Empir Econ
DOI 10.1007/s00181-014-0861-3

Should all microfinance institutions mobilize microsavings? Evidence from economies of scope

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Received: 11 October 2013 / Accepted: 22 June 2014

Abstract We extend a recently developed generalized local polynomial estimator into a semiparametric smooth coefficient framework to estimate a generalized cost function. The advantage of the generalized local polynomial approach is that we can simultaneously choose the degree of polynomial for each continuous nonparametric regressor and the bandwidths via data-driven methods. We provide estimates of scope economies from the joint production of microloans and microdeposits for a dataset of Microfinance Institutions from over 50 countries. Our approach allows analysis on all Microfinance Institutions rather than only those offering just microloans. Moreover, the smooth coefficient estimator provides a general interface in which to account for both direct and indirect environmental factors. We find substantial scope economies in general, of about 10 % at the median, as well as evidence that economies of scope

We thank Daniel Henderson, participants at the 2013 Western Economic Association International conference, and seminar participants at Hebei Finance University for helpful feedback.

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Published online: 17 August 2014

vary across the type of services and country in which the MFIs operate, suggesting key insights into policy prescriptions.

Keywords Microfinance institutions · Efficiency · Scope economies · Semiparametric smooth coefficient · Generalized local polynomial · Cross-validation · Environmental variables

1 Introduction

Modern microfinance has been evolving away from its original focus on microcredit, when Microfinance Institutions (MFIs) mainly extended tiny loans, typically without collateral. Today, MFIs strive to offer a variety of loan products, as well as microsavings accounts, microinsurance, and payment facilities. Empirical evidence suggests the poor demand more than just microloans (Collins et al. 2009). From the supply side, however, joint production of microloans and microdeposits must produce scope economies to justify the costs of obtaining a license to collect microdeposits from the poor. Moreover, cost advantages must be substantial to justify rewriting national laws to permit MFIs to collect microsavings. This paper estimates the scope economies of the joint production of microloans and microdeposits for a large, global sample of rated MFIs with a semiparametric smooth coefficient model, which seamlessly incorporates factors specific to microfinance.

Given that banks intermediate between surplus and deficit units, most of the empirical literature on efficiency in commercial banking applies an intermediation approach to estimate economies of scale and scope. In this approach, deposits are inputs in the production of various types of loans and investments. However, unlike commercial banks, MFIs remain focused on serving marginalized clientele and not on intermediation (Cull et al. 2011). The cost of delivering deposits to the poor in urban slums or remote rural areas remain very high, and microdeposits are not the main input used to produce loans (Garmaise and Natividad 2010). Thus, we use the alternative production approach to microfinance cost efficiency because the production approach is better suited to study the economies of scope in MFIs and has been used previously in the banking literature. Previous research suggests that poor savers and borrowers may be different groups and that scope economies arise from sharing physical infrastructure, not sharing of information regarding microborrowers and savers to improve product design (Hartarska et al. 2011). Therefore, we estimate a multiproduct cost function, which can directly account for zero-valued inputs, following those used in earlier bank efficiency studies—e.g., Berger and Humphrey (1991) and Mitchell and Onvural (1996). In particular, we focus on scope economies between microloans and microsavings, where these two outputs are measured in dollar volume but account for the cost of capital as in Caudill et al. (2009).

To estimate our multiproduct cost function, we deploy recently developed semiparametric regression methods tailored for a smooth coefficient setup. This model accommodates two important peculiarities of the microfinance industry. Specifically, the method allows zero output values; thus, we include MFIs that do not take microdeposits.[1] This is important because, unlike commercial banks which offer both savings and loans, many MFIs only lend (Garmaise and Natividad 2010). In addition, while some MFIs have private capital investment, most continue to use donor funds. Thus, market-based control mechanisms are insufficient to ensure that the more efficient MFIs—those offering both microloans and microdeposits—will survive. Therefore, better estimates of scope economies for the industry should include both types of MFIs in the sample to more accurately develop suitable policies regarding the operation of MFIs.

We provide two separate econometric innovations for our semiparametric estimation. First, we adapt the recently developed generalized local polynomial estimator of the univariate nonparametric regression model of Hall and Racine (2013) to a multivariate semiparametric smooth coefficient setup. Hall and Racine (2013) propose using a cross-validation procedure to select both the degree of polynomial (in the local polynomial regression) and the bandwidth parameter. The advantages of this approach are (i) the commonly used local constant or local linear regression models are nested as a special case and can be selected via cross-validation if either estimator provides a superior fit; (ii) if the true function is globally polynomial, the cross-validation procedure will return a set of bandwidths and polynomial order to reflect this fact; and (iii) this generalized approach provides improvements in finite-sample efficiency and rates of convergence.

Second, we deploy the recently proposed cross-validation procedure of Henderson et al. (2012) for choosing the bandwidths based on our estimates of scope economies, rather than the semiparametric cost function. Since our interest is on scope economies, not the cost functions per se, it is not known whether bandwidths chosen to be optimal for cost function estimation are also optimal for estimation of scope economies. It is well known in applied nonparametric kernel estimation that careful selection of the bandwidth is crucial for obtaining reliable estimates. Henderson et al. (2012) provide a data-driven approach for selecting the smoothing parameter of an unobserved function, rendering our estimates selected based on scope economies better suited for scope estimation than bandwidths selected for cost estimation. Hence, we adapt this method to the scope economies case.

Outside of these unique econometric issues related to studying economies of scope across MFIs, perhaps most important is our ability to accommodate impact of the external environment in which MFIs operate because it may have both direct and indirect effect on cost and scope economies (Armedráriz and Szafarz 2010; Ahlin et al. 2011). The semiparametric approach permits environmental factors to affect the existence and the magnitudes of scope economies in a general fashion, both directly and through their interaction with input prices. For example, costs of delivery of microfinance services in remote areas are higher, so we control for the population density in a country. On the macro level, we control for the level of financial system development since MFIs in countries with higher bank penetration serve more marginal clients (Cull et al. 2009). Due to the unique dataset we use, we can control for MFI-

[1] Throughout the paper, we use microdeposits (microsavings) to mean voluntary microdeposits since mandatory savings that MFIs require are a part of some of the lending technology associated with solidarity groups and village banks.

specific factors not possible with alternative datasets, namely the type of markets served; e.g., primarily urban, primarily rural, and the type of microfinance lending technology—village banking, solidarity groups, or individual lending. Unlike previous studies of scope economies in microfinance, we are able to use three instead of two input prices—the price of labor, and the prices of financial and physical capital, which makes this study more in line with the banking literature. Finally, we further calculate economies of scale using our semiparametric cost function and consider the joint distribution of economies of scope and scale.

Our results indicate that, at the median, MFIs possess scope economies of 10 %. However, we also find that roughly 25 % of the MFI-year observations have estimated diseconomies of scope. Moreover, the environment in which MFIs operate both on a macro and regional level affects their cost economies. In particular, we see the highest potential economies of scope in Sub- Saharan Africa and South East Asia. Additionally, we see that MFIs using village lending in rural areas have higher scope economies than those using individual lending in urban areas. Overall, we find scope economies in microfinance, but they do depend on the environment in which MFIs operate. When considering the joint distribution of economies of scope and scale, we find that the modal observation in our dataset has economies of scope, but diseconomies of scale. Thus we are able to provide important insights into the debate on whether microsavings should be promoted and what financial results we should expect from MFIs offering microsavings. Since we find that not all MFIs can deliver microsavings in a sustainable manner since there are scope diseconomies, if delivery of savings is important from a policy perspective, it should not be expected to be financially sustainable in every environment and for every MFI.

The rest of the paper is organized as follows. Section 2 presents relevant literature and arguments for why the study of scope economies in microfinance is important. Section 3 outlines the semiparametric setup deployed to estimate scope economies. Section 4 details the generalized local polynomial estimator for a semiparametric smooth coefficient model, and discusses bandwidth and polynomial order selection. Our rated MFI data is discussed in Sect. 5. The results of our econometric study are presented in Sect. 6. Conclusions and directions for future research are contained in Sect. 7.

2 Summary of the relevant literature

While there is a well-developed literature on efficiency, scale, and economies of scope for various financial institutions, most studies are for banks in developed countries (Hughes and Mester 2009). Efficiency issues in financial institutions in developing countries are much less understood (Berger et al. 2009). Furthermore, efficiency within the MFIs is typically evaluated with various industry benchmarks (Balkenhol 2009, reviews various ratios). For instance, Cull et al. (2007) study if there is a mission drift with MFIs focusing on serving larger borrowers, while Cull et al. (2009) study how various MFI characteristics impact their efficiency and outreach.

A structural approach, requiring cost (or profit) function estimation, is used by Caudill et al. (2009) who study the evolution of MFIs in time, Hartarska and Mersland

(2012) study the impact of governance mechanisms on managerial (in)efficiency, and Hermes et al. (2011) study trade-offs between sustainability and outreach. Typically, cost functions rather than profit functions are estimated because MFIs minimize costs, and do not necessarily maximize profits. Moreover, cost functions are more appropriate than profit functions because MFIs are price takers on the input market, and have some monopoly on the output market for marginal clients (Varian 1984). Estimation methods include data envelopment analysis (Paxton 2007; Gutierres-Nieto et al. 2007), stochastic frontier analysis (Hartarska and Mersland 2012; Hermes et al. 2011), or mixture modeling (Caudill et al. 2009).

Microfinance studies adapt the efficiency framework used to study financial institutions. There are two main structural approaches: production and intermediation, described in detail in Humphrey (1985). For commercial bank data, the intermediation approach has produced better results, while the production approach has been less popular since crucial, required variables such as the number of accounts are not easily available (Freixas and Rochet 1997). In banking, Berger and Humphrey (1991) and Mitchell and Onvural (1996) propose modifications to the approach by treating 'purchased funds' as an input, by including interest expense for purchased funds in total cost, and by measuring outputs by dollar amounts. More recently, a production-like approach has been found more appropriate for other financial firms (van Cayseele and Wuyts 2007).

In the microfinance literature, Hartarska et al. (2010, 2011) estimate scope economies using a semiparametric generalization of the model of Berger and Humphrey (1991). Hartarska et al. (2011) use MIX market data, which only has two input prices—financial capital and operating expense per employees—but their data do not allow controls for the type of market served: rural, urban, or a mixture of the two. These are important differences among MFIs. In the present paper, we use a more detailed and higher-quality dataset from external raters and follow more closely banking studies in that we use three classical inputs in the cost function: average wage per worker to measure price of labor, non-labor operating expense to net-fixed capital ratio to measure the price of physical capital, and the cost of capital (Mitchell and Onvural 1996). Following these banking studies, we also measure outputs in dollar value. This is important because, in our dataset, the number of savers has not been systematically collected by all rating agencies whose reports were used to assemble the database. However, Hartarska et al. (2010) show that the average values of estimated scope economies in MFIs do not differ if dollar values, rather than savings and lending account numbers, are used as the output, even in a dataset with many outliers such as the MIX market dataset.

Finally, this paper is a contribution to the literature on semiparametric methods as nonparametric efficiency studies are few; even fewer are applications to financial institution efficiency in developing countries (e.g., Ariff and Can 2008). Semiparametric methods are appropriate to study such institutions because of their flexibility and ability to control for the impact of environmental variables, which is especially important in a cross-country setting. The microfinance literature has revealed that the external environment matters and that these factors must be accounted for in studies of efficiency (Ahlin et al. 2011; Garmaise and Natividad 2010).

3 Economies of scope, economies of scale, and cost estimation

3.1 Economies of scope

Economies of scope can emerge from two sources: (i) allocation of fixed costs over an extended product mix, and (ii) cost complementarities across categories in production. Allocating fixed costs over a firm's product mix can contribute to scope economies when excess capital capacity is reduced by providing both savings and loans rather than individual provision of these services. Alternatively, cost complementarities result in scope economies when consumer information developed in the production of either savings or loans is used to reduce the monitoring requirements of the other product.

Given trustworthy estimates of scope economies, it is straightforward to assess the production consequences of narrow services provided by microfinance institutions. We describe here the general estimation of scope economies, followed by a detailed discussion of a flexible, yet broad, methodology using semiparametric methods that are robust to myriad functional form issues arising in empirical work.

Pulley and Humphrey (1993) define overall economies of scope as the percentage of cost savings from producing all outputs jointly as opposed to producing each output separately. Here, we have only two outputs, loans and deposits, so our estimates of scope economies are:

$$\text{SCOPE}_i = \frac{C(q_{1i}, 0; r_i) + C(0, q_{2i}; r_i) - C(q_{1i}, q_{2i}; r_i)}{C(q_{1i}, q_{2i}; r_i)}, \tag{1}$$

where $i = 1, 2, \ldots, n$ denotes the sample of size n, r is a vector of R input prices, here taken to be the relative price of labor and borrowed funds, and $C(\cdot)$ is the cost function. q_1 and q_2 are loans and deposits, respectively. Hence, given an estimate of $C(\cdot)$, it is straightforward to construct an estimate of economies of scope.

An alternative measure of economies of scope provided by Pulley and Braunstein (1992) is the quasi economies of scope measure; this measure does not restrict the calculation of scope economies to the case of perfectly specialized output. That is, the quasi economies of scope measure allows the researcher to calculate economies of scope under the assumption that all firms produce some nonzero amount of each potential output. Formally, quasi economies of scope is defined as

$$\text{QSCOPE}_i = \frac{C[(1-\epsilon)q_{1i}, \epsilon q_{2i}; r_i] + C[\epsilon q_{1i}, (1-\epsilon)q_{2i}; r_i] - C[q_{1i}, q_{2i}; r_i]}{C[q_{1i}, q_{2i}; r_i]}, \tag{2}$$

in which ϵ is defined as the proportion of non-specialized outputs produced. That is, the cost function $C[(1-\epsilon)q_{1i}, \epsilon q_{2i}; r_i]$ implies that firm i specializes primarily in q_1, with a $(1-\epsilon)$ share of total output being q_1 and only an ϵ share of total output consisting of q_2. Notice that, in the two output case, we consider, $0 < \epsilon < \frac{1}{2}$, with $\epsilon = 0$ being the perfectly specialized case defined by our primary measure of scope economies, and $\epsilon = \frac{1}{2}$ being the opposite extreme in which the firm is entirely non-specialized. The difficulty in practice of deploying the quasi-scope measure is choosing the value of

ϵ; Pulley and Braunstein (1992) consider a range of values for ϵ and calculate scope based on each different value in this range.

Our preferred measure of scope economies is the standard scope measure, given in Eq. (1). For robustness, we consider the quasi-scope economies measure in Eq. (2) setting $\epsilon = 0.15$. Results reported by Pulley and Braunstein (1992) show that setting ϵ close to zero returns estimates that are close to the standard scope estimates, and that scope estimates generally decline as ϵ increases (since the firm is less specialized with larger values of ϵ). From their results, $\epsilon = 0.15$ seems to provide a natural balance between relaxing the perfect specialization restriction embedded in the standard scope measure without assuming that the firms are already non-specialized to the extent that there are no longer estimable cost reductions from choosing to specialize primarily in a single output.

3.2 Economies of scale

An alternative measure of the difference between joint and specialized production is economies of scale. Our main focus is on our estimates of economies of scope, described in the previous section; however, we further explore economies of scale in microfinance that stem from joint production of loans and savings, in addition to important interactive effects between both economies of scope and scale. For instance, do we find that microfinance institutions that exhibit economies of scope from joint production of savings and loans also exhibit economies of scale?

We follow Pulley and Braunstein (1992) and define economies of scale in our two-output setup as

$$\mathrm{SCALE}_i = \frac{C(q_{1i}, q_{2i}; r_i)}{q_{1i}\frac{\partial C(q_{1i},q_{2i};r_i)}{\partial q_{1i}} + q_{2i}\frac{\partial C(q_{1i},q_{2i};r_i)}{\partial q_{2i}}}. \tag{3}$$

Note that estimates of scale that are greater than unity indicate scale economies, while estimates of scale that are less than unity indicate diseconomies of scale. This formulation of scale economies is different than the standard measure from a cost function, $(1 - Ecy_i)$, which is based on the sum of the output elasticities, $Ecy_i = \frac{\partial \ln C(q_{1i},q_{2i};r_i)}{\partial \ln q_{1i}} + \frac{\partial \ln C(q_{1i},q_{2i};r_i)}{\partial \ln q_{2i}}$. This measure is not suitable here given the large number of microfinance institutions that we have in our data that do not offer deposits to their clientele. The formulation in (3) allows for zero output activities in the construction of scale economies and is consistent with our specification of the cost function.

3.3 Cost estimation

Given that the data used to estimate the cost function represent a mix of firms producing loans and deposits jointly and firms specializing in the production of loans exclusively, the use of standard cost functions in production econometrics is not suitable. Consider, for example, the transcendental logarithmic cost function (Christiansen et al. 1971):

$$\ln C_i = \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln q_{mi} + 0.5 \sum_{m=1}^{M} \sum_{\eta=1}^{M} \alpha_{m\eta} \ln q_{mi} \ln q_{\eta i} + \sum_{m=1}^{M} \sum_{l=1}^{R} \delta_{ml} \ln q_{mi} \ln r_{li} + \sum_{l=1}^{R} \beta_l \ln r_{li} + 0.5 \sum_{l=1}^{R} \sum_{\ell=1}^{R} \beta_{l\ell} \ln r_{li} \ln r_{\ell i}. \quad (4)$$

This setup cannot handle zero outputs. Given the appeal of this flexible functional form in applied settings, such as the banking or financial services industries, various authors have dealt with the zero output (or zero input price) problem in a variety of ways. The simplest approach is to add a small number to all observations that have a zero output value (Berger and Humphrey 1991) or to introduce a Box-Cox transformation parameter to all outputs, i.e., instead of using $\ln q_{mi}$ one would replace it with $q_{mi}^{\phi} = (q_{mi}^{\phi} - 1)/\phi$ when ϕ is nonzero and is equal to the standard logarithmic function when it is zero. This is problematic for several reasons. First, it abstracts from the linear in parameters appeal of estimating a transcendental logarithmic function. Second, if the estimate of ϕ is not statistically different from zero, then further recourse is required. Lastly, all of the outputs are transformed by the same parameter. Thus, the use of a translog cost function for the study of economies of scope is, in general, restrictive, and inappropriate for a wide array of empirical problems.

An empirical cost function for estimating scope economies was suggested by Pulley and Braunstein (1992), based on the theoretical cost function suggested by Baumol et al. (1982). Their cost function is multiplicatively separable in outputs and input prices and is quadratic (as opposed to log-quadratic) in outputs, thus alleviating the empirical issue of zero-valued outputs in real-world datasets. More formally, the cost function deemed appropriate for estimating economies of scope by Baumol et al. (1982) is

$$C(q_i, r_i) = F(q_i) \cdot G(r_i), \quad (5)$$

where $F(q_i)$ is a quadratic form in outputs, while $G(r_i)$ is a linearly homogeneous function of input prices. The empirical model suggested and estimated by Pulley and Braunstein (1992) is

$$C(q_i, r_i) = F(q_i, r_i) \cdot \exp\{G(r_i)\} + u_i. \quad (6)$$

The reason that *both* q_i and r_i appear in $F(\cdot)$ is that there is no explicit reason for imposing separability between input prices and outputs. $F(q_i, r_i)$ is still required to be quadratic in outputs. Pulley and Braunstein (1992) suggest that the exponential of $G(\cdot)$ is required given that one is using costs and not logarithmic costs. However, the theoretical suggestion of Baumol et al. (1982) only requires $G(r_i)$ to be linearly homogeneous. In our empirical analysis that follows, we have roughly 10 % of our data with 0 input prices. Thus, the use of logarithmic input prices is not feasible. To avoid making arbitrary transformations of the data, we follow the actual cost function proposal of Baumol et al. (1982) and use input prices in levels when we estimate the cost function.

The composite cost model of Pulley and Braunstein (1992) can be written more succinctly as

$$C(q_i, r_i) = F(q_i, r_i) \cdot \widetilde{G}(r_i) + u_i. \tag{7}$$

While taking the logarithm of both sides of Eq. 5 will produce an additively separable model in $F(\cdot)$ and $G(\cdot)$, the generalized form of the Baumol et al. (1982) cost function advocated initially by Pulley and Braunstein (1992) is sufficient to investigate costs with the purpose of studying scope and scale economies.

The empirical form of the composite cost function advocated by Pulley and Braunstein (1992) is:

$$C_i = \left[\alpha_0 + \sum_{m=1}^{M} \alpha_m q_{mi} + 0.5 \sum_{m=1}^{M} \sum_{\eta=1}^{M} \alpha_{m\eta} q_{mi} q_{\eta i} + \sum_{m=1}^{M} \sum_{l=1}^{R} \delta_{ml} q_{mi} r_{li}\right] \times \exp\left(\beta_0 + \sum_{l=1}^{R} \beta_l r_{li} + \sum_{l=1}^{R} \sum_{\ell=1}^{R} \beta_{l\ell} r_{li} r_{\ell i}\right) + \varepsilon_i. \tag{8}$$

A variation of this model involves taking the logarithm of both sides, which transforms the cost function into a composite log-quadratic structure. The following symmetry conditions need to be imposed onto the above cost function: $\alpha_{m\eta} = \alpha_{\eta m}$ and $\beta_{l\ell} = \beta_{\ell l}$. To ensure homogeneity, the following conditions need to bind: $\sum \beta_l = 1$; $\sum_l \beta_{l\ell} = 0\ \forall \ell$; $\sum_m \delta_{ml} = 0\ \forall l$. Equation (8) can be estimated using standard maximum likelihood estimation routines assuming that the errors are normally distributed, or using a general nonlinear least-squares algorithm if one was unwilling to make a specific assumption on the distributive law of the error terms.

3.4 The semiparametric smooth coefficient cost function

Pulley and Braunstein's (1992) model reflects a composite structure suitable for estimating scope economies, yet it is grounded in a parametric functional form, which leaves concerns over functional form specification. Given the large number of covariates that we have access to, a fully nonparametric approach does not seem reasonable. Thus, we use the recently proposed semiparametric smooth coefficient cost function of Hartarska et al. (2011). This model takes a similar form as that in Pulley and Braunstein (1992), but relaxes the functional form restrictions on $\widetilde{G}(r_i)$. With this style of cost function, the structure of Pulley and Braunstein's (1992) model still remains, but the researcher is afforded sufficient flexibility to model costs. We also mention here that another appealing feature of this setup is that accounting for environmental variables (such as type of market served by the MFI or load method) is straightforward and does not require *a priori* specification.

For our purposes, we estimate the model of Hartarska et al. (2011). Let the function $G(r_i) \equiv \exp(\beta_0 + \sum \beta_l r_{li} + \sum \sum \beta_{l\ell} r_{li} r_{\ell i})$, then Eq. (8) can be rewritten as

$$C = \left[\overline{\alpha}_0 + \sum_{m=1}^{M} \overline{\alpha}_m q_{mi} + 0.5 \sum_{m=1}^{M} \sum_{\eta=1}^{M} \overline{\alpha}_{m\eta} q_{mi} q_{\eta i} + \sum_{m=1}^{M} \sum_{l=1}^{R} \overline{\delta}_{ml} q_{mi} r_{li} \right], \tag{9}$$

where $\overline{\alpha}_0$, $\overline{\alpha}_m$, $\overline{\alpha}_{m\eta}$ and $\overline{\delta}_{ml}$ are the coefficients α_0, α_m, $\alpha_{m\eta}$ and δ_{ml} in Eq. (8) multiplied by $G(r_i)$. We can therefore specify $\overline{\alpha}_0$, $\overline{\alpha}_m$, $\overline{\alpha}_{m\eta}$ and $\overline{\delta}_{ml}$ as functions of $G(r_i)$ and a set of environmental variables, V_i. In our empirical setup, we include categorical indicators for region and time in V to flexibly control for unobserved heterogeneity that often arises in panel data applications.

We can write Eq. (9) in the following semiparametric form:

$$Y_i = X_i \beta(Z_i) + \varepsilon_i \tag{10}$$

where $Y_i \equiv C_i$, $X_i = [1, q_i, q_i q_i', q_i r_i']$, $Z_i = [r_i, V_i]$. We do not have to introduce quadratic and interaction terms in Z_i since the semiparametric estimator will select the appropriate higher order/interaction terms. Here, $q_i q_i'$ is the $m^2 \times 1$ vector of squares and interactions of the outputs and $q_i r_i'$ is the $ml \times 1$ vector of interactions between outputs and input prices.

Another way to think of this model is that for a given level of Z_i, we have a linear in parameters model where the slopes possibly differ for differing levels of Z_i. Since Z_i and X_i can contain the same variables, this model is more general than that of Pulley and Braunstein (1992). One can also view the Pulley and Braunstein (1992) model as a smooth coefficient model, with $\exp\left(\beta_0 + \sum \beta_l r_{li} + \sum \sum \beta_{l\ell} r_{li} r_{\ell i}\right)$ representing the smooth coefficient on q_{mi} in Eq. (6). The key difference between the semiparametric smooth coefficient model in Eq. (10) and the parametric smooth coefficient model in Eq. (6) is that the coefficients are identical, up to scale, in Eq. (6) while in Eq. (10) they can be entirely different functions altogether. At this point, it is important to emphasize that imposing linear homogeneity is difficult in our semiparametric setup given that we are not imposing any structure on $\beta(Z_i)$.[2] However, this is a small price to pay since even the use of the popular translog specification, which violates global concavity, is traditionally used in production econometrics.

The semiparametric smooth coefficient model can be specified as quadratic in output, as recommended by Baumol et al. (1982), but is more general in the input price structure, due to the lack of specification on $\beta(Z_i)$.

[2] See Du et al. (2013) for an approach to impose linear homogeneity in this setting.

4 Generalized local polynomial estimation for SPSCM

4.1 Estimation

We rewrite model (8) in the form

$$Y_i = \sum_{\ell=0}^{L} \beta_\ell(Z_i) X_{\ell i} + \varepsilon_i, \quad \ell = 0, 1, \ldots, L \tag{11}$$

in which ℓ indexes the number of regressors. Recall that Y is a scalar outcome, and rewrite X as $X \equiv (X_0, X_1, \ldots, X_L)$ is a $(L+1)$-dimensioned vector in which $X_0 \equiv 1$ and $X_{\ell \neq 0}$ are the L regressors. Assume that Z_i is vector valued of dimension S. Using the local polynomial approach, we can approximate each coefficient at a point $z \in Z$ via

$$\beta_\ell(z) \approx a_\ell + \sum_{s=1}^{S} \sum_{j=0}^{p_s} b_{\ell s}^{(j)} (Z_{si} - z_s)^j \tag{12}$$

for polynomial order p_s for each s element in Z. The notation $b_{\ell s}^{(j)}$ denotes the jth derivative of coefficient function ℓ with respect to component s. Notice that in this formulation, while we allow for an arbitrary order of polynomial for each different component in Z, we restrict the polynomial interactions across s to be zero. Then, we are interested in the solution to the weighted least-squares problem

$$\frac{1}{nh} \sum_{i=1}^{n} \left[Y_i - \sum_{\ell=0}^{L} a_\ell X_{\ell i} - \sum_{\ell=0}^{L} \sum_{s=1}^{S} \sum_{j=0}^{p_s} b_{\ell s}^{(j)} (Z_{si} - z_s)^j X_{\ell i} \right]^2 \mathcal{K}\left(\frac{Z_i - z}{h} \right) \tag{13}$$

in which $\mathcal{K}(\cdot)$ is a product kernel function and h is a bandwidth vector. In this setup, a_ℓ is our estimate of the ℓth coefficient function at a point $z \in Z$, and $b_{\ell s}^{(j)}$ denotes the partial derivative of order j for coefficient k with respect to component s.[3]

[3] Note that this generalized formulation nests the familiar local constant least squares problem when $p_s = 0, \forall s$

$$\frac{1}{nh} \sum_{i=1}^{n} \left[Y_i - \sum_{\ell=0}^{L} a_\ell X_{\ell i} \right]^2 \mathcal{K}\left(\frac{Z_i - z}{h} \right)$$

or the local linear least-squares problem when $p_s = 1, \forall s$

$$\frac{1}{nh} \sum_{i=1}^{n} \left[Y_i - \sum_{\ell=0}^{L} a_\ell X_{\ell i} - \sum_{\ell=0}^{L} \sum_{s=1}^{S} b_{\ell s} (Z_{si} - z_s) X_{\ell i} \right]^2 \mathcal{K}\left(\frac{Z_i - z}{h} \right).$$

Let $\widetilde{Z}_{si} \equiv \left((Z_{si}-z_s)^1, (Z_{si}-z_s)^2, \ldots, (Z_{si}-z_s)^{p_s}\right)$ and then define $\widetilde{Z}_i \equiv \left(\widetilde{Z}_{1i}, \widetilde{Z}_{2i}, \ldots, \widetilde{Z}_{Si}\right)$. Then, for $\widetilde{X}_i \equiv \begin{pmatrix} X_i \\ \widetilde{Z}_i \otimes X_i \end{pmatrix}'$, we seek the $(L+1) \times (\sum p_s + 1)$ estimator $\widehat{\delta}$ given by

$$\widehat{\delta} = (\widetilde{X}'\mathcal{K}(z)\widetilde{X})^{-1}\widetilde{X}'\mathcal{K}(z)Y \tag{14}$$

Note that our estimates of the functions $\beta_\ell(z)$ are recovered by $\widehat{\beta}_\ell(z) = e_1\widehat{\delta}$ for e_1 being a $(L+1) \times (\sum p_s + 1)$-dimensioned vector with the first $L+1$ elements being unity and the remaining $(L+1) \times \sum p_s$ elements being zero.

To make our estimator operational in a mixed data setting, we follow Racine and Li (2004) and deploy the generalized product kernel function for $\mathcal{K}(\cdot)$.

$$\mathcal{K}(\cdot) = \prod_{c=1}^{S_c} k^c\left(\frac{Z_i^c - z^c}{h_c}\right) \prod_{u=1}^{S_u} k^u(Z_i^u - z^u; h_u) \prod_{o=1}^{S_o} k^o(Z_i^o - z^o; h_o) \tag{15}$$

in which

$$k^c\left(\frac{Z_i^c - z^c}{h_c}\right) = \frac{1}{\sqrt{2\pi}}\exp\left[\frac{1}{2}\left(\frac{Z_i^c - z^c}{h_c}\right)^2\right] \tag{16}$$

is a univariate Gaussian kernel function used for each of the S_c continuous variables in Z_i,

$$k^u(Z_i^u - z^u; h_u) = \begin{cases} 1 & \text{if } Z_i^u - z^u = 0 \\ h_u & \text{if } Z_i^u - z^u \neq 0 \end{cases} \tag{17}$$

is a univariate discrete kernel function used for each of the S_u unordered discrete variables in Z_i, and

$$k^o(Z_i^o - z^o; h_o) = \begin{cases} 1 & \text{if } Z_i^o - z^o = 0 \\ h_o^{|Z_i^o - z^o|} & \text{if } Z_i^o - z^o \neq 0 \end{cases} \tag{18}$$

is a univariate discrete kernel function used for each of the S_o ordered discrete variables in Z_i (Li and Racine 2007). In the above product kernel setup, h_c is a S_c-dimensioned vector of bandwidths for the continuous variables and h_u and h_o are S_u- and S_o-dimensioned vectors of unordered and ordered discrete variable bandwidths.

4.2 Automatic selection of bandwidths and polynomial order

Following Hall and Racine (2013), we propose to automatically select both the bandwidths, h, and polynomial order, p_s, via cross-validation. They show that simultaneous data-driven selection of both the bandwidth and degree of polynomial yields improvements in finite-sample efficiency and rates of convergence of the nonparametric estimator. In the case that the true underlying data generating process is a polynomial, the cross-validation procedure will select the appropriate order of polynomial and achieve the parametric $\sqrt{n}$ rate of convergence. We adapt their method into a multivariate smooth coefficient setting, and consider both continuous and discrete variables.

In our case, however, we are interested primarily in scope economies—scope economies is a function that we must construct based on cost estimates and therefore is not directly observed. Consequently, the general cross-validation approach to selecting bandwidths (i.e., minimizing the mean-squared error between the observed outcome and conditional mean) is not applicable. Of course, one might choose bandwidths based on cross-validation over the cost function model, but it is not clear that the bandwidth that is optimal for cost function estimation is optimal for economies of scope estimation.

Recently, Henderson et al. (2012) have proposed a way to use cross-validation to select the optimal smoothing parameter for function estimation when the function is not observable. Specifically, they propose the following approach (adapted to our context of scope). Denote scope in (1) via S, noting that scope is a function of cost. Then, we seek the bandwidth and polynomial pair that minimizes the integrated squared error given by

$$\begin{aligned}\text{ISE}(h, p) &= \int \left[\widehat{S}(C_i) - S(C_i)\right]^2 dC \\ &= \int \widehat{S}(C_i)^2 dC - 2\int \widehat{S}(C_i)S(C_i)dC + \int S(C_i)^2 dC. \end{aligned} \tag{19}$$

Since the last term does not depend on (h, p), minimizing ISE is equivalent to choosing (h, p) to minimize the first two terms. However, since $S(C_i)$ is not observed in the second term, Henderson et al. (2012) propose replacing it with its leave-one-out estimator: $\widehat{S}(C_{-i})$. Therefore, we arrive at our cross-validation function by minimizing the sample analog

$$\min_{h,p} \sum_{i=1}^{n} \widehat{S}(C_i)^2 - 2\widehat{S}(C_i)\widehat{S}(C_{-i}). \tag{20}$$

Note that we construct $\widehat{S}(C_{-i})$ from a leave-one-out estimator of C_i. It is clear that using the generalized local polynomial approach of Hall and Racine (2013), combined with the bandwidth selection approach of Henderson et al. (2012), constitutes an econometric approach that is both general with respect to the nonparametric local polynomial estimator, and robust by selecting the optimal bandwidth for estimating economies of scope.[4]

One important issue for implementing the generalized local polynomial procedure is the complication that the set (h, p) contains different numerical restrictions that must hold during optimization of the cross-validation procedure. That is, h contains both continuous and discrete regressors and must be bounded between $[0, \infty)$ for the continuous components, yet $[0, 1]$ for the discrete components. Yet, within these bounds, the bandwidths are allowed to vary continuously. p, on the other hand, must be defined over the set of natural numbers. Hence, these restrictions impose substantial demands on the nonlinear optimization algorithm. Hence, we follow Hall and

[4] We also explore the robustness of our primary results by selecting bandwidths that are optimal for estimation of economies of scale. We find that, in general, our empirical results are qualitatively consistent when we smooth over scale.

Racine (2013) and use the Nonsmooth Optimization by Mesh Adaptive Direct Search (NOMAD) optimizer developed by Abramson et al. (2011), and available in the `crs` package (Nie and Racine 2012) in `R`.

5 Data

The data used are collected from the rating reports of MFIs and includes publicly available data from www.ratingfund2.org, as well as data collected with special permission from private rating reports. In the early 2000s, microfinance rating was believed to be a market-based mechanism of control that would discipline managers by providing independent reporting for potential donors and investors. Many MFIs submitted to this independent evaluation and opened their books, signaling that they were more transparent than the average MFI. The rating fund offered financial support and required that the rating reports remain publicly available online.

The dataset used here contains rating reports completed by June 2007. The data comprise an unbalanced panel from 1999 to 2006 for 244 MFIs operating in 53 countries with about 3 years of data per MFI for a total of 777 observations.[5] The two outputs used—loans and savings—are measured as the dollar value of loans outstanding and the dollar value of voluntary deposits, respectively. Unlike previous microfinance studies, these data allow us to use more precise input prices in-line with the main banking literature. In particular, it allows us to separate the price of labor from that of fixed capital. The input price of labor is the average annual salary per employee, the cost of capital is the weighted cost of borrowed funds (deposits and loans), and the input price of physical capital is the ratio of non-labor operating expenses to the value of net-fixed assets. Total costs are the sum of input prices and input quantities.

Summary statistics of the variables used in the scope estimation are in Table 1.[6] Of our rated MFI observations, 76 % only extend loans while the remaining 24 % offer both loans and mobilize savings, confirming that most MFIs still offer only credit. MFIs in the largest to date MFI dataset maintained by mixmarket show the same distribution of lending-only and lending and deposit institutions. The average MFI has about \$4.1 million in loan portfolio outstanding, with a range from slightly more than \$3,500 to \$34.6 million. The volume of savings (when offered) is \$914,669 on average and the largest case is about \$24 million. The average value of annual salaries is \$5,516, the cost of capital (deposits and borrowed funds) is 8 %, and the ratio of non-labor operating expense to net-fixed assets is 4.2. The average value of the population density in the country in which the MFIs operate is 71 people per square kilometer, and it varies from sparsely populated countries with 2 to very densely populated countries with 1,050 people per square kilometer. Financial depth is the ratio of money aggregate including currency, deposits and electronic currency (M3) over GDP and measures the level of financial development. It is 0.39 on average varying from 0.07 to 1.39. We see that 34 % of our MFIs serve urban markets only and an additional 38 % serve

[5] For a detailed comparison of this with other available datasets see Mersland (2009).

[6] Distribution of MFIs by country is presented in the "Appendix". Comparison with other publicly available data shows that these data have more observations from Latin America.

Table 1 Summary statistics of variables used in estimation

Variable	Mean	SD	Minimum	Maximum
Loans ($)	4,071,677	5,111,683	3,586	34,604,000
Savings ($)	914,669	3,060,310	0	23,954,000
Total cost	1,086,463	1,288,910	2,689	12,197,321
Average wage ($)	5,515.85	4,054.15	18.07	26,572.67
Cost of capital (ratio)	4.22	29.04	0.04	800.00
Cost of funds (%)	0.08	0.09	0.00	0.93
Population density	71.13	86.79	2	1,050
Financial depth	0.39	0.20	0.07	1.39
Market served				
Urban	0.34	–	0	1
Rural	0.14	–	0	1
Urban and rural	0.38	–	0	1
No information	0.14	–	0	1
Loan methods				
Village banks	0.16	–	0	1
Solidarity groups	0.21	–	0	1
Individual	0.58	–	0	1
Other	0.01	–	0	1
Unclassified	0.04	–	0	1

both urban and rural markets. Service mainly to rural markets is rare for the group of rated MFIs that compose our dataset. Additionally, we see that 58 % of our rated MFIs provide loans on an individual basis while another 21 % use solidarity groups to provide loan services.

The wide range in cost of capital is natural in an industry with lots of subsidized debt where some MFIs receive an abundance of subsidized debt while other MFIs do not. For example, Mersland et al. (2013) studied differences between Christian founded MFIs and secular MFIs and determined that the Christian MFIs had greater access to international networks which resulted in significantly lower funding costs. In particular, since the microfinance industry is international, but the level of internationalization varies substantially, differences in access to funding sources result in wider ranges of funding costs (Mersland et al. 2011). Another reason for the wide range in funding cost is that some countries have very generous and cheap public funding for MFIs. Moreover, some MFIs are allowed to mobilize savings, and interest paid on savings can differ substantially. Furthermore, some MFIs take mandatory savings on which they normally pay no interest. Taken together, the funding environment differs considerably resulting in the wide range in cost of capital for MFIs which appears in our data.[7]

[7] Differences in funding costs may also stem from differences in inflation across countries and different risk premiums. Inflation is, however, to a large extent taken care of in the dataset since all amounts are converted into US dollars.

It is the presence of MFIs with 0 savings that require us to eschew a traditional cost function approach to estimating scope economies and, in addition, the fact that some MFIs have zero input costs for funding implies that we must include input prices into our semiparametric smooth coefficient cost function in level form as well. The added generality afforded by our approach is key for analyzing these types of datasets as ad hoc approaches to dealing with zeros are unappealing in applied settings. Further, using level input prices as opposed to logarithmic prices is consistent with the theoretical cost function of Baumol et al. (1982).

Lastly, a natural concern one may have with our empirical results is that lending-only MFIs may self-select and this will drive the results on scope economies we detail here. We assume that there is no endogenous process of selection into deposit collecting for lending-only MFIs. MFIs vary by size so even institutions capable of collecting deposits may operate as lending-only if the local laws do not permit deposit collection by (small) MFIs. Many countries have adopted MFI-specific regulations allowing variations in lending and savings (so it is not necessarily the underlying cost structure that determines if an MFI collects deposits). For example, for a large cross-country sample, Hartarska et al. (2013) report that 63 % of the deposit-taking MFIs and 14 % of the lending-only MFIs were subject to central banking regulation. Hartarska and Nadolnyak (2007) allow for regulatory status to be correlated with MFI-specific characteristics and estimate a Hausmann-Taylor model of MFI performance but do not find a difference in outreach and sustainability by regulatory status. In a consequent article, Cull et al. (2011) observe that MFIs in the same country face different enforcement, and find that the stringency of the country prudential regulations (onsite visits and their frequency) do not affect financial results but affect the depth of outreach (poverty level of clients). Numerous other studies have found that regulation (presumably of mainly deposit-taking institutions) does not affect performance, and previous studies on the presence of scope economies for MFIs have assumed that there is no endogenous selection into deposit-taking MFIs (Mersland and Strøm 2009; Hartarska et al. 2010, 2011, 2013).

6 Results

For the model discussed in the previous section, we estimate both a parametric cost setup using nonlinear least squares following Pulley and Braunstein (1992) and a semi-parametric smooth coefficient cost function with two outputs and two input prices.[8] Input prices are scaled by the price of physical capital (price of capital ratio) to produce two relative input prices to be used in each piece of the cost function: labor costs and financial costs. Total costs and loans and deposits are scaled by 1,000,000 and 10,000,000, respectively. All results were computed using `R` (R Development Core Team 2008). Bandwidths and polynomial order for the semiparametric model were selected simultaneously via cross-validation over scope, discussed previously, using

[8] Since the cost function is homothetic in input prices, we can always normalize by one of the input prices. Thus, while we have three inputs, only two of them enter into our analysis.

Table 2 Scope economy measures summarized at the quartiles

	Overall scope	Diseconomies	Economies
Q1	0.0342 (0.0447)	−0.0046 (0.0154)	0.0430 (0.1184)
Q2	0.1476 (0.2203)	−0.0030 (0.0148)	0.1568 (2.1859)
Q3	0.4253 (0.4294)	−0.0017 (0.1145)	0.4353 (1.0951)

Standard errors for each estimate are given below in parentheses. Estimates obtained via nonlinear least squares estimation of the parametric cost function

5 multistarts.[9] In addition to normalized input prices entering the unknown smooth coefficients, we also included the year in which the MFI was observed and its region (see "Appendix" for country and region classifications), as well as the main type of lending methodology the MFI uses (village bank, solidarity group, individual loan), the main market the MFI services (urban, rural or both), the population density of the area in which the MFI operates, and the level of financial depth of the country. Given our ability to smooth discrete variables, year, loan methodology and main market served were all smoothed using discrete kernels (see Li and Racine 2007).

6.1 Parametric cost function

As a first cut, we estimate the parametric cost function proposed by Pulley and Braunstein (1992) using nonlinear least squares. Our estimates of scope economies are reported in Table 2 at the 25th, 50th, and 75th percentiles for overall scope economies, scope economies, and scope diseconomies. Our estimates are not statistically significant, but are qualitatively consistent with our expectations. For overall scope economies, the median estimate indicates that there is a 15 % reduction in costs from offering both loans and savings. We conjecture that one reason for the lack of statistical significance of our parametric estimates may be due to model misspecification, and turn next to our preferred semiparametric models.

6.2 Bandwidths and polynomial order

Before discussing our estimates of scope economies and their implications, we first discuss the bandwidths obtained via our cross-validation selection procedure since bandwidth and polynomial order selection is important for semiparametric estimation and forms the heart of generalized local polynomial regression estimation. Table 3 presents our cross-validated bandwidths and polynomial order for the regression model that includes and excludes our additional environmental variables (population density, financial depth, area, and lending method). Further, as discussed at length in Li and Racine (2007), cross-validated bandwidths have an important interpretation of their

[9] Multistarts are the number of different trials used to calculated the minimum of the least-squares cross-validation function. Given the nonlinearity of this function with respect to multiple bandwidths, it is good practice to use numerous multistarts to avoid obtaining bandwidths indicative of a local minimum as opposed to the global minimum.

Table 3 Bandwidths and degree of polynomial for our semiparametric estimates

Variable	Including controls		Excluding controls		Cutoff
	Bandwidth	Polynomial	Bandwidth	Polynomial	
WL	0.5194	3	1.0824	2	3.0750
WF	0.9048	4	0.2863	3	5.3450
Pop. dens.	0.1743	3	–	–	2.4405
Fin. depth	0.6680	1	–	–	1.0221
Year	0.1683	–	0.3182	–	1.0000
Region	0.9422	–	0.5218	–	1.0000
Area	0.5940	–	–	–	1.0000
Method	0.3841	–	–	–	1.0000

Bandwidths and polynomial are selected via GLP LSCV as in (20)

own in an applied setting. In the local constant regression setting—i.e., when the order of polynomial is zero—bandwidths that are 'close' to their upper bounds are smoothed out of the regression model, meaning that they are irrelevant in terms of predicting the response variable. In the local polynomial context, bandwidths that are 'close' to their upper bounds enter the regression function globally of the same order of polynomial. For example, in a local linear setting (polynomial order 1), a variable with a bandwidth 'close' to its upper bound enters the regression globally linearly. For continuous variables, Li and Racine (2007) suggest that 2 standard deviations of the variable is an effective upper bound, while for discrete variables, the effective upper bound is unity. (Note that for discrete variables, the local constant interpretation of relevance/irrelevance always holds, regardless of the degree of local polynomial, because the local polynomial order is only with respect to continuous variables.)

For ease of reference, we have included our cutoffs for each variable in Table 3: twice the standard deviation for each continuous variable, and unity for each discrete variable. At first glance, two points are apparent. First, none of the bandwidths on our variables have reached their upper bounds. This insight tells us that all of the variables in our regression are relevant and/or local predictors of scope economies (recall that we select bandwidths over scope economies directly and not cost). This is particularly important for understanding the implied model specification selected by cross-validation. Omission of any of the variables in our set of controls likely leads to an omitted variables bias because our automatic cross-validation approach has demonstrated that each variable is important for prediction of scope economies. This is consistent with recent theoretical criticisms by Armedráriz and Szafarz (2010) who argue that environmental factors are important to account for in cross-country studies, and in contrast to Beck et al. (2008) who argue that variables utilized to measure financial sector development and financial depth, in particular, have low correlation with outreach in cross-country studies of banks. Moreover, any global specification that one might wish to impose (e.g., a standard linear, parametric cost structure) is likely to be misspecified because our cross-validation procedure has identified significant local nonlinearities and has assigned relatively 'small' bandwidths accordingly.

Table 4 Scope economy measures summarized at the quartiles

	Overall Scope		Diseconomies		Economies	
	Controls	No controls	Controls	No controls	Controls	No controls
Q1	**−0.0257**	0.0000	**−0.3584**	−0.3680	**0.0795**	0.0780
	(0.0104)	(0.0000)	(0.0949)	(0.1975)	(0.0211)	(0.0621)
Q2	**0.0961**	**0.1040**	**−0.1300**	−0.1534	**0.2215**	**0.1848**
	(0.0007)	(0.0450)	(0.0131)	(0.0954)	(0.0599)	(0.0570)
Q3	0.3523	**0.3243**	−0.0497	**−0.0496**	**0.4847**	**0.4127**
	(10.3081)	(0.0769)	(0.0434)	(0.0000)	(0.0593)	(0.0879)

Standard errors for each estimate are given below in parentheses. Statistically significant scope estimates at the 5 % level are highlighted in bold. Estimates obtained via (1) with the SPSCM model described in (10). Bandwidths are those displayed in Table 3

Second, except for financial depth in our model with full controls, the orders of polynomial on the continuous variables are greater than one. This second insight tells us that the commonly imposed orders of local polynomial in standard nonparametric local polynomial kernel regression—local constant (order 0) and local linear (order 1)—do not provide the best fit for scope economies estimation in the context of this data. Indeed, Hall and Racine (2013) have shown that the generalized local polynomial procedure may obtain a faster rate of convergence and higher degree of efficiency, compared to both local constant and local linear nonparametric regression estimators. Our cross-validation procedure suggests that these standard nonparametric models may not be efficient. We mention here that the work of Hartarska et al. (2011) uses only a local constant estimator.

Finally, we point out that the bandwidth on region is substantially larger in our setup with additional controls than in our setup with limited controls (0.9422 and 0.5218). We cautiously interpret a bandwidth of 0.94 for a discrete variable to indicate that this variable has limited relevance (it is not quite at its upper bound). This indicates that in our limited controls setup, our estimates rely more on the generality of a regional indicator to absorb much of the variation in scope economies that is not explained by other controls. Our inclusion of additional control variables accounts for this variation, decreasing our reliance on our regional indicator.

6.3 Scope economies

Our estimates of scope economies and their standard errors are summarized in Table 4, also at the 25th, 50th (median) and 75th percentiles. We find scope economies in microfinance institutions indicating substantial cost savings from mobilizing deposits and extending loans instead of only extending loans (assuming of course that the same cost structure of the MFIs are preserved). The results suggest that MFIs achieve substantial reductions in costs by offering both savings and loans to their customer base.

Looking at the median estimates of scope economies, we see that regardless of whether environmental factors are included, there is a 10 % reduction in costs from offering both loans and savings. We find that there is not much difference in scope estimates at the quartiles across both controls and limited controls specifications. We find that inclusion of our controls leads to a negative estimate of scope at the lower quartile, and a slightly higher estimate at the upper quartile. We find that in both models, scope economies are generally statistically significant at a 5 % confidence level. Furthermore, it is apparent that our estimates of scope are more heterogeneous in the model with full set of controls. These results indicate that there is heterogeneity induced by our additional set of control variables.

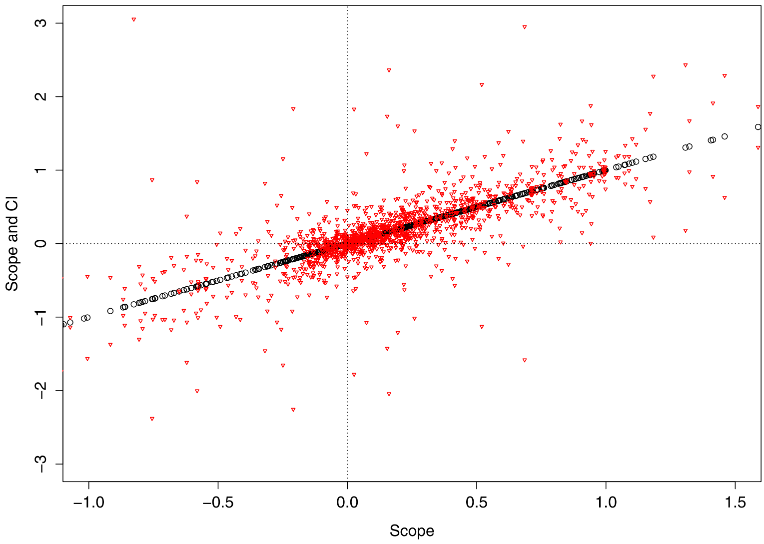
Focusing on scope diseconomies, we see that the MFIs with estimated scope diseconomies have slightly lower levels of diseconomies when we account for our environmental controls. The median estimated scope diseconomies is -0.13, while the median scope diseconomies for our model without controls is -0.15. The interquartile range is slightly smaller. In general, however, these differences across set of controls are not large enough to statistically distinguish between scope diseconomies in each model. Notice that for our diseconomies estimates, we do not find as much statistical significance in the model excluding our additional controls as in the full controls specification.[10]

Considering only those MFIs with scope economies, we see that our summary measures are higher in the model with controls than our model without controls. Further, we find significance at each reported quartile, while our estimates without full controls are only significant at the 50th and 75th percentiles. The statistical significance, as well as relatively larger magnitude of scope economies estimates in the full controls model suggest that our control variables have a strong influence on the scope economies of MFIs; such heterogeneity we explore in the following subsections.

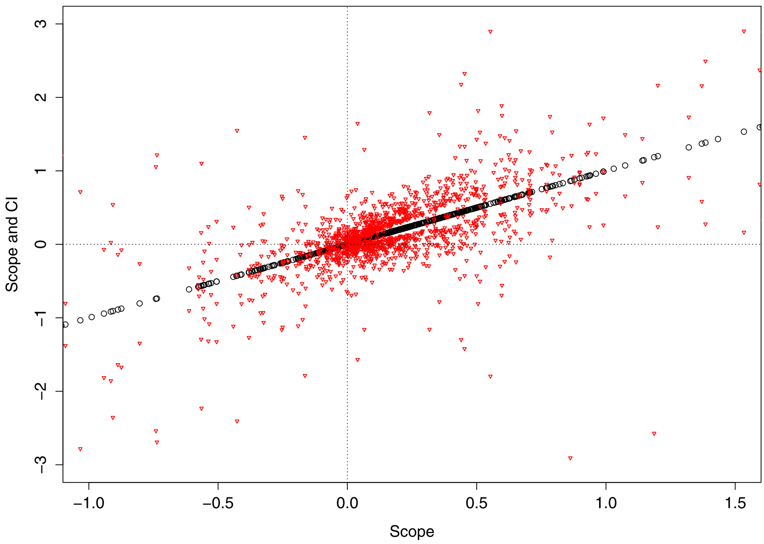
We now turn to statistical significance of our scope estimates, presented concisely in Fig. 1. To show statistical significance of observation-specific estimates in nonlinear regression models, Henderson et al. (2012) propose using 45° gradient plots to simultaneously show the sign, significance, and distribution of estimates. We construct these plots by placing the estimates of scope economies on the 45° line, and then overlaying a 95 % bootstrap confidence interval above and below each estimate. Since our estimates and standard errors are observation-specific, we have an observation-specific confidence interval. Then, if for any observation, the horizontal line at zero lies outside of the confidence interval that estimate is statistically significant.

We see that most of our estimates for both specifications are positive and significant, suggesting that in general MFIs realize positive and significant reductions in cost from offering both loans and savings. We further see that the distribution of scope estimates

[10] We note that with the use of flexible estimation methods that theoretical consistency may be sacrificed. In our case, this entails the estimated cost function satisfying given axioms of producer theory, notably monotonicity of the cost function in both outputs, loans and deposits. The percentage of observations where our estimated cost function is non-monotonic for loans is 6.7 % when we include controls and roughly 3 % with no controls. However, for deposits, across both models roughly 50 % of the estimated cost function derivatives are negative. What drives this behavior is a single, smooth coefficient term which dominates the expression—the interaction between loans and deposits. The coefficient on this term is largely negative, and when multiplied by the amount of loans in the derivative of cost w.r.t. deposits, we have a largely negative term. This matters because many other terms in this derivative are zero, since deposits is mostly zero for almost 75 % of the observations. While this is certainly an important issue to explore, we leave it for future research to combine the approach detailed here with constrained nonparametric methods.



(a)



(b)

Fig. 1 Statistical significance of scope economies. **a** 45° gradient plots for scope economies with controls, **b** 45° gradient plots for scope economies with no controls

varies substantially, with a substantial portion of our estimates exceeding 0.5. The distribution of diseconomies is relatively sparse over the range $(-1, 0)$, and it is also clear that there is a group of observations with small scope estimates that are not statistically significant. We find statistical significance of scope economies in both sets of estimates, however, as indicated by our quartile summaries of scope estimates,

Table 5 Summary of scope economies by output structure at each quartile

	Including controls		Excluding controls	
	Loans	Savings and loans	Loans	Savings and loans
Q1	**−0.0270**	**−0.0246**	0.0000	−0.0037
	(0.0007)	(0.0045)	(0.0000)	(0.0501)
Q2	**0.0881**	**0.1353**	0.0929	0.1800
	(0.0003)	(0.0301)	(0.1438)	(0.1073)
Q3	**0.3166**	**0.4744**	0.2611	0.5332
	(0.0275)	(0.1350)	(0.1856)	(0.4209)

Standard errors given below each estimate. Statistically significant estimates at the 5 % level are highlighted in bold

we find a larger share of estimates are significant in the specification with full controls. Specifically, we find that 65 % of our scope estimates are statistically significant in the full controls specification, whereas only 45 % are significant in the model without additional controls. We point out that regardless of our set of controls, both sets of controls allow for general unknown forms of heterogeneity in the scope estimates.[11] Hence, our results are consistent with the cautionary tone expressed in the theoretical paper of Armedráriz and Szafarz (2010) and the empirical work of Ahlin et al. (2011) showing that cross-country studies should account for the environment in which they operate.

6.4 Scope economies across output structure

In Table 5, scope economies in MFIs which actually provide loans and savings facilities are compared with those in MFIs which only lend. We find that regardless of which set of control variables we use, MFIs that offer both savings and loans have substantially higher scope economies than MFIs that only offer loans. It is important to point out that, at the quartiles, we do not find any statistical significance of our scope estimates in the model without controls, but we do find statistical significance for each of our estimates in the model with full controls. These results are intuitive and indicate that these additional variables are important factors in the cost function of different MFIs—omission of which will lead to an omitted variables bias in our estimates of scope economies.

Given the magnitudes of our bandwidths when we include control variables in our smooth coefficients of our cost function, statistical significance, and the visual evidence provided by the distributional plots, we choose to more carefully analyze

[11] We also considered augmented variants of the 45° plots presented in Fig. 1 that differentiate between institutions in our sample that offer only loans and those that jointly offer savings and loans, to assess whether there are large distributional differences between scope estimates across these groups. We omit these plots since we were not able to identify distinct differences across the scope estimate distributions across these two groups. Note that this merely indicates that the heterogeneity we identify in our estimates of scope economies affects scope economies across these two groups similarly.

Table 6 Scope economy measures across regions, summarized at the quartiles

	ECA	LA	SSA	SEA	MENA
Q1	**−0.0325**	**−0.0592**	0.0519	**0.0615**	**−0.0287**
	(0.0007)	(0.0238)	(0.0764)	(0.0076)	(0.0078)
Q2	**0.0795**	0.0772	**0.2409**	**0.2958**	**0.0315**
	(0.0211)	(0.0524)	(0.0516)	(0.0609)	(0.0052)
Q3	**0.2648**	**0.3056**	**0.7005**	**0.6333**	**0.2334**
	(0.0305)	(0.0402)	(0.0111)	(0.0270)	(0.0539)

Standard errors for each estimate are below in parentheses; statistical significance at the 5 % level are highlighted in bold

scope economies estimated via inclusion of these variables directly into the smooth coefficients. All three of our key discrete variables—region, area and lending method—are not smoothed out of our model and therefore suggest an impact on the smooth coefficients of our cost function and consequently our estimates of scope economies.

6.5 Scope economies across control variables

Given the fact that nonparametric models deliver estimates which are observation-specific, an intuitive way to present results is to condition on specific levels of the variables of interest. To that end, we present our estimates of scope economies here by focusing on how they vary across three of our most important controls, the region the MFI is located, the area in which the MFI provides services, and the type of loan structure the MFI uses.

Scope economies are larger in countries with higher population density. For example, countries with scope diseconomies have average population densities of 47 persons per square km, while it is 81 persons per square km in countries with scope economies. This result seems to suggest that MFI's working in less densely populated countries will have (or experience) diseconomies of scope. Here, MFIs may not have a consumer base large enough to provide savings accounts as well as lending opportunities. Recall, the presence of scope economies is such that cost sharing is available to the MFI via a product mix. In this case, it could turn out that MFIs in rural areas are not able to experience these cost-sharing opportunities the way that MFIs in more urban and population dense areas are.

Focusing on the regions where our MFIs operate, Table 6 presents quartile summaries of estimated scope economies based on our regional definitions (see "Appendix" for specific countries and regions), and Fig. 2 contains a 3-dimensional plot of the joint density of scope economies and region. In general, our scope estimates are statistically significant in each region. We observe from the table that the highest scope economies are realized within Sub-Saharan Africa (SSA) and South East Asia (SEA), and further note that in these regions, there are no MFIs with diseconomies of scope (at least at the quartiles). MFIs in Eastern Europe and Central Asia (ECA), Latin America (LA), and the Middle East and Central Africa (MENA) have scope economies

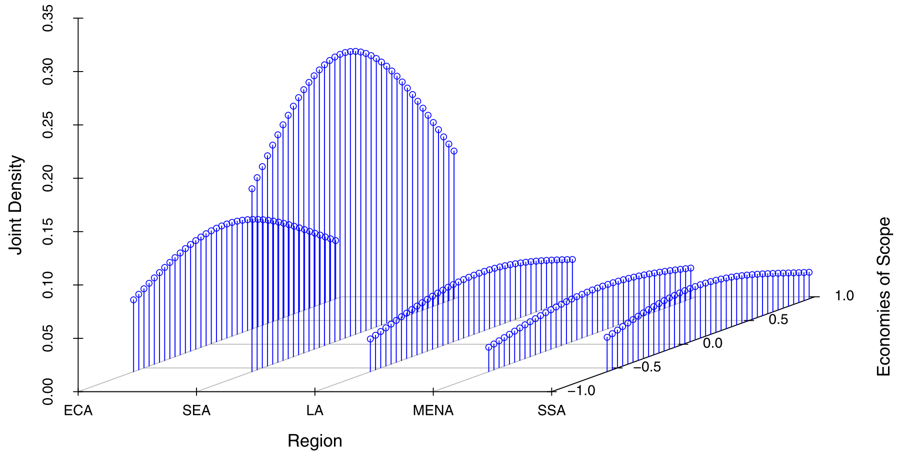


Fig. 2 Joint density plots for scope economies based on region

Table 7 Summary of scope economies by main market served and lending method for each quartile

	Main market served			Lending method		
	Urban	Rural	Both	Village	Solidarity	Individual
Q1	−0.0440	0.0089	**−0.0169**	−0.0007	0.0061	**−0.0556**
	(0.0256)	(0.0211)	(0.0010)	(0.2265)	(0.0113)	(0.0238)
Q2	**0.0832**	**0.1586**	0.0805	**0.1915**	0.1867	0.0411
	(0.0002)	(0.0388)	(0.0653)	(0.0433)	(0.2089)	(0.1525)
Q3	0.3165	**0.4386**	0.2772	0.5894	0.4635	**0.2332**
	(0.2308)	(0.1136)	(0.1924)	(0.3941)	(0.3508)	(0.0353)

Standard errors are given in parentheses below each estimate. Statistically significant estimates at the 5 % level are highlighted in bold

of smaller magnitude and have some observations with diseconomies of scope. Figure 2 shows us that these regions also have different shaped distributions of scope economies. The distribution plot for SEA is highly bell-shaped, while other regions are more uniformly distributed. We point out that at the median and upper quartile, every region has economies of scope from both savings and lending. Our results indicate, however, the extent of cost savings for MFIs varies considerably across regions, with the highest cost savings being in SSA and SEA.

Scope economies in MFIs targeting mainly urban markets are, at the median, 8 %, in those serving predominantly rural markets are 16 %, and those without clear specialization are at 8 % but insignificant (Table 7). MFIs using both village banking and solidarity lending exhibit the largest median economies of 19 %, but the scope estimate for the solidarity group is not significant. Those providing individual loans have the lowest median scope economies of 4 %. These results are consistent with our urban/rural division of scope economies: most villages are located in rural areas, both of which showing the highest median scope economies. Thus, within the group-

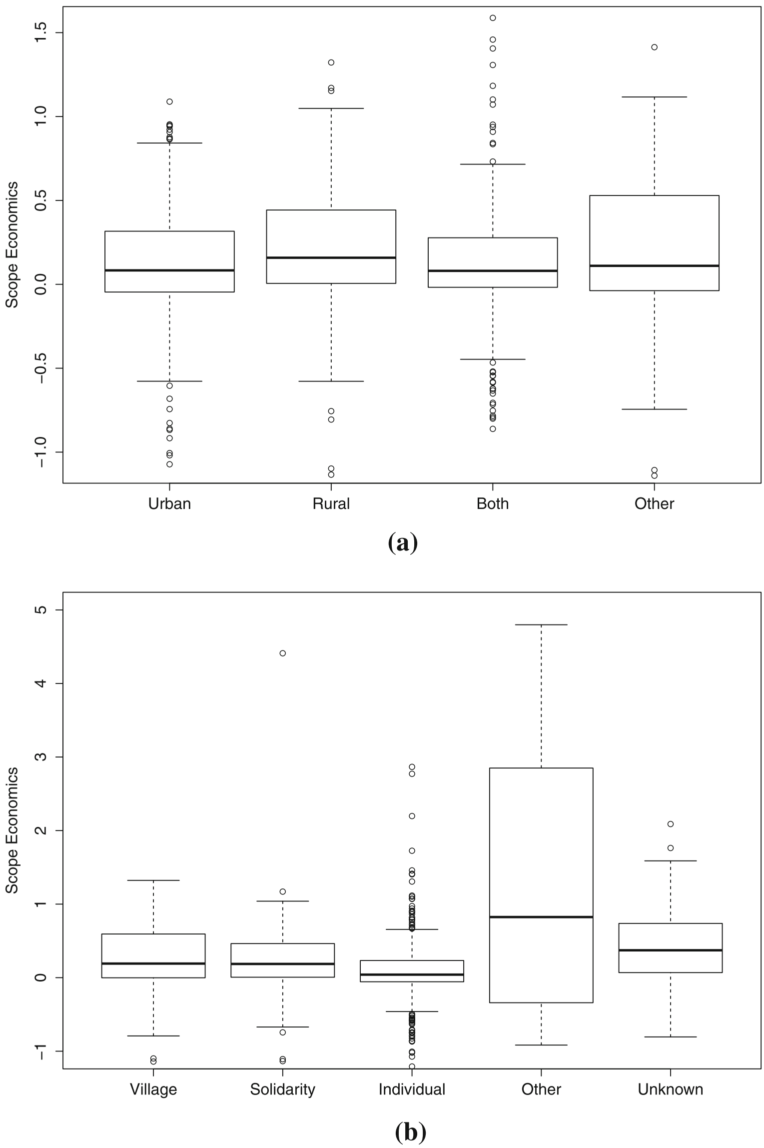


Fig. 3 Boxplots for scope economies based on service area and loan method. **a** Scope economies by service area. **b** Scope economies by loan method

lending methodologies, village banks are more likely to be cost effective in mobilizing deposits. We believe this is because in village banking the MFI has a captured audience with whom credit officers can relate to and understand.

We present visual evidence of these estimates in Fig. 3 where we plot boxplots of our estimated scope economies over the area of service (panel (a)) and type of loan (panel (b)), respectively. It is clear from the plots that the distributions of scope estimates over each of these different groups varies substantially; not only do these distributions have different central tendencies and interquartile ranges, it is clear that several of these distributions are asymmetric. The top panel in the figure shows that the rural areas generally have a higher estimate of scope economies, as does the village banking group in the bottom panel.

6.6 Quasi economies of scope

So far, our analysis has focused on the standard scope economies estimate based on Eq. (1). As pointed out by Pulley and Braunstein (1992), this measure assumes that each firm perfectly specializes, which may not be reflected empirically by the data. As a robustness check of our primary scope estimates, we focus on the subsample of firms in our dataset (178 observations) that jointly produce both savings and loans and estimate quasi economies of scope defined in Eq. (2).[12] We follow our earlier econometric strategy and deploy the generalized local polynomial estimator for the smooth coefficient cost function, with bandwidths selected by smoothing over quasi scope. We assume the degree of specialization of each firm is $(1 - \epsilon) = 0.85$.

Our restricted sample of microfinance institutions of 178 observations renders semi-parametric estimation with the full set of environmental variables infeasible because of dimensionality issues relative to the small sample size. We therefore focus on the restricted set of environmental controls, namely the cost of labor and financial capital inputs, year and region. Before reporting summaries of our estimates of quasi economies of scope, we report that our bandwidths on each of our nonparametric variables lie below their respective upper bounds, indicating that each variable is both relevant and a nonlinear predictor of heterogeneity in the cost coefficient functions. Further, our generalized local polynomial optimization results indicate that the optimal order of local polynomial for both continuously distributed nonparametric environmental variables is of order 3. As in our scope economies estimates, we find evidence that the standard local constant or local linear estimators are not of optimal polynomial order for constructing our estimate of quasi-scope economies.

Table 8 reports quartile summaries of the quasi economies of scope estimates. We see that our estimates of quasi economies of scope are slightly larger in magnitude than our estimates of scope economies reported previously, with a median effect of approximately 0.12. It is apparent, however, that the upper quartile of quasi-scope is substantially higher than for scope. This suggests that the distribution of quasi-scope economies is left skewed. Notice that while we find some evidence of diseconomies of scope for a subset of observations, none of these diseconomies estimates are statistically significant at any of the reported quartiles of diseconomies of scope.

Figure 4 shows the joint density plot between regions and quasi economies of scope. We see that the distribution of quasi economies of scope is indeed left skewed, as suggested by the quartiles reported in Table 8. Notice that this skewed shaped dis-

[12] As a comparison, we consider our standard scope measure for only this subset of 178 countries and find that, while there is a wider interquartile range of our estimates, the qualitative conclusion from our main results is unchanged.

Table 8 Quasi-scope economy measures summarized at the quartiles

	Scope	Diseconomies	Economies
Q1	**−0.1217**	−0.5429	0.2284
	(0.0053)	(0.4510)	(0.2509)
Q2	0.1167	−0.1955	**0.7877**
	(0.1465)	(0.1582)	(0.3986)
Q3	**0.9694**	−0.0740	**1.4835**
	(0.2704)	(0.1450)	(0.3133)

Standard errors for each estimate are given below in parentheses. Statistically significant scope estimates at the 5 % level are highlighted in bold

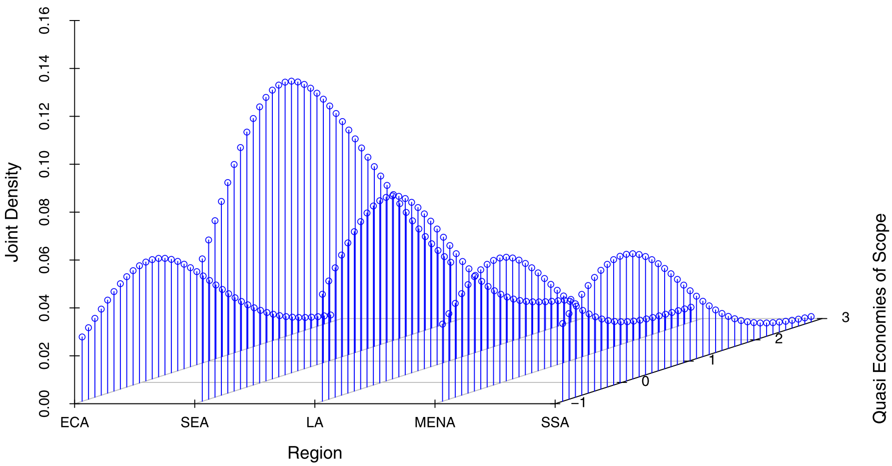


Fig. 4 Joint density plots for quasi-scope economies based on region

tribution of quasi-scope estimates is substantially different from the distribution of scope estimates reported previously for our standard scope economies measure.

While we do find some differences between our estimates of quasi economies of scope and the standard economies of scope reported as our primary results, the qualitative conclusion across both scope measures is the same. At the median, we find evidence that specialization in both savings and loans lead to reductions in costs of about 10 %.

6.7 Economies of scale

We now turn to our estimates of economies of scale. Our reported estimates use the bandwidths selected by smoothing over scope. We also considered a complete set of results (scope and scale) estimated using generalized local polynomial bandwidths selected by smoothing over scale, but did not find much qualitative difference in any of our estimates compared to our results using the scope bandwidths. Table 9 contains a summary of economies of scale measured at each quartile, with observation-specific standard errors given below, for both cost models with and without full set of envi-

Table 9 Scale economy measures summarized at the quartiles

	Overall scale		Diseconomies		Economies	
	Controls	No controls	Controls	No controls	Controls	No controls
Q1	**0.5164**	**0.7666**	0.3373	0.4654	**1.2747**	**1.1923**
	(0.0601)	(0.2317)	(0.1980)	(0.3022)	(0.1610)	(0.3353)
Q2	**0.8940**	1.0585	**0.5584**	0.7319	**1.7627**	**1.4886**
	(0.0172)	(1.0355)	(0.0660)	(0.5207)	(0.1084)	(0.2594)
Q3	**1.5928**	**1.5684**	**0.7690**	**0.8660**	**2.8881**	2.2047
	(0.1308)	(0.1523)	(0.0159)	(0.1969)	(0.0090)	(2.9465)

Standard errors for each estimate are given below in parentheses. Statistically significant scale estimates at the 5 % level are highlighted in bold

ronmental controls. Recall that, in contrast to scope economies, diseconomies and economies of scale are defined by whether the scale estimates are less than or greater than unity, respectively.

We see that the median estimate of scale economies is 0.89 in the model with full controls, indicating that the median observation in our sample experiences diseconomies of scale. We find the median scale estimate in the model without full controls is 1.06, but is statistically insignificant. The interquartile range of scale economies for both models spans both diseconomies and economies of scale. Focusing exclusively on diseconomies and economies of scale, it is worth noting that we do not find large differences in interquartile range across the controls and no controls specifications. We do find more statistical significance in the model with full set of controls.

To understand the relationship between both scope and scale economies, Fig. 5 plots the joint distribution of scale and scope economies for the full controls model (the same plot for the no controls model looks virtually identical). It is clear from the figure that nearly all of the scale estimates are positive, but that the mode is just below unity, suggesting that a majority of the institutions in our sample experience diseconomies of scale. It is also clear, as was shown in previous plots, that the majority of our observations have economies from scope (i.e., scope is greater than zero). Combined, this puts the mode of this joint distribution just below unity on the scale axis, and just above zero on the scope axis. In other words, the majority of the institutions in our sample exhibit economies of scope, but diseconomies of scale. It is worth recognizing that there is a large part of the joint density that exhibits economies of scope, and either increasing or constant returns to scale (scale equals unity). It is also interesting to note that nearly every observation with diseconomies of scope also shows diseconomies of scale.

While it may be unexpected that we find a large number of microfinance institutions that have diseconomies of scope, suggesting that they are too large, this result should be taken in the broader context of our analysis that suggests accounting for both deposits and loans. Other studies which pay attention to purely the loan side of microfinance can be criticized for ignoring this aspect.[13] From Table 9 we see that nearly all firms

[13] It is also worth noting that most of these studies measure output by the number of active borrowers (or clients), while we use the volume of loans and deposits.

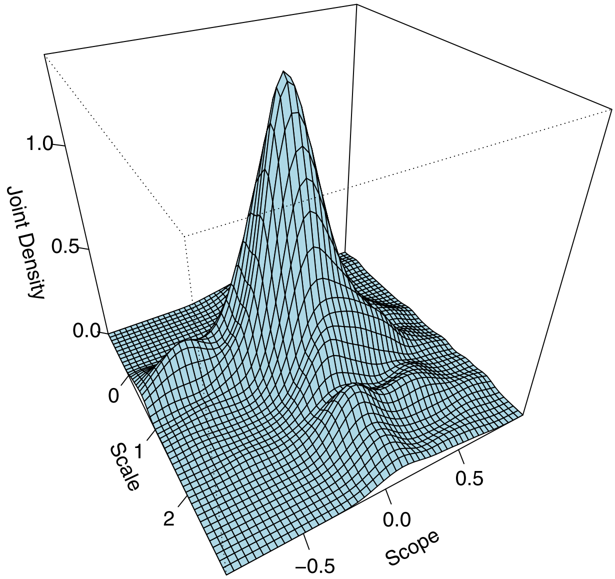


Fig. 5 Joint density of scale and scope economies

with estimated economies of scope have increasing returns to scale, suggesting they should continue (or begin) to offer deposits and increasing their operations. With the operating environment controlled for, these estimates of economies of scale are statistically significant. It is also interesting that those firms with estimated diseconomies of scope have estimated decreasing scale economies, suggesting scaling back operations.

7 Conclusions

Economies of scope of lending and mobilizing deposits in banking are justified theoretically (Diamond 1984), and policy makers recommend MFIs offer savings alongside credit. However, in microfinance, the existence and magnitude of scope economies of providing both loans and savings products has not been sufficiently investigated. We use a semiparametric smooth coefficient model to estimate these economies using a dataset put together from rated MFIs with 777 annual observations from MFIs across the world. This semiparametric model affords the researcher sufficient flexibility in incorporating zero-valued input prices and outputs into the cost function without resorting to ad hoc data replacement techniques. This is important because many MFIs offer only loans, and there is a need to know how transition to loans and savings could affect MFIs.

Our interest in scope economies provides two important challenges for implementing our semiparametric model. First, since scope economies are not observed, it is not clear that the bandwidths chosen to be optimal for cost function estimation are also optimal for scope estimation. Second, it is not *a priori* clear which degree of polynomial is most efficient when implementing a semiparametric local polynomial estimator to estimate our semiparametric model of economies of scope. We address these issues simultaneously by combining two novel econometric approaches: a generalized local polynomial estimator that allows both the bandwidth and degree of polynomial to be selected via data-driven cross-validation, and a cross-validation method that allows for bandwidth selection over an unobserved measurement. We point out that (i) neither of these methods have been used empirically; (ii) these methods have never been used simultaneously; and (iii) these methods have never been considered in a semiparametric regression context.

We estimate two models of scope economies, one where only variables typically used in a cost function approach are included (total cost, output values, and relative input prices) and a model where in addition to these variables we include population density, a measure of financial sector development, type of market served (urban, rural or both), and the predominant loan methodology (village banking, solidarity groups and individual loans), as well as controls for time and region. We find that scope economies are substantial across both settings and, for either model, that most of the MFIs in our dataset have (or would) experience reductions in cost by offering both savings and loan services. We find that our estimates of scope economies are generally more significant when we include the full set of environmental variables, and that while most of our observations exhibit economies of scope, the modal observation also exhibits diseconomies of scale.

Overall, our finding of scope economies is intuitive and relevant. In tumultuous financial markets, the finding that MFIs mobilizing local savings may not only provide much needed services for the poor but may also have cost advantages is important. This suggests that agencies providing funding to MFIs could encourage both microsavings and microloan services be offered. This requires increased attention on creating a regulatory environment allowing MFIs to accept deposits, or strengthening the MFI and maybe even donor support for them to become licensed deposit mobilizing institutions. However, since around 25 % of MFIs experience diseconomies of scope, largely stemming from environmental factors, the implication for policy makers is that general recommendations should be avoided. More research is needed to understand microfinance regulations, the costs and benefits involved and what type of regulation is actually needed for the mobilization of microsavings. For example, in the environments where MFIs operate, could there be other governance mechanisms that would protect the depositors as well as a public regulator? Future work on scope economies in microfinance should attempt to obtain a more comprehensive data set for MFIs and determine if other environmental variables are relevant in MFIs' cost structures.

Appendix

Distribution of MFIs by country is presented in Table 10. Comparison with other publicly available data shows that these data have more observations from Latin America, perhaps because they needed external funds.

Table 10 Distribution of MFIs by region and country

Country	# Obs.	% Obs.	Country	# Obs.	% Obs.
Eastern Europe and Central Asia (ECA)					
Albania	10	1.29	Kazakhstan	9	1.16
Armenia	4	0.51	Kyrgyzstan	8	1.03
Azerbaijan	16	2.06	Moldova	8	1.03
Bosnia and Herzegovina	39	5.02	Romania	3	0.39
Bulgaria	4	0.51	Russia	30	3.86
Georgia	13	1.67	Tajikistan	11	1.42
Latin America (LA)					
Argentina	3	0.39	Guatemala	16	2.06
Bolivia	53	6.82	Haiti	3	0.39
Brazil	36	4.63	Honduras	22	2.83
Chile	3	0.39	Mexico	55	7.08
Colombia	22	2.83	Nicaragua	28	3.60
Dominican Republic	14	1.80	Paraguay	4	0.51
Ecuador	51	6.56	Peru	98	12.61
El Salvador	11	1.42			
Sub-Saharan Africa (SSA)					
Benin	11	1.42	Mozambique	3	0.39
Burkina Faso	5	0.64	Senegal	8	1.03
Cameroon	9	1.16	South Africa	3	0.39
Ghana	5	0.64	Tanzania	3	0.39
Kenya	13	1.67	Togo	1	0.13
Madagascar	3	0.39	Uganda	12	1.54
Mali	3	0.39	Zambia	3	0.39
Southeast Asia (SEA)					
Bangladesh	1	0.13	Indonesia	1	0.13
Cambodia	11	1.42	Mongolia	5	0.64
India	29	3.73	Philippines	10	1.29
Middle East and North Africa (MENA)					
Chad	2	0.26	Jordan	9	1.16
Egypt	14	1.80	Morocco	12	1.54
Ethiopia	24	3.09	Tunisia	3	0.39

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