure of (real) output simply as revenues deflated by an industry price index – as is typically done when measuring output for firms in other service industries like accounting and manufacturing.

[7] Thus, the relevant output from lending services can be measured by interest revenues net of the return one would have had on securities subject to the same risk and maturity but without any services attached. Similarly, the

circumvent these opposing views on the classification of deposits within a production function framework by presenting estimates for both the loans-only sample of MFIs and the total sample. As it turns out, the estimations are very similar in both samples suggesting that expanding the intensive margin enhances efficiency irrespective of of how the credit portfolio is financed.

Furthermore, our paper is relevant for the MFI productivity literature such as Gutierrez-Nieto et al. (2007), Hermes et al. (2011), Servin et al. (2012), and Bassem (2014). These productivity or efficiency studies use frontier techniques like data envelopment analysis (DEA – a non-parametric method or stochastic frontier analysis (SFA - a parametric method) to estimate a best practice production or cost function frontier for a broad sample of MFIs. Subsequently, MFI-level data can be used to analyze how "close" institutions are to the specified efficient frontier, and thus how efficiently they make use of their inputs[8]. While conceptually appealing, the results from this literature depend fundamentally on how output is measured, which is typically posited instead of derived[9]. From our production function derivation, we reject that the output of an MFI can be measured by the number of clients alone or by gross outstanding loans alone, which has been the standard practice in the literature (see, e.g., the overview in Wijesiri and Meoli, 2015). As we will show in the paper, average loan size is an essential moderating variable that needs to be taken into account when studying the true production technology of MFIs.

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relevant output from deposit services can be computed by the risk-free return net of interests on deposits. See Basu, Inklaar, and Wang (2011) and Alon, Fernald, Inklaar, and Wang (2011) for further applications and discussions of this framework.

[8] MFIs can be ranked in terms of how far they are from the frontier and, if available, panel data can be used to study whether an MFI is getting closer to the efficient frontier and/or whether the frontier is shifting over time.

[9] In particular, the most frequently used output measures are the number of outstanding loans and the value of the gross loan portfolio, either in combination or alone. Regarding the above references, Gutierrez-Nieto et al. (2007) use the number of outstanding loans and the gross loan portfolio, Servin et al. (2012) use the number of outstanding loans, Hermes et al. (2011) use the gross loan portfolio, and Bassem (2014) uses the number of outstanding loans, the gross loan portfolio, interest, and fee income.

We believe this study is the first to quantify the tradeoff between providing additional credit to the existing clientele and reaching out to new clients. This estimate is fundamental for MFIs interested in making ethically grounded decisions when designing their expansion strategies. The result exposes a transmission channel through which a tradeoff between social and financial performance can occur in microfinance. We show that there is a powerful efficiency mechanism and thus a strong financial-performance incentive that pushes MFIs toward increasing the loan size to its existing clients. However, such credit expansion may reduce social performance since the MFI will be less interested in attracting new clients and will provide larger loans to existing clients, thereby reducing both the breadth and depth of its outreach.

Our study has important implications for the management and governance of MFIs, and for hybrid enterprises in general that face the challenging task of balancing between financial and social goals. In line with the management insights developed in Pache and Santos (2013) and Battilana et al. (2015), our result shows that the social logics of an MFI cannot be taken for granted but must be safeguarded and institutionalized in order to counteract the powerful underlying efficiency mechanism that drives MFIs to push additional credit onto existing clients. Thus, credit expansion can lead not only to mission drift for the MFI (Armendariz and Szafarz, 2011) but also to over-indebtedness and reduced welfare for the clients receiving the larger loans (Schicks, 2014). Unless adequate incentives are put into place to protect the social mission of the MFI, the underlying economic law of efficiency will push MFIs toward the expansion strategy that requires the least resources. Therefore, this paper contributes to the literature on business ethics regarding hybrid organizations. It demonstrates that balancing their social and financial goals presents an ethical challenge that requires serious attention of their boards and managers.

Section 2 presents the production function and discusses the main parameters of interest. In Section 3 we derive the econometric specifications to be estimated and discuss our estimation strategy. In Section 4 we present the data, main results, and additional estimations. In Section 5 we conclude and discuss the main implications and contributions.

2. A production function approach

Our goal is to estimate a production function of the following type for an MFI:

$$Y_{it} = F(K_{it}, L_{it}, M_{it})e^{\omega_{it}} \quad (1)$$

In equation (1), Y_{it} is a single-dimensional measure of the output of MFI i in year t, K_{it} is physical capital, L_{it} is labor, and M_{it} are intermediate inputs like electricity, fuel, and services. As discussed in the previous section, there is no universally accepted measure of Y_{it} in the literature. Below we suggest how we can construct a conceivable scalar measure of output from readily available information and let the data decide how the measures combine. Assuming, for now, that a measure of output exists, $F(.)$ describes how the inputs translate into the maximal output combined with the MFIs' level of Hicks-neutral productivity, $e^{\omega_{it}}$. Of course, we can also let MFIs of different types differ by specifying $F(.) = F_j(.)$ such that each type j has a separate production function.

The challenges involved in estimating a function like (1) have been recognized for more than half a century in the literature on productivity[10]. A primary concern is that shocks to productivity, ω_{it}, are observed by the firm but not by the econometrician. Furthermore, these shocks are likely to be correlated with input choices such that OLS will produce biased estimates. We shall return to these challenges, along with the most prominent solution, i.e., the "proxy method," in the next section.

[10] See Griliches and Mairesse (1995) and Ackerberg et al. (2015) for excellent discussions.

The above framework has mostly been applied to manufacturing firms. A main obstacle for estimating production functions for the service sectors is the difficulty of defining appropriate output measures; see Griliches (2008), as well as the discussion on measuring financial output in the previous section. However, if an appropriate measure of service output is available, there is no reason why a production function cannot be estimated.

Our approach to constructing a single-dimensional measure of output is to adjust the number of loan clients with characteristics that affect the use of inputs to attract and support these clients. In this paper we shall focus on average loan size, $\bar{A}_{it} = A_{it}/N_{it}$, where A_{it} is the value of gross outstanding loans from the balance sheet and N_{it} is the number of loan clients. Other characteristics emphasized in the literature might be the share of female clients or the share of rural clients (D'Espallier & Goedecke, 2019). Let $\boldsymbol{D}_{it}$ denote the vector of the above characteristics other than average loan size. Our key assumption is that there is a function, $\mathrm{g}(\bar{A}_{it}, \boldsymbol{D}_{it})$, such that

$$Y_{it} = N_{it}\mathrm{g}(\bar{A}_{it}, \boldsymbol{D}_{it}) \tag{2}$$

Equation (2) states that output of a loans-only MFI can be measured by the number of loan clients scaled by an unknown function $g(.)$ of the characteristics of these loan clients. Given the flexibility of the function $g(.)$ we consider this a weak assumption. By equations (1) and (2), we then have

$$N_{it} = g^{-1}(\bar{A}_{it}, \boldsymbol{D}_{it})F_j(K_{it}, L_{it}, M_{it})e^{\omega_{it}} \tag{3}$$

Except for the unknown productivity, equation (3) is now an equation of observable variables. It states that once we control for the characteristics of the loan clients via the function $g^{-1}(.)$, the production function $F(.)$ shows how the use of inputs transforms into the production of loan clients, N_{it}. In principle, we could estimate (3) non-parametrically or semi-parametrically, by allowing for flexible forms of $g(.)$ and $F(.)$, respectively. However, this would embed unknown productivity shocks into the estimated marginal effects. To identify structural parameters, we therefore choose explicit functional forms for $F(.)$ and $g(.)$.

Let us illustrate the workings of the above framework under the simplifying assumptions we shall use in this paper. First, we leave it to future studies to explore the dependence of variables measured in $\boldsymbol{D}_{it}$, and assume that output can be measured by the information contained in the number of clients and their average loan size. To use the terminology of Schreiner (2002), output is measured in terms of the *breadth of outreach* and the *depth of outreach.* We further assume that $g(\bar{A}_{it}) = \bar{A}_{it}{}^{\alpha}$, where α is an unknown parameter. We can then write equation (2) as follows:

$$Y_{it} = N_{it}\bar{A}_{it}{}^{\alpha} \tag{2'}$$

This simple specification treats the two polar cases for measuring output that are used in the MFI performance literature as special cases. Specifically, if $\alpha = 0$, the output is the number of loan clients; in other words, the production of a loan client is independent of the loan size. At the other extreme, if $\alpha = 1$, the output is the monetary value of gross outstanding loans; in other words, the production of a loan dollar on the balance sheet is independent of how many loan clients it is distributed over. Both cases are unlikely to reflect the true production technology of MFIs, and we would expect to find that $0 < \alpha < 1$ when confronting this framework with data. If the true alpha is in $\langle 0, 1\rangle$, then an increase in clients (holding average loan size constant), as well as an increase in average loan size (holding clients constant) represents an increase in output.

Assume, as we shall do in the empirical implementation in this paper, that the production function is Cobb–Douglas, i.e., $F(K_{it}, L_{it}, M_{it}) = \beta_0 K_{it}{}^{\beta_K} L_{it}{}^{\beta_L} M_{it}{}^{\beta_M}$; then, by equations (3) and (2'), we have that $N_{it} = \beta_0\, \bar{A}_{it}{}^{-\alpha} K_{it}{}^{\beta_K} L_{it}{}^{\beta_L} M_{it}{}^{\beta_M} e^{\omega_{it}}$. If we let lowercase letters denote the natural logarithm of the variable, we can write this equation as[11]:

$$n_{it} = \beta_0 - \alpha\bar{a}_{it} + \beta_K k_{it} + \beta_L l_{it} + \beta_M m_{it} + \omega_{it}. \tag{4}$$

Basically, equation (4) says that once we control for the possibly endogenous depth of outreach, we can estimate outreach as a function of the inputs. Let us now define the scale elasticity, s, as the percentage increase in loan clients if we increase the use of all inputs by 1 percent while holding average loan size constant. We then have that $s = \beta_K + \beta_L + \beta_M$. In Section 5 we discuss how this scale elasticity measure relates to the corresponding scale elasticity measure derived from the cost function estimation.

The direct interpretation of α in (4) is the percentage change in loan clients due to a 1% increase in average loan size, all else held constant. However, since $\bar{a}_{it}$ is a control variable, and not necessarily a driver of outreach, the following counterfactual interpretation might be useful: if the average loan size is increased by 1 percent and the number of loan clients is held constant, what is the proportional increase in all inputs necessary to support these clients? Some simple calculus (see the appendix) shows that the answer is α/s.

3. Econometric specification and estimation strategy

As noted in the previous section, a primary challenge in estimating (4) is that productivity shocks are likely to be correlated with the MFI's input choices. In general, when a firm is exposed to a positive (negative) productivity shock we would expect it to produce more (less) and use more (less) inputs. However, ω_{it} is observed by the firm, but not by the researcher.

[11] We can arrive at the same equation more directly by just assuming that log output is a log linear combination of the value of gross outstanding loans and the number of clients. We then have $\alpha a_{it} + (1-\alpha)n_{it} = \beta_0 + \beta_K k_{it} + \beta_L l_{it} + \beta_M m_{it} + \omega_{it}$. Noting that $\bar{a}_{it} = a_{it} - n_{it}$, we obtain equation (4) by some simple manipulations.

Thus, OLS estimation will produce biased estimates. Suggested solutions like fixed effects and IV methods have proven unsatisfactory, the former because it restricts productivity to being constant for each firm, and the latter because of difficulties in finding appropriate instruments[12].

To tackle the above endogeneity problem, we shall use a variant of the "proxy method," or "control function approach," pioneered by Olley and Pakes (1996; henceforth OP) and refined by Levinsohn and Petrin (2003; LP), Ackerberg et al. (2015; ACF), and Wooldridge (2009). The econometric equation we take to the data is

$$n_{it} = \beta_0 + \beta_A \bar{a}_{it} + \beta_K k_{it} + \beta_L l_{it} + \beta_M m_{it} + \omega_{it} + \varepsilon_{it}, \tag{5}$$

and by equation (4) we expect the estimate of β_A $(= -\alpha)$ to be negative and the input parameters β_K, β_L, and β_M to be positive. The error term is decomposed into two terms: ε_{it} is the regression error term representing any unanticipated shocks to production (both for the firm and for the researcher) and assumed to be iid. The term ω_{it}, on the other hand, represents shocks to productivity observed by the firm, but not by the researcher. Following Syverson (2011), we can divide possible sources of productivity change into internal factors that the firm to some degree can affect, and external forces in the firm's environment outside of the firm's control. Examples of the former include changes in managerial practices or organizational structure, learning-by-doing, R&D, IT investments, improved human capital, and more. Examples of external drivers of a firm's productivity might be changes in competitive environment, productivity spillovers, changes in macroeconomic conditions, and regulatory change.

The key insight from the proxy method literature is that even if we do not know the exact drivers of a firm's productivity, we can use a proxy function to "observe" and hence control for the endogenous productivity term. We return to the exact specification of this in equation (7) below. In addition, identification of the parameters in (5) requires that we specify the law of motion of

[12] See Griliches and Mairesse (1995) for a general discussion.

the productivity term. In OP, LP, and ACF, this process is assumed to be totally exogenous. However, if variables that affect productivity are available, they should be included, with a lag, in this law of motion[13]. A candidate variable in the present setting is the share of the loan portfolio that is at risk. A common risk measure in the MFI literature is $PAR30$, which is the share of gross outstanding loans overdue by 30 days. High $PAR30$ is generally found to be associated with higher cost; see e.g. Hartarska, Shen, and Mersland (2013). Intuitively, a higher share of overdue loans increases cost by increasing monitoring and enforcement activities for the involved loan clients[14]. It follows that $PAR30$ should affect current productivity negatively by drawing resources away from generating new loans. We follow the modeling idea in the endogenous productivity papers discussed above and assume that productivity is given by

$$\omega_{it} = \rho_1 \omega_{it-1} + \rho_2 PAR30_{it-1} + \xi_{it}. \tag{6}$$

Actual productivity in period t is here decomposed into expected productivity conditional on information at t-1, i.e., the first two terms on the right-hand side, and a random innovation, ξ_{it}, which is assumed uncorrelated with ω_{it-1} and $PAR30_{it-1}$. Since loans persist across periods, thereby causing $PAR30$ to be a dynamic variable, the lagged formulation in (6) makes sense. An MFI with a low $PAR30$ in t-1 will enter period t with a low $PAR30$. Hence, an MFI can affect productivity in the *next period* positively by undertaking activities that decreases $PAR30$ in the current period.

Turning to the estimation of the parameters in (5) and (6), we build on the LP-estimator for the main estimations[15]. We treat capital as a state variable and so k_{it} is determined by the

[13] see De Loecker (2013) for an example with (lagged) export quotas and Doraszelski and Jaumandreu (2013) for an example with (lagged) R&D expenditures.

[14] We thank Valentina Hartarska for suggesting this.

[15] ACF argue that the procedures in LP suffer from functional dependence problems such that the parameters in a regression like (5) cannot be identified without additional assumptions; see also Bond and Söderbom (2005). The proposed alternative of ACF, however, requires a value-added production function that we do not find attractive

investment decision in period t-1. The terms l_{it} and m_{it}, on the other hand, are decided in period t, after the firm observes ω_{it}. A question for the current application is whether average loan size should be treated as predetermined or not. MFIs are commonly viewed as entities with a goal to maximize outreach to the poor in a cost-efficient way. In practice, this goal must also specify which segment of the poor the MFI should target. Since average loan size is frequently viewed as a proxy for the poverty level of the clients, $\bar{a}_{it}$ may simply reflect this specified goal. Under this interpretation, $\bar{a}_{it}$ is a predetermined variable set by board decisions in a previous period. On the other hand, we could treat average loan size as a possibly endogenous variable that is chosen in period t according to the MFI's optimization problem. This distinction is important in defining the moment conditions used in the estimation. For now, we shall be agnostic about this, and in the empirical applications we shall report the results of estimations treating $\bar{a}_{it}$ as predetermined or contemporaneous, along with overidentification tests of exogeneity.

A key idea in LP (and ACF) is to proxy for the unknown productivity by inverting the demand for flexible inputs, like intermediate inputs[16]. We assume that the demand for intermediate inputs is determined, at least partly, after the firm has observed productivity. The unconditional demand for intermediate inputs is then a function of productivity, the predetermined capital stock, the number of clients at risk at the start of the period, and average loan size if it is a

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for the present framework. Gandhi, Navarro, and Rivers (2020) utilize the first-order condition for intermediate inputs to help identify the parameters of a gross output function like (5). An important topic for future work would be to implement an estimation along these lines to check the robustness of the current results.

[16]The original idea of OP is that a firm's investment demand is a monotonic function of the unknown productivity term conditioned on the firm's level of capital. This function can then be inverted to control for the unobserved productivity. LP note that this approach requires that the firm have strictly positive investments, which is frequently not the case, and they suggest using a flexible input instead.

predetermined variable,[17] i.e., $m_{it} = m_t(k_{it}, \bar{a}_{it}, PAR30_{it-1}, \omega_{it})$. In line with the proxy method literature, we assume that $m_t(.)$ is strictly increasing in ω_{it} so that we can invert it to get:

$$\omega_{it} = m_t^{-1}(k_{it}, \bar{a}_{it}, PAR30_{it-1}, m_{it}). \tag{7}$$

Substituting this equation for ω_{it} in (5), we get $n_{it} = \beta_0 + \beta_A \bar{a}_{it} + \beta_K k_{it} + \beta_L l_{it} + \beta_M m_{it} + m_t^{-1}(k_{it}, \bar{a}_{it}, PAR30_{it-}\ , m_{it}) + \varepsilon_{it}$, or

$$n_{it} = \beta_L l_{it} + \varphi_t(k_{it}, \bar{a}_{it}, PAR30_{it-1}, m_{it}) + \varepsilon_{it}\ , \tag{8}$$

where $\varphi(k_{it}, \bar{a}_{it}, lPAR30_{it-1}, m_{it}) = \beta_0 + \alpha \bar{a}_{it} + \beta_K k_{it} + \beta_M m_{it} + m_t^{-1}(k_{it}, \bar{a}_{it}, m_{it})$. Equation (8) is a partially linear equation where only the coefficient on labor is identified. Following LP, we can provide an estimate of β_L in a *first-stage* semi-parametric regression. We approximate $\varphi_t(.)$ to a third-degree polynomial in $k_{it}, \bar{a}_{it}, PAR30_{it-1}$ and m_{it}..

From the first-stage estimation we construct the estimate $\widehat{\Phi}_{it} = \hat{n}_{it} - \hat{\beta}_L l_{it}$. At the true values of the coefficients, by (5) and (6), we can define the residual function as[18]

$$e_{it} = n_{it} - \hat{\beta}_L l_{it} - \beta_A \bar{a}_{it} - \beta_K k_{it} - \beta_M m_{it} - \rho_1\big(\widehat{\Phi}_{it-1} - \beta_A \bar{a}_{it-1} - \beta_K k_{it-1} - \beta_M m_{it-1}\big) - \rho_2 PAR30_{it-1}, \tag{9}$$

where $e_{it} = \varepsilon_{it} + \xi_{it}$. In the *second stage* we form moments to estimate the remaining parameters $\beta_A, \beta_K, \beta_M$ and ρ_1, ρ_2 by GMM. The moments for an exactly identified estimator are

[17] If average loan size is an endogenous variable, $m_t(.)$ is a conditional demand function, that is, the demand for intermediate input conditional on average loan size.

[18] We have suppressed the constant β_0 in this formulation as it is not separately identifiable from the mean of the productivity term (Kim, Luo, & Su, 2019). In the estimations, we include a (not reported) constant.

$$E\left[e_{it}\begin{bmatrix} k_{it} \\ \bar{a}_{it} \\ m_{it-1} \\ \widehat{\Phi}_{it-1} \\ PAR30_{it-1} \end{bmatrix}\right] = 0. \tag{10}$$

The arguments for the validity of the moments are as follows: physical capital in period t is decided by the MFI's investments in the previous period and therefore uncorrelated with the contemporary innovation to productivity, ξ_{it} (and ε_{it}), by construction. The same holds for average loan size if it is decided by board decisions in a previous period as assumed in (10). To identify the coefficient on the endogenous m_{it}, we use its one-period lag, which should be uncorrelated with the current innovation to productivity. Finally, $\widehat{\Phi}_{it-1}$ and $PAR30_{it-1}$ should be uncorrelated with ξ_{it} and serve as instruments by themselves. We can also form additional moments using further lags of the instruments. In the next section, we make use of these moments to test the exogeneity assumption with respect to average loan size as given in equation (10).

4. Data and results

Data. We utilize a panel dataset of MFIs from the MIX Market database which comprises financial and market information on financial service providers targeting low-income and unbanked clients in developing market throughout the world[19]. In addition, we use an indicator from Penn World Tables (Feenstra et al., 2015) such that all financial variables are in real, PPP adjusted 2017 USD[20]. After data cleaning we have an unbalanced panel of 1139 MFIs observed

[19] https://datacatalog.worldbank.org/search/dataset/0038647

[20] https://www.rug.nl/ggdc/productivity/pwt/

in 2004 to 2018 with a total of 5758 observations[21]. The production function we have developed in the previous chapters is designed for loans-only MFIs, which account for just over 50% of the total sample, or 3016 observations. The remaining 2742 observations come from MFIs that provide both loan and deposit services[22]. Our main focus is on the loans-only sample, but for comparison we shall also provide results for the total sample. Table 1 below gives the means of the variables used in the analysis of the loans-only sample, the deposits and loans sample, and the total sample.

<Insert Table 1 here>

As can be seen, the average number of loan clients for loans-only MFIs is 57 176, which is considerably lower than the corresponding 73 320 loan clients for deposits and loans MFIs. We also note that the loans-only MFIs tend to provide slightly smaller loans than the deposits and loans MFIs. The mean of the average loan size for loans-only MFIs is 2 423 real PPP-adjusted 2017 USD, whereas the deposits and loans MFIs have a corresponding mean of 2 775. A lower number of clients and lower average loans size should imply that the loans-only MFIs tend to use fewer inputs than the deposits and loans MFIs. From Table 1 we see that this is indeed the case. The loans-only MFIs use less physical capital, labor, and intermediate inputs than the deposits and loans MFIs. Finally, we see that the deposits and loans MFIs have a slightly higher fraction of loans overdue by 30 days.

Estimation results. Columns (1) and (2) of Table 2 below report the results from estimating the parameters in equations (5) and (6) for the loans-only sample. Columns (3) and (4) report

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[21] To obtain the estimation samples, we excluded observations within the highest and lowest 1% of the variable values used. Even after this trimming, some MFIs had average loan size incompatible with serving poor clients. We chose to exclude observations where average loan size is above 15000 USD. Finally, for the sample that includes banks providing deposit services we removed observations with a deposit to loans ratio exceeding one. Results are not very sensitive to these sampling choices.

[22] An MFI is defined as a loans only MFI if the measure on retail deposits from the balance sheet is zero or missing.

the corresponding results for the total sample (All). In Columns (1) and (3) we use the exactly identified estimator from equation (10), while in Columns (2) and (4) we use $\bar{a}_{it-1}$ as an additional instrument.

<Insert Table 2 here>

The table shows that the modeling approach works very well. All estimated coefficients have the expected sign and, as we shall discuss below, reasonable magnitudes. Moreover, except for the coefficient on physical capital, all coefficients are very precisely estimated[23].

The first result we want to emphasize is that the estimated coefficients on loans-only MFIs (Columns (1) and (2)) and on all MFI (Columns (3) and (4)) are very similar. Thus, even if the framework we have developed in this paper focuses on the lending side of MFI banking activity, there are no significant changes in the estimated parameters if we include MFIs that also provide deposit services. Apparently, whether an MFI uses deposits or other sources to finance its lending portfolio does not affect the loan production technology of MFIs. We also note the similarity of the estimates using the exactly identified estimator defined by the moments in equation (10) compared to the overidentified estimates using $\bar{a}_{it-1}$ as an additional instrument. As confirmed by the Hansen J statistics, we cannot reject that all instruments are valid. Consequently, we cannot reject that the average loan size can be treated as a predetermined variable in the estimations.

[23] We have tested the robustness of our results in several ways. First, we have run our estimator on a different data set constructed from rating agencies' assessments reports containing data in the period 2000-2014. The rating agencies were initially approved by the Consultative Group to Assist the Poor (CGAP) administered by the World Bank. This dataset has been used in a number of MFI studies, e.g., Mersland and Strøm (2009) and Van der Auwera et al. (2023). The results from this exercise are reported in a previous version of this paper and are qualitatively very similar to those presented here. Second, we obtain qualitatively, very similar results using a Wooldridge (2009) type estimator, and also when assuming a value-added production function and using a ACF-type estimator, but see the comment in footnote 10.

We now turn to the estimated coefficient in the production function. In Column (2), the output elasticities with respect to labor, intermediate output, and physical capital are 0.8, 0.2, and 0.02, respectively. This confirms, not unexpectedly, that provision of loans to the poor is a highly labor-intensive activity. The estimated scale elasticity across all regressions is in the interval [1.02-1.04] and, as seen from the results of the Wald test reported in the last row of Table 2, we cannot reject that the industry is subject to constant returns to scale. This result is contrary to MFI studies that use a cost function approach to estimate returns to scale and find that the MFI industry is subject to increasing returns to scale (Hartarska & Nadolnyak, 2019). For example, Hartarska et al. (2013) find increasing returns to scale when they use either the number of loan clients or gross outstanding loans as the output measure.

Even if comparison of our result with the scale estimates from cost function studies is blurred by other modeling differences, we would like to emphasize that our estimates of scale elasticity are conditional on holding average loan size constant, whereas estimates from cost function studies using either the number of loan clients or gross outstanding loans as the output measure are not. The unconditional scale estimates from cost function studies therefore implicitly embed changes in average loan size in their estimates and obtain larger (smaller) estimates than ours if an increase in loan clients is accompanied by a decrease (increase) in average loan size. Some recent MFI cost function studies include both gross outstanding loans and the number of loan clients to measure lending output; see, e.g., Cozarenco, Hartarska, and Szafarz (2018). When these studies estimate scale elasticity by assuming a proportional increase in both measures, their approach is conceptually equal to ours since it implies that average loan size is held constant. Interestingly, as noted by Hartarska and Nadolnyak (2019), such cost function studies tend to obtain reduced scale estimates: constant returns to scale or even decreasing returns in some geographical areas.

The estimates of the coefficient on average loan size, i.e., $\hat{\beta}_A$, are in the interval [-0.39, -0.42] across all specifications and samples, and with very small standard errors. For example, the 95% confidence interval of the estimate from Column (3) is [-0.48, -0.33]. Since $\hat{\beta}_A = -\hat{\alpha}$, we strongly reject that the output of an MFI can be appropriately measured by either the number of loan clients alone ($\alpha = 0$) or gross outstanding loans alone ($\alpha = 1$). We can further quantify the efficiency of expanding the intensive versus the extensive margin by using the interpretation from Section 2 (and recalling that we cannot reject that $s = 1$): a 10% higher average loan size would need a proportional increase of 4% in all inputs to support the same number of clients. Or, if we look at it from the asset sheet side, increasing assets by 10% solely by increasing the number of loan clients while holding average loan size constant would require a 10% proportional increase in all inputs. By contrast, increasing assets by 10% by increasing average loan size by 10%, while holding the number of loan clients constant, would require only a 4% proportional increase in all inputs. Thus, when expanding the credit operations, expanding the extensive margin is more than twice as costly as expanding the intensive margin[24].

Turning to the productivity coefficients in Table 2, we see that the estimated autoregressive coefficients, ρ_1, are in the interval [0.64, 0.71]. In his survey of productivity studies, Syverson (2011) reports that regressing a producer's current total factor productivity on its one-year lag typically yields autoregressive coefficients in [0.6 to 0.8]. Thus, our results square well with the typical finding in manufacturing productivity studies. Finally, we see that having a high number of clients with loans in arrears for over 30 days at the start of the period indeed lowers productivity in the current period. The coefficients on $PAR30_{it-1}$ are in the interval [-0.061, -0.057] across the regressions, and the coefficients are significant at the 0.01 level in all four regressions.

[24] See the appendix for the simple calculus behind these interpretations.

Productivity growth. The coefficient estimates obtained from the above estimations enable us to calculate total factor productivity (tfp), i.e., the contribution to output not explained by the use of inputs. Using (5) and the estimated production function parameters, we get $\widehat{tfp}_{it} = \widehat{\omega_{it} + \varepsilon_{it}} = n_{it} - \hat{\beta}_0 + \hat{\beta}_A \bar{a}_{it} + \hat{\beta}_K k_{it} + \hat{\beta}_L l_{it} + \hat{\beta}_M m_{it}$. Thus, this estimate of firm-time specific total factor productivity (Solow residual) is the sum of the technology measure, ω_{it}, and the idiosyncratic error, ε_{it}. An advantage of the LP estimator (and the aforementioned control function approaches in general) is that we can subtract the estimate of the idiosyncratic error (which includes measurement errors and pure noise) from the first-stage regression, $\hat{\varepsilon}_{it}$, to get an estimate on factor-neutral technological innovation without (or with less) noise, i.e., $\widehat{\omega}_{it} = \widehat{tfp}_{it} - \hat{\varepsilon}_{it}$. Van Biesebroeck (2007) simulates various approaches to measuring total factor productivity, and shows substantial efficiency gains from removing the idiosyncratic first-stage error. Table 3 reports the means of the year-by-year growth rate in $\widehat{\omega}_{it}$ for the loans-only and total samples.

<Insert Table 3 here>

The point estimates on the average productivity growth rates, $\widehat{\omega}_{it}$, for the loans-only and total sample are 0.35% and 0.23%, respectively, and as seen from the t-values, we cannot reject the null hypothesis that the true value is zero. Considering the substantial productivity growth that has taken place in the banking industry in the time span of the present analyses, we find these growth rates very moderate and even somewhat alarming. Thus, MFIs seem to be lagging behind when it comes to efficiency gains compared to traditional banking. This illustrates the claim put forward by Mersland and Strøm (2010) that the main challenge that MFIs must overcome to better fulfill their social mission is to reduce their costs.

Table 4 below shows the year means of the variables used in the previous analyses, along with the year mean of the estimated productivity. We display estimates from the loans-only sample, but the total sample displays very similar trends.

<Insert Table 4 here>

The numbers in Table 4 illustrate some interesting facts. First, we see that the average MFI more than doubled the number of loan clients over the 15 years studied, while average loan size exhibits a weak downward-sloping or at least stable trend. The increase in the number of clients seems to be accompanied by a nominal increase in all input-factors. This finding suggests that, while there is a significant individual incentive for MFIs to upscale the existing client base, the industry as a whole has not been operating under the most efficient path of expansion. This is reassuring from a mission drift perspective, but alarming from a productivity perspective. In a more favorable scenario for both MFIs and their clients, mission drift can be avoided and productivity can be improved at the same time. This finding is further confirmed when looking at yearly levels of productivity $\widehat{\omega}_t$ (last column in Table 4) where there is no clear upward trend in productivity over the sample period. On the contrary, there are several years notably in the first half of the sample period where the productivity drops compared to the previous year. The most notable event is the drop in productivity in year 2010 and 2011 possibly because of a reallocation of resources from loan production to financial handling in the aftermath of the financial crisis.

5. Conclusions and discussion

We derive and estimate an augmented production function for a sample of MFIs using a control function approach. This allows us to assert the efficiency of two complementary credit expansion strategies, namely, providing larger loans to existing clients (i.e., expanding the intensive margin) versus adding new clients to the credit portfolio (i.e., expanding the extensive margin). Our estimates show that more than twice as many inputs are required for credit expansion when adding new clients than when providing larger loans to existing clients. Thus, from a banking perspective, it is significantly more cost efficient to expand the credit supply by providing larger loans to existing clients than by attracting new clients. This finding illustrates and quantifies an important tradeoff between social and financial goals that MFIs and hybrid organizations in general have to balance out.

Our estimations are remarkably stable as evidenced by small standard errors and tight confidence intervals. The results are similar for loans-only MFIs and for deposits and loans MFIs, suggesting that expanding the intensive margin enhances efficiency regardless of how the credit portfolio is financed. Also, our joint model statistics are reassuring, and estimates are consistent across specifications. For example, the results are consistent whether we use an exactly identified estimator or an overidentified estimator that includes an additional instrument. Finally, our results reflect unmodeled productivity shocks such as the aftermath of the financial crisis, thereby lending further credibility to the validity of our modeling approach.

A number of additional insights can be gleaned from the analysis. We find that lower productivity levels are observed when the credit portfolio has a larger share of overdue loans (past 30 days) and can thus be considered risky. This confirms that non-performing loans can be a costly burden to the MFI as highlighted in other studies (see Zamore et al., 2019; Blanco-Oliver et al., 2021). Next, our estimated scale elasticity is in the interval [1.02, 1.04] across all specifications, suggesting that the MFI industry is, on average, subject to constant returns to scale. This finding is at odds with earlier cost function studies that use either the number of clients or gross outstanding loans as a standalone output measure and typically find increasing returns to scale. Our result is more in line with the recent study by Cozarenko et al. (2018) that, like ours, employs both the number of loan clients and gross outstanding loans to capture lending output. Further, and related to this last point, our results reject that MFI output can be adequately measured by the number of loan clients or gross outstanding loans solely. Following our above conceptualization (see equation (2')) as well as our data estimates (with α in the range of 0.39–0.42), average loan size is an essential moderating variable that needs to be taken into account when studying the true production technology of MFIs.

The minimal efficiency gains likely caused by excessive labour intensity and lack of innovation especially in digitalisation, an area where banks have made significant efficiency gains in recent decades, pose a significant challenge to the industry. Numerous studies show that clients often struggle to translate loans into better outcomes for their microenterprises and improved quality of life for their families (Banerjee et al., 2015). This limited impact is partly due to high interest rates (Cull et al., 2009), which result from the low productivity and high operating costs of microfinance institutions (Mersland and Strøm, 2010). It is important that practitioners, regulators and researchers acknowledge and address this issue and explore innovations that can increase productivity without compromising the social mission of MFIs.

Our findings demonstrate the main ethical dilemma faced by expanding MFIs: adding new clients will enhance their social performance while increasing the loan sizes to existing clients will improve their financial performance. There is thus an underlying efficiency mechanism that may drive expanding MFIs to provide larger loan amounts to existing clients. From a development perspective, this can be considered a negative outcome since this expansion strategy reduces both breadth of outreach (higher average loans reduce outreach to new clients) as well as the depth of outreach (higher average loans are typically given to less-indigent clients). Moreover, it may lead to clients taking on a too high debt burden, leading to over-indebtedness and reduced welfare (Schicks, 2014). By showing that increasing the credit supply on the intensive margin is more efficient from a production viewpoint, our paper reveals an important mechanism through which mission drift may occur in microfinance (Beisland et al., 2019). Increasingly, though our contact with industry players, we hear stories about how regulators, lenders and owners of MFIs push for increased growth and better financial performance. MFIs are thus faced with an uphill challenge when trying to satisfy their various stakeholders and at the same time maintain their focus on outreach to poor clients.

At the same time, however, our univariate statistics (Table 4) show that in the period 2000–2015, the number of loan clients almost doubled, while the average loan size in PPP-adjusted dollars remained stable. While this may be at least partially the result of sample attrition (where new MFIs offering small loans may substitute older and established MFIs offering larger loans), it may also imply that the MFI industry as a whole was able to withstand the underlying efficiency mechanisms and to safeguard its social mission. One could argue that, although it is more efficient to expand the intensive margin, MFIs put sufficient protection mechanisms in place to safeguard their social mission, as can be expected from genuine social enterprises. A growing literature has identified several protection mechanisms that hybrid organizations can put in place to avoid the social mission being jeopardized. For example, the research by Pache et al. (2018) emphasizes the board of directors as a crucial mechanism for maintaining a good balance between opposing institutional logics. Agrawal and Hockerts (2019) suggest that impact investors seek regular engagement with hybrid investee companies in order to align their social interests and exert pressure on management to ensure sufficient focus on the social goals of the hybrid company. Gamble et al. (2019) argue for better "anchoring" the company's social mission and present a tool to assess and monitor the integration of the social mission within the revenue model of the hybrid company. Mersland et al. (2011) show that in the microfinance industry, international investors are better at ensuring that the social mission is the primary focus of the MFI, compared to local investors. This is in line with D'Espallier et al. (2024) who show that donors providing subsidies to MFIs can induce a long-lasting positive influence on

MFIs' social performance. In sum, there is evidence that an effective corporate governance system can help to protect the social goals of hybrid entities (Cossey et al., 2023).

With increasing competition, however, we expect that balancing the social and financial logics will continue to pose significant challenges for individual MFIs (Hossain et al., 2020). Therefore, more research is needed to address the ethical challenges faced by hybrid organizations striving to balance their social and financial goals. For instance, researchers could incorporate isomorphic theories (DiMaggio and Powell, 1983) to gain a better understanding of the ethical challenges that hybrid organizations encounter when confronted with growing competition. Additionally, it is observed that an increasing number of MFIs are regulated by public banking regulators who have little or no understanding of the hybrid nature of MFIs' business models. Researchers should investigate how public regulators introduce additional ethical challenges to the balancing of social and financial goals in MFIs. Finally, from a technical perspective, it is recommended to identify alternative measures for the depth of outreach used in our production function. The average loan size is a crude measure of poverty levels among clients, as illustrated by Armendariz and Szafarz (2011).

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List of Tables

Table 1. Means

Variable	Symbol of log of variable	Explanation	Loans only	Deposits and loans	All
		Sample:	**Loans only**	**Deposits and loans**	**All**
				Mean	
Deposits/loans		Short deposits divided by gross outstanding loans.	.000	0.36	0.17
Loan clients	n	Number of loan clients.	57176.36	73320.47	64864.30
Average loan size	$\bar{a}$	Gross outstanding loans divided by number of loan clients, PPP-adjusted USD.	2422.90	2775.22	2590.68
Physical capital	k	Book value of total fixed assets, in 1000 PPP-adjusted USD.	2420.80	5137.75	3714.63
Labor	l	Number of employees.	335.65	575.12	449.69
Intermediate inputs	m	Non-wage operational expenses, in 1000 PPP-adjusted USD.	4365.13	8217.81	6199.80
PAR30	$PAR30$	Fraction of loans 30 days overdue.	.050	.059	.055
		Obs:	3016	2742	5758

Source: Rating agency reports; see footnote 14 above. All monetary variables are in real PPP-adjusted 2017 USD. The PPP adjustment factor is taken from Penn World Table, version 10.01.

Table 2. MFI production functions

	(1)	(2)	(3)	(4)
Production function coefficients:				
β_A	-0.414***	-0.389***	-0.404***	-0.421***
	(0.064)	(0.045)	(0.036)	(0.031)
β_K	0.0182	0.0246	0.0413	0.0366
	(0.048)	(0.045)	(0.034)	(0.035)
β_M	0.225***	0.218***	0.184***	0.189***
	(0.075)	(0.070)	(0.046)	(0.049)
β_L	0.800***	0.800***	0.79***	0.79***
	(0.017)	(0.017)	(0.012)	(0.012)
Productivity coefficients:				
ρ_1	0.710***	0.694***	0.637***	0.664***
	(0.081)	(0.072)	(0.073)	(0.067)
ρ_2	-0.0577***	-0.0608***	-0.0596***	-0.0568***
	(0.012)	(0.011)	(0.0092)	(0.0086)
Obs.	3016	3016	5758	5758
MFIs	623		1139	1139
Hansen J (P-value)		0.357		0.614
$\hat{s}$	1.043	1.042	1.019	1.019
Prob(s = 1)	0.363	0.342	0.457	0.487

Notes: The dependent variable in all regressions is n_{it}. Hansen J is the P-value of the Hansen J statistic, using $\bar{a}_{it-1}$ as an additional instrument to those described in equation (10). $\hat{s} = \hat{\beta}_K + \hat{\beta}_L + \hat{\beta}_M$, i.e., the scale elasticity defined in Section 3, Prob(*s* = 1) is the P-value of the test of H0: *s* = 1. Cluster robust standard errors are reported in parentheses below the coefficients, cluster variable is MFI. *, **, and *** denote P<0.1, P<0.05, and P<0.01, respectively.

Table 3. Productivity growth rates

Sample:	Loans only	All
$\Delta\widehat{\omega}_{it} = \widehat{\omega}_{it} - \widehat{\omega}_{it-1}$	0.0035	0.0023
Standard error	(0.0053)	(0.0035)
H0: $\Delta\widehat{\omega}_{it} = 0$ (t-value)	0.65	0.64
Obs.	720	914

Notes: $\Delta\widehat{\omega}_{it}$ is calculated using the estimated coefficients from Columns (1) and (3) of Table 2 for the respective samples.

Table 4. Year means

Year	Obs.	Loan clients	Average loan size	Physical capital	Labor	Interm. inputs	$\widehat{\omega}$
2004	56	33209,50	2250,46	2,01	205,18	2,75	0,73
2005	100	30620,15	2364,10	1,85	193,25	2,86	0,63
2006	148	33228,02	2264,41	1,86	206,75	2,88	0,71
2007	205	48390,29	2533,96	2,23	273,68	3,57	0,74
2008	246	38626,93	2571,16	1,70	237,22	2,72	0,62
2009	265	37965,46	2609,59	2,03	255,52	2,84	0,62
2010	278	38598,08	2457,88	1,85	255,07	3,01	0,59
2011	268	41259,54	2357,08	1,97	261,27	3,36	0,57
2012	226	67400,20	2194,24	2,48	356,54	4,83	0,64
2013	221	66807,54	2113,58	2,16	355,29	4,99	0,67
2014	244	63414,75	2220,21	1,90	335,50	4,17	0,65
2015	256	79499,00	2371,70	2,95	440,51	5,70	0,64
2016	192	89592,04	2492,80	3,75	522,86	6,63	0,69
2017	166	100522,40	2606,26	3,80	583,07	7,48	0,76
2018	145	80160,57	2953,40	4,57	530,34	8,42	0,71

Notes: The table shows the year means for variables and the estimated productivity level for the loans-only sample. The variables are defined in Table 1.

Appendix: Interpretations of α

Let dx denote percentage change in x. If we differentiate equation (4), holding productivity constant, we have

$$dn = -\,\alpha\, d\bar{a} + \beta_K dk + \beta_L dl + \beta_M dm.$$

Let $s = \beta_K + \beta_L + \beta_M$ denote the scale elasticity, and consider the same proportional increase in all inputs, $di = dk = dl = dm$. The above equation can then be written as

$$dn = -\alpha d\bar{a} + s di. \tag{A1}$$

From (A1) it follows that if we increase the average loan size by 1% while holding the number of clients constant, the necessary proportional increase in all inputs is

$$\left.\frac{di}{d\bar{a}}\right|_{dn=0} = \frac{\alpha}{s}. \tag{A2}$$

Thus $\alpha > 0$ implies that more resources are required to support a portfolio with a higher average loan size.

If we add da to both sides of equation (A1) and rearrange we can write

$$da = (1-\alpha)\, d\bar{a} + s di. \tag{A3}$$

From A3 it follows that if we increase the gross outstanding loan balance by 1% while holding the average loan size constant, the necessary proportional increase in all inputs is

$$\left.\frac{di}{da}\right|_{d\bar{a}=0} = \frac{1}{s}. \tag{A4}$$

Equations (A2) and (A4) can be used to compare our two credit-expansion strategies. From (A2) it follows that if we expand the intensive margin (i.e., increase the average loan size while holding the number of loan clients constant), then the necessary proportional increase in all inputs to support a 1% increase in total assets is α/s.

From A4 it follows that if we expand the extensive margin (i.e., increase the number of loan clients while holding the average loan size constant), then the necessary proportional increase in all inputs to support a 1% increase in total assets is $1/s$.

Using our estimates on α and s, we get that is about twice as costly to increase assets (total gross loan portfolio) by expanding the extensive margin than by expanding the intensive margin.