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Is the model "loans-plus-savings" better for microfinance in ECA? A PSM comparison

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Microfinance institutions are gradually evolving into multi-service organizations offering not only loans but also savings, and other financial and non-financial services. Both in practice and in academic writing, savings is gaining interest in microfinance programs, and is becoming a significant part of MFIs' service portfolio. The current evolution of microfinance leads the MFIs to diversify their portfolios to better meet their clients' needs as well as to benefit from economies of scope. We contribute to the literature aimed at identifying how combining credit with savings affects outreach and sustainability in microfinance institutions (MFIs). We apply the propensity score matching (PSM) method as well as its augmented dose response version to compare the performance of loans-plus-savings MFIs to that of lending-only in a sample of 710 observations from Eastern Europe and Central Asia (ECA). We use new panel data from MFIs operating in the ECA region during the 2005 -2009 period. Owing to our unique capital structure data, we control for the use of subsidized capital, which related work ignores while recent evidence points to tradeoffs between subsidies and savings (Cozarenco et al., 2016). We find that financial performance and breadth of outreach are positively associated with savings mobilization, while the evidence on depth of outreach points to a possible mission drift. In the light of the ongoing debate on the "mission drift" (Armendariz and Szafarz, 2011) which creates new forms of exclusion, this question is important for policymakers, practitioners and scholars. We also note that in most countries in the region, only regulated financial institutions are allowed to mobilize savings, suggesting difficulties in overcoming entry barriers to becoming deposit-collecting MFI.

We contribute to the literature by using PSM approach to establish if in the ECA region savings collection by MFIs improves financial sustainability and credit outreach and thus strengthens the case for continuing the trend toward commercialization that is taking place across the industry. Another major contribution is our ability to control for the role of subsidy, which has not been previously considered.

The empirical results clearly show advantages (better financial results and breadth of outreaches) and disadvantages (mission drift since depth of outreach suffers) for a sample of MFIs in the Eastern Europe and Central Asia region. Further research could use a larger sample of institutions from different regions of the world or a worldwide sample of MFIs for which the capital structure variables including subsidies (donations, nonconventional loans, in-kind payments, subsidized interest loans etc). Further research could also recognize the diversity of the savings products. Moreover, since other work has found that around 25 percent of MFIs experience diseconomies of scope, largely stemming from environmental factors, more research is needed to understand the role of microfinance regulations.

Keywords: Microfinance institutions, savings, economies of scope, propensity score matching
JEL: G21, F30, O16

1. Introduction

Microfinance Institutions (MFIs) emerged as an economic and social development mechanism in Eastern Europe and Central Asia (ECA) a little more than two decades ago. The MFIs have changed their focus from small-scale credit-only services to the provision of multiple financial services such as collecting savings, and related remittances payment facility, insurance etc. The challenge for the industry is no longer only about making loan products accessible, but about responding to a wider variety of clients' needs and offering more inclusive and flexible financial products and, in particular, savings. This paper uses Propensity Scored Matching (PSM) approach to evaluate if the trend toward diversification and multiple-services and the combination of loans with savings has been associated with improvements in the financial results and outreach of MFIs in ECA region.
Previous work attributes improvements in MFIs productivity to economies of scope in savings-collecting MFIs, providing evidence for lower costs when small scale loans are combined with small scale savings (Hartarska et al., 2010; Delgado et al., 2015; Malikov and Hartarska, 2017).
Recent study of Lensink et al. (2017) examines the impact of combined financial and nonfinancial services (so called microfinance 'plus') on the performance of MFIs. The authors find that the provision of social services is associated with improved loan quality and greater depth of outreach. Similarly empirical work suggests that the poor savers and borrowers may be two different groups, and that scope economies arise from sharing physical infrastructure, and not from sharing of information from micro-borrowers to improve savings product design and vice versa (Hartarska, Parmeter and Nadolnyak, 2011). Thus, more underserved clients – both borrowers and savers - may be reached as a result of the joint provision of loans and savings. Yet, this work does not show if serving more client (borrowers and savers) may be at the expense of reaching fewer poor and larger number of wealthier borrowers. Our work contributes to filling in this gap. We use PSM approach to establish if in the ECA region savings collection by MFIs improves financial sustainability and credit outreach and thus strengthens the case for continuing the trend toward commercialization that is taking place across the industry.
Another major contribution is our ability to control for the role of subsidy, which has not been previously considered. Yet, Cozarenco, Hudon and Szafarz (2016) find that savings crowds out subsidies because MFIs collecting voluntary savings (not only compulsory savings, which act as collateral for loans) receive fewer subsidies than their credit-only counterparts. Our detailed capital structure data allows us to control for the source of capital that the MFIs use (subsidized or not) and thus we are able to incorporate concerns not addressed explicitly in previous work[1].
Despite the general consensus on the need for savings, MFIs offering savings products are still under-studied. Moreover, there is a gap in the literature to assess the simultaneous impact of offering loans and savings on the MFIs financial (efficiency) and social (outreach) performance: depth and breadth. In the light of the ongoing debate on the "mission drift" (Armendariz and Szafarz, 2011) which creates new forms of exclusion, this question is important for policymakers, practitioners and scholars. The third contribution is to the discussion on mission drift by establishing differences in depth of credit outreach between savings-offering and loan-only MFIs.
We use data from MFIs operating in 19 countries in ECA region reported by individual MFIs in Microfinance Information Exchange (MIX) over five years. The capital structure variables are collected from a unique database provided by a grass-root network Microfinance Centre (MFC) and available only for 2005-2009 period. We apply semi-parametric quasi-experimental (PSM), as well as dose-response function approaches to estimate the impact of offering savings on financial sustainability and credit outreach of MFIs. Estimation of dose-response function (Guardabascio and Ventura, 2014) provides an opportunity to take into account the continuous nature of treatment, which in our case is relative share of deposits. In both settings we use data on capital structure of MFIs, operations profile (age, outreach direction, profit status, risk profile) and country level macro data.
Our main findings suggest that the simultaneous delivery of loans and savings is associated with better financial performance measured by return on asset (ROA) by about 3 percentage points. We also find that MFIs offering savings service have over 5,000 more borrowers, likely due to scale economies. At the same time, those MFIs offering savings seem to focus more on richer borrowers (have lower depth of outreach, measured by the average loan size divided by the country's gross national income (GNI) per capita). These results support the ideas for mission drift for savings collecting MFIs in ECA region. We also note that in most countries in the region, only regulated financial institutions are allowed to mobilize savings, suggesting difficulties in overcoming entry barriers to becoming deposit-collecting MFI.
The rest of the manuscript is organized as follows. Section 2 sets the theoretical foundations. Section 3 describes the empirical methods and the data. Section 4 discusses the results and Section 5 offers concluding remarks and policy implications.

1. Scope Economies studies do not control for subsidy but use the actual cost of capital that managers face, while subsidy studies do not use comparable groups to evaluate credit outreach and financial returns impacts.

2. Relevant literature

Like banking, microfinance is a capital-intensive activity, and MFIs require sustained injections of capital for on-lending. One of the pioneering studies exploring whether combined microfinance services (loans plus savings or insurance) affects MFI performance measured by efficiency, productivity, sustainability or portfolio quality indicators was done by Rossel-Cambier (2012). The author applies a cross-sectional multiple regression analysis on data from 250 Latin American and Caribbean MFIs covering the fiscal year 2006. The findings suggest positive effects of both savings and insurance on the efficiency and productivity of MFIs that the author attributes to economies of scope, especially in a context of large and mature MFIs exhibiting organizational readiness to provide these services. However, the econometric approach used in this study does not address the issue of the possible endogenous choice to be a savings-offering institution, which may bias the OLS estimates.

One of the few recent studies with regard to the combined microfinance services and increase in performance is Delgado et al. (2015). It provides estimates of scope economies from the joint production of loans and savings for rated MFIs with 777 annual observations over 50 countries for the period up to 2006. The study uses a semiparametric smooth coefficient model and controls for both direct and indirect environmental factors. The results show scope economies in ECA region as well as evidence that economies of scope vary across the type of services and country in which the MFIs operate. Since the authors find that not all MFIs can deliver savings in a sustainable manner given the scope diseconomies, they argue that if delivery of savings is important from policy perspective, it should not be expected to be financially sustainable in every environment and for every MFI. Recent work by Malikov and Hartarska (2017) estimates endogenous scope economies in MFIs and finds that, on average, the microfinance industry largely exhibits invariance to scope, but finds regional differences and significant scale economies.

Cozarenco, Hudon and Szafarz (2016) study the characteristics of MFIs that collect voluntary savings. Using random-effect probit estimation on a dataset of 722 MFIs active over the 2005-2010 period, the authors find that the MFIs mobilizing savings received fewer subsidies than their credit-only counterparts. This means subsidies crowd-out savings products, thus allowing the authors to claim that donors may generate negative externalities on product diversification.

By nature MFIs are hybrid institutions with double bottom-line principle of poverty alleviation (social logic) and becoming self-sustainable (commercial logic). Within MFIs performance assessment, there is an ongoing debate on trade-off between efficiency and outreach dimensions of MFIs' performance, suggesting that financial success may come at the expense of serving fewer and less poor clients (known as "mission drift"). There is evidence confirming the existence of the "mission drift" (Cull et al., 2007 & 2009; Augsburg and Fouillet, 2010; Armendariz and Szafarz, 2011; Hermes et al., 2011; D'Espallier et al., 2017). Other scholars show that it is possible for MFIs to pursue this double logic and achieve success on both fronts (Gonzalez and Rosenberg, 2006; Schicks, 2007). Combining loans and savings may improve long term MFI organizational sustainability as savings allow to be less dependent on external loans (Armendariz and Morduch, 2010). At the same time, since the positive impact of saving products on clients' welfare is documented, MFIs collecting savings enhance their social mission to provide security and stability to clients (Karlan et al., 2014; Hirschland, 2005; Delgado et al., 2015).

D'Espallier et al. (2017) show that the institutional transformation of MFIs from NGO to commercial deposit collecting MFI, leads to a cut in their operational expenses and funding costs, and increase in their commercial debt leverage, deposits and average loan size. The latter is often taken as an indicator for mission drift. This allows us to assume that offering saving services might erode MFIs from their dual mission by not targeting less poor clients.

Therefore, we address this concern by evaluating whether combining loans with savings enhances MFIs performance by increasing their efficiency and outreach. Our focus is on MFIs in ECA during the period of 2005-2009. Our motivation is twofold: first, we have accessed to detailed data that include information on sources of external capital needed for such analysis. Such data is available only for this region and period. In addition, unlike previous work, we have data on two additional indirect types of subsidy – non-market interest rates loans and loans provided by social investors. Only few studies on microfinance performance include these categories. For instance, Caudill et al. (2009) show that subsidy-dependent MFIs are less efficient over time in contrast to MFIs using savings as loanable funds, while Caudill et al. (2012) argue that subsidies are associated with higher costs. Focusing on the ECA region Khachatryan, Hartarska and Grigoryan (2017) assess the link between MFI capital structure and performance and find that subsidies have an ambiguous effect on financial performance but argue that lack of subsidies may entail socially harmful consequences. Given our detailed data on subsidies, we are able to control for the efficiency of subsidized and unsubsidized MFIs when diversifying their product portfolio and offering loan services together with savings.

Second, we believe that the diversity of MFIs in the region and their institutional transformation provide an interesting ground to explore whether loan-and-savings offering improves their performance and whether that can be attributed to economies of scope.

3. Method: Propensity score matching approach

The PSM methodology can be applied in any evaluation study where it is possible to identify: (i) a treatment; (ii) a group of treated units, and (iii) a group of untreated units (Caliendo and Kopeinig, 2005). In the literature, it is well recognized that the estimate of a causal effect obtained by comparing a treatment group with a non-experimental comparison group could be biased because of problems such as self-selection or some systematic judgment by the researcher in selecting units to be assigned to the treatment.

We start by defining as a treatment the dummy variable, Ddeposit, which indicates whether a given MFI collects savings or not. As a robustness check, later we revisit this assumption and look at the continuous treatment effect. We consider a set of outcome variables that characterize the profitability, as well as social performance of MFIs. Our ultimate goal is to understand whether collecting savings has any significant impact on the parameters of MFI operations.

As a measure of MFI operational performance we use the standard indicator of Return on Assets (ROA). Here our assumption is that MFIs offering savings would be more profitable, as they are essentially providing wider variety of financial services. We account for the social performance by looking at two dimensions of outreach – the number of poor clients (breadth of outreach) and depth of outreach or how poor the clients are relative to the general population. First, in order to measure the breadth of outreach, or how many clients (borrowers) the MFIs reach, we use the total number of active borrowers. Next, we account for the poverty level of clients (depth of outreach) and use the ratio of the total average loan balance per borrower scaled by the gross national income (GNI) per capita. Adjusting the average loan size by GNI per capita normalizes the variable for different income levels found in different countries, thereby controlling for cross-country differences. This measure shows whether a MFI addresses the needs of the poorest or targets better-off clients because higher values indicate that MFI is providing smaller loans to poorer borrowers.

To estimate the propensity score we apply a set of variables related to MFI specific internal characteristics and macro level data. We consider only those variables that influence simultaneously the savings collection and the three outcome variables (Caliendo and Kopeinig, 2008). Since our sample is not very large, it is better to exclude variables that are weakly associated with the outcome, as the reduction of bias due to their inclusion is traded-off against the "noise" of treatment effect estimates (Garrido et al., 2014). In addition, limits on data availability dictate the choice of covariates to be used in propensity score estimation. We briefly discuss the variables applied in estimation of the propensity score.

First, we include a set of variables related to operations of MFIs that should be associated with their financial and social performance: debt-to-equity ratio as a measure of leverage; total assets (inflation adjusted), as an measure of size since larger MFIs are more cost-effective (Caudill et al., 2009; Hartarska et al 2013); and the ratio of administrative expenses to total assets, as cost efficiency measure. We adjust for asset quality and risk taking, using the standard portfolio at risk ratio (PAR) which is a measured percentage of loans overdue more than 30 days to total loans. This is needed because lower asset quality (e.g. higher nonperforming loan ratio) requires more resources to manage the higher risk (Hartarska, Nadolnyak and Shen, 2012). Finally, we control for gender focus by including the percentage of female borrowers. For many MFIs the female orientation has become a stated goal (Strom, D'Espallier and Mersland, 2014). Women may be regarded as riskier borrowers because of their limited repayment capacity (D'Espallier, Guérin, and Mersland 2011; Hermes, Lensink, and Meesters 2011). However, because women living in developing regions often have fewer opportunities to access financial services, they will be more inclined to exhibit higher repayment rates in order to continue to be financed (Hartarska, Nadolnyak, and Shen 2012; Van Tassel, 2004).

Second, we use a group of dummy variables to capture differences in regulation, profit orientation, experience of the organization and target market (Low-end, Broad, High-end and Small Business).[2, 3] Non-for profit organizations might be less focused on profitability and care more on the social performance, that is why we include a dummy for not-for-profit MFIs. MFI age is included because older, more experienced MFIs, may be more productive as efficiency is found to improve over time, at least in some MFIs (Caudill et al., 2009). With time the efficiency may improve due to better managerial and financial skills to mobilize savings as well as to extend loans. In some jurisdictions, non-banking MFIs are legally prohibited to collect savings. While we do not have hard data on such practices, when estimating the propensity score of deposit taking we include a dummy variable which separates the countries where none of the non-banking institutions of our sample is allowed to collect savings (country level deposit restrictions dummy).

Third, in the propensity score estimation we include MFI capital structure and its elements. A number of studies show that the capital structure affects the performance of MFIs (Bogan, 2012; Caudill et al., 2009; Khachatryan, Hartarska and Grigoryan, 2017). The capital structure is defined as the share of capital by each source of funds. The

2. MFI age is divided into the following three categories by the MIX: New (1 to 4 years), Young (5 to 8 years) and Mature (more than 8 years). Each type of age is presented by a dummy variable.

3. Target market dummy groups four different categories of MFIs based on the average balance of loans served: for international comparison, this balance is stated as a percentage of local income levels (GNI per capita).

capital structure elements are grouped into five categories: (1) shareholder equity, (2) grants, (3) retained earnings, (4) deposits, and (5) loans. Loans are further disaggregated into loans at subsidized interest rates or concessional loans, standard bank loans, and social investment loans (which involve "socially responsible" investment coming from both private and institutional social investor funding in the region, such as BlueOrchard, Oikocredit, and IFC).[4] The base group against which the categories are compared is equity. As noted previously, unlike other work, we control for subsidized financing (grants, concessional loans, and socially oriented investment) that might interfere with the overall performance of the organizations in terms of both outreach and financial results.

The last group of variables includes country-level macroeconomic indicators. Existing empirical work shows that external factors related to a country's macroeconomic environment, level of financial development, population density, and other indicators affect significantly the MFIs operations, and need to be accounted for. For example, lending to rural borrowers, which in the ECA region are perceived as borrowers without permanent employment and regular income or liquid assets, might be associated with higher risk and further increase of loan default probability in a country where the MFI is located (see Sheremenko, Escalante and Florkowski, 2017). We include a measure of the agricultural value added as percentage of GDP to control for the fact that borrowers engaged in agricultural production may be more reliable since they have fewer alternative sources of funds. Another competing argument is that MFIs perceive agriculture-related borrowers as farmers with a consistent employment, income, and marketable asset ownership. GDP growth is another important indicator of a country's macroeconomic context, which could affect borrowers' purchasing power and could be associated with their risk of default. Finally, the private credit bureaus coverage is important in terms of credit evaluation and portfolio management by MFIs. The existence of credit registers can reduce the extent of asymmetric information by making a borrower's credit history available to MFIs. The higher coverage can be associated with decrease in lending to high risk individuals, with poor repayment histories, defaults or bankruptcies.

3.1. Data

The data set includes 710 observations on MFIs in 19 countries from the ECA region reported by individual MFIs in Microfinance Information Exchange (MIX).[5] The capital structure variables are collected from a unique database provided by the MFC available only for 2005-2009 period. The data on country specific socio-economic characteristics comes from the World Development Indicators (WDI).[6] Table 1 presents the summary statistics for both outcome variables and MFI level independent variables applied in our estimations. Out of overall 710 MFI's included in the study 35 percent (which is about 210 MFIs) offer saving opportunities to their clients. At the same time only quarter of non-banking MFIs, which makes 615 MFIs in the sample, is involved in savings collection. Statistically significant difference in means is observed for both breadth and depth of outreach, but not for financial performance: savings offering MFIs have higher number of borrowers and at the same time larger average outstanding loan size. Tangible differences can be noted also in many of the control variables, in particular administrative expenses, experience of MFI as well as target market. These factors call for much attention in testing the balancing properties of the propensity score.

4. These funds are commercially priced and, in most cases, come from international microfinance investors. Microfinance investors are socially motivated to work with MFIs, but the contract conditions of their funding is usually commercial.
5. The sample includes the following countries classified in the ECA region by the MIX Market: Albania, Armenia, Azerbaijan, Bosnia and Herzegovina, Bulgaria, Georgia, Kazakhstan, Kyrgyzstan, Macedonia, Moldova, Mongolia, Montenegro, Poland, Romania, Russia, Serbia, Tajikistan, Ukraine and Uzbekistan.
6. The dollar-value figures in the dataset are in 2010 values.

Table 1. MFI Summary Statistics by savings collecting and lending only MFIs

	Savings collecting MFIs		Lending only MFIs		Difference in means
	Mean	St. dev.	Mean	St. dev.	(Savings minus No Savings)
Dependent Variables					
ROA(%)	2.68	8.73	3.43	8.87	-0.74
Number of Active Borrowers(#)	19,261	39,839	9,024	15,259	10,237***
Average Loan Balance/GNI (%)	182.23	322.19	91.81	146.67	90.42***
Independent Variables					
MFI Characteristics					
Debt/Equity(%)	5.39	10.18	3.08	4.95	2.32***
Total Assets (mln. USD)	107.49	212.30	16.72	26.52	90.78***
Admin Expense/Asset (%)	5.97	3.84	7.41	5.04	-1.44***
Portfolio At Risk>30 Days (%)	3.53	7.28	4.08	7.12	-0.54
Women Borrowers (%)	45.23	24.39	48.68	22.28	-3.45
Regulated Dummy	0.78	0.41	0.83	0.37	-0.05
For-Profit Dummy	0.68	0.47	0.45	0.50	0.23***
Deposit restrictions dummy	0.46	0.50	0.43	0.50	0.03
Capital Structure (shares of capital):					
Equity	26.43	22.28	38.68	26.48	-12.25***
Grants	3.16	11.43	9.57	14.20	-6.41***
Deposits	37.75	29.12	-	-	-
Retained earnings	3.13	5.46	7.75	8.53	-4.62***
Loans	29.53	24.26	43.99	29.42	-14.46***
Concessional loans	3.08	7.66	8.11	17.06	-5.03***
Bank loans	1.96	7.11	3.53	11.18	-1.58
Social investor loans	24.49	23.60	32.35	28.14	-7.86**
MFI Age categories (share)					
New	0.36	0.48	0.20	0.40	0.16***
Young	0.30	0.46	0.33	0.47	-0.03
Mature	0.34	0.47	0.47	0.50	-0.13***
Target Market categories					
Broad	0.57	0.50	0.72	0.45	-0.16***
Low-end	0.08	0.28	0.12	0.33	-0.04
High-end	0.14	0.34	0.08	0.27	0.06*
Unclassified	0.04	0.20	0.02	0.15	0.02
Small business	0.17	0.38	0.05	0.22	0.12***
Macro Indicators					
Private credit bureau coverage as % of adults	6.75	17.04	12.46	20.52	-5.72***
Rural population as % of total population	50.29	15.68	50.69	13.51	-0.41
Agriculture value added as % of GDP	15.16	8.08	13.53	7.91	1.63*
GDP growth annual %	6.95	6.17	6.84	7.44	0.11
Observations	250		460		710

Note: Difference significant at: *10%; **5%; ***1%.

4. Results

The variables described are used to estimate the propensity of collecting deposits. We apply the approach of Garrido et al. (2014) and Heinrich et al. (2010) which guarantees that the propensity score is balanced after matching, and that standard errors are properly estimated. In particular, we start by estimating propensity score of collecting savings, and make sure that balancing property is satisfied before matching. As suggested in the literature, we apply flexible functional form and include interactions of two categorical variables included in our set. This helps identify the set of covariates that ensures satisfactory balancing by blocks of estimated propensity score.[7]

Next we implement an intermediate nearest neighbor with replacement matching exercise with the purpose of ensuring covariates balance also after matching.[8]

One way to proceed could be to use bootstrapping but for matched data bootstrapping provides unreliable results; therefore we calculate the standard errors with the Abadie-Imbens (AI) method (Abadie and Imbens, 2011). Post-matching testing also enables to choose the method that achieves better matching as measured by pre- and post-matching standardized differences in means and variance ratios. Finally, we apply the matching method so that AI standard errors are reported as well.[9]

This multistage estimation approach provides robust evidence of treatment effect on treated MFIs. Table 2 summarizes the intermediate step of estimating propensity scores for our three outcome variables. We estimate three separate logit models for each for the variables for which we estimate the counterfactual because we have different number of observations with complete set of variables. For example, for the estimation of ROA, we only have 462 observations, but we have 492 for the other variables of interest. Thus, matched sample varies from 119 treated and 373 control MFIs (overall 492 observations for outcome variables: Active borrowers (#) and Average loan balance/GNI (%) to 98 treated and 364 control (overall 462 observations for outcome variable Return on Assets (%), see Table 2). The specification of propensity score model has been identified through iterative process aiming to guarantee satisfactory balancing properties among treated and control matched observations.

Table 2. Estimation of propensity score applied for matching (outcome variable – deposit taking), marginal effects of logit model

Explanatory Variables in the selection model	Sample used in ROA (%) estimation	Sample use in estimation for Active borrowers (#) and Average loan balance/GNI (%)
Log of Total Assets	-0.004	-0.001
Debt to Equity Ratio	0.007**	0.006
Portfolio at risk	-0.002	-0.002
Women borrowers	0.002	0.002
Profit status dummy	0.098**	0.112***
Deposit restrictions dummy	-0.246**	-0.232**
Regulation dummy	0.259**	0.197*
Social Investor Loans	-0.001	-0.001*
Grants	-0.001	-0.002*
Earnings	-0.003	-0.004**
Concessional loans	-0.004***	-0.005***
Bank loans	0.001	0.000
New	-0.016	-0.017
Young	-0.101**	-0.072

Explanatory Variables in the selection model	Sample used in ROA (%) estimation	Sample use in estimation for Active borrowers (#) and Average loan balance/GNI (%)
Broad	-0.074	-0.076
Low-end	-0.094	-0.073
High-end	-0.161**	-0.154**
Rural population share	-0.020	-0.061
Agriculture share in GDP	-0.015	-0.011
GDP growth	-0.004	-0.007**
Private credit bureau coverage	-0.001	-0.001
Year	-0.084***	-0.112***
Profit x Regulated	-0.009***	-0.008***
New x Country Deposit restrictions dummy	0.068	0.092
Country fixed effects	Yes	Yes
Number of observations	462	492
Pseudo R2	0.32	0.34

Note: * Significant at 10%; ** significant at 5%; *** significant at 1%.

7. -pscore- routine is applied at this stage.

8. We apply-psmatch2- and post estimation -pstest- commands (Leuven and Sianesi, 2003). Note that when reporting standard errors this routine explicitly states that it does not take into account that the propensity score is estimated.

9. -teffects- routing is applied at the final stage.

The results from this table do not have a direct impact on counterfactual, it is still revealing to consider some of the result. First, we notice that the estimated models have satisfactory fit as the R2 is about 0.32 and 0.34 respectively. Next we observe that MFIs that collect savings are about 10-11 percent more likely to be for-profit MFIs, 20-25 percent more likely to be regulated, and 23 percent less likely to be from a country where non-bank institutions do not mobilize savings, which is unsurprising given the regulatory environment that we describe for ECA region. While there is some evidence that savings-offering MFIs are more leveraged than those who do not offer savings, the magnitude is small - only the size percent - and the debt to asset coefficient is statistically significant in only one of the two logit regressions. In fact, the estimated marginal effects on the capital structure variables show that ten percentage-point increase of the concessional loans ratio within the capital structure is associated with about 4-5 percent lower probability of the MFI offering savings. Similarly, in one of the two specification (two of the three), ten percentage-point increase in the share of social investors in the capital structure is also associated with one percent lower probability that the MFI offers savings. These results are consistent with possible trade-off between collecting savings and soft loans discovered in Cozarenco et al. (2016).

The logit results also reveal that MFIs offering savings are 97 percent less likely to be of young (ranging from 5 to 8 years) age rather than mature MFIs (more than 8 years) suggesting that either MFIs are not likely to transform into savings-collecting MFIs but more likely they have started as savings mobilizing institutions. The results also reveal that MFIs targeting high-end clients (depth between 150 percent and 250 percent)[10] and less poor borrowers are 1.6 to 1.5 times less likely to offer savings relative to MFIs targeting small business (depth over 250 percent) base of borrowers. This may be due to the fact that savings taking MFIs with broader target group have advantages in reaching more clients via savings products, while MFIs targeting less poor entrepreneurs do not have to meet the savings needs of these customers in ECA region.

Table 3 shows the effect of collecting savings on outcome variables with standard errors calculated according to AI method. We apply nearest neighbor matching to 5 control observations. This is done in order to minimize the standardized differences in means (which should typically be less than 0.25), and the variance ratio (Rubin's R, should be close to 1) (Stuart and Rubin, 2008).

Table 3. Average Treatment Effect on the Treated (ATT), PSM, 5 nearest neighbors with replacement

Outcome Variable	Effect of offering savings	St. Error (AI)	P>|z|	95% Conf. Interval	
ROA (%)1	3.04	1.52	0.046	0.06	6.01
Number of Borrowers (#)1	5,386	2,035	0.008	1,397	9,374
Average Loan Balance / GNI (%)[1]	65.6	38.5	0.088	-9.8	140.9

1. Balancing after matching is satisfactory as measured by Rubin's R and mean bias before and after matching.

The results show that offering savings has statistically significant impact on profitability (ROA). Saving-collecting MFIs seems to earn 3 percentage points higher return on assets relative to loan-only MFIs. This result is contrary to the simple comparison of non-matched groups, which shows that there is no statistically significant difference between loan-only and savings-collecting MFIs. Thus, our results show that not accounting MFIs self-selection of offering saving products may be misleading. Our results are line with Rossel-Cambier (2012), who find that offering savings has a positive effect on the financial performance of MFIs. Also, our results for the ECA region support previous findings for economies of scopes and scale (Hartarska et al. 2011, Hartarska, Shen, and Mersland, 2013; Delgado et al., 2015, Malikov and Hartarska, 2017). These economies arise from the fact that delivery of both loans and savings may allow MFIs to reach easier the customers and strengthen client loyalty.

Next, we examine social performance, and specifically credit outreach measurements. We focus on credit outreach because lending-only MFIs do not offer savings, thus they reach out to borrowers, as opposed to outreach to clients (borrowers and savers), and thus we can do a proper comparison between lending-only and savings-collecting MFIs. We observe a positive association of the breadth of outreach (number of borrowers reached by a MFI) and savings mobilization. On average, we find that a saving-collecting MFI serves 5,386 more borrowers. This result comes to support the argument that savings should be encouraged as a better instrument to reach out to more customers. Similar to the financial performance it is likely that this result is attributable to economies of scope.

10. For international comparison, this balance is stated as a percentage of local income levels (GNI per capita)

Furthermore, it is possible that there are economies of scale because savings-offering MFIs are larger than lending only MFIs because they need to reach minimum scale in order to overcome entry barriers associated with obtaining a license to collect savings.
The last outcome of interest is the depth of credit outreach, namely the poverty level of borrowers. If they are serving more disadvantaged (poorer) borrowers, it has deeper outreach. Such link would be reflected in a negative coefficient on the depth of outreach measure which is the average loan size scaled by the country level GNI. We find that this measure is positively associated with offering savings, suggesting that MFIs which collect savings lend to less poorer borrowers. This result is important as it suggests trade-off between depth of outreach and sustainability and speaks for a mission drift. It is in line with D'Espallier et al. (2017) argument that savings mobilization might not allow MFIs to reach out and offer loans to more vulnerable layers of the poor and unbanked population suggesting a potential shift toward wealthier clients, which is an indicator for a mission drift.

5.1. Robustness check: Additional matching methods

The most obvious way of checking the robustness of the results obtained is to make sure that these are not due to specific matching approach applied. At the same time, various matching algorithms give similar results only asymptotically (Caliendo and Kopeinig, 2005). In table 4 we report results with three different options for nearest neighbors and caliper matching. The limited number of treated and control observations might result in leading to different results from the matching methods, nevertheless we find that the main results are robust. They are reported in Table 4 below. Specifically, the result on ROA is statistically significant in 2 of the 4 additional robustness check specifications and of the same size. The results on credit outreach is significant and almost the same in 3 out of the 4 specification, while the results for the depth of credit outreach is significant in 2 out of the 4 specifications and of the same or even larger size.

Table 4. Average Treatment Effect on the Treated (ATT), various matching algorithms

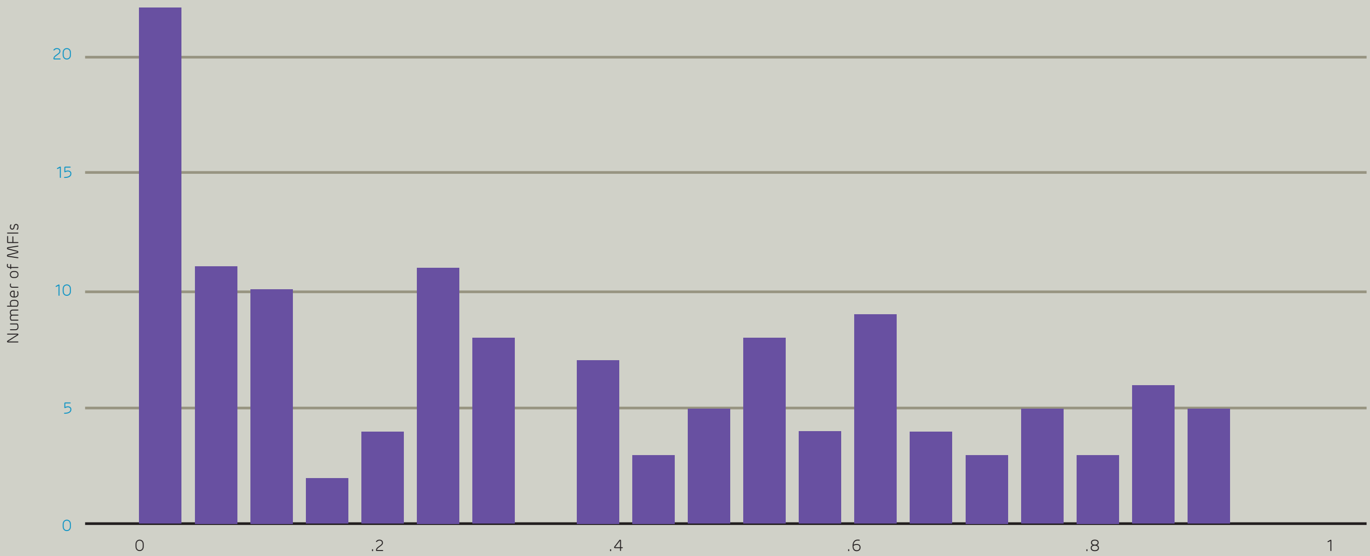
Outcome	Matching Algorithm			
	Nearest 5 Neighbors(1)	Nearest 3 Neighbors(2)	Nearest 1 Neighbor(3)	Kernel(4)
ROA	3.04**	3.72***	2.18	0.20
	[1.52]	[1.11]	[1.35]	[1.12]
Number of active borrowers	5,386***	5,010**	4,219*	1,946.7
	[2,035]	[2,096]	[2,351]	[1,943.7]
Average Loan Balance	65.6*	47.3	9.99	127.1**
	[38.5]	[46.5]	[36.0]	[36.4]

Note: each column reports matching with a different matching approach: (1) nearest neighbor matching with 5 neighbors, (2) and (3) the same with 1 and 3 neighbors (both with replacement), (4) Epanechnikov Kernel with radius matching. AI (columns 1, 2 and 3) and bootstrapped (column 4) standard errors in square brackets.
* Significant at 10%; ** significant at 5%; *** significant at 1%.

5.2. Robustness check: Dose response Function

For a further robustness check we also estimate dose response function as suggested by Hirano and Imbens (2004) for the situations where the treatment is not homogenous across treated units. Figure 1 presents the deposit's share in the capital structure across the MFIs analyzed. We notice that while the average share of deposits within the capital structure is about 38 percent, there are variations with the majority of MFIs having relatively low deposit shares, with only few heavily reliant on deposits observations.

Figure 1. Frequency of MFI with different shares of deposits in the capital structure

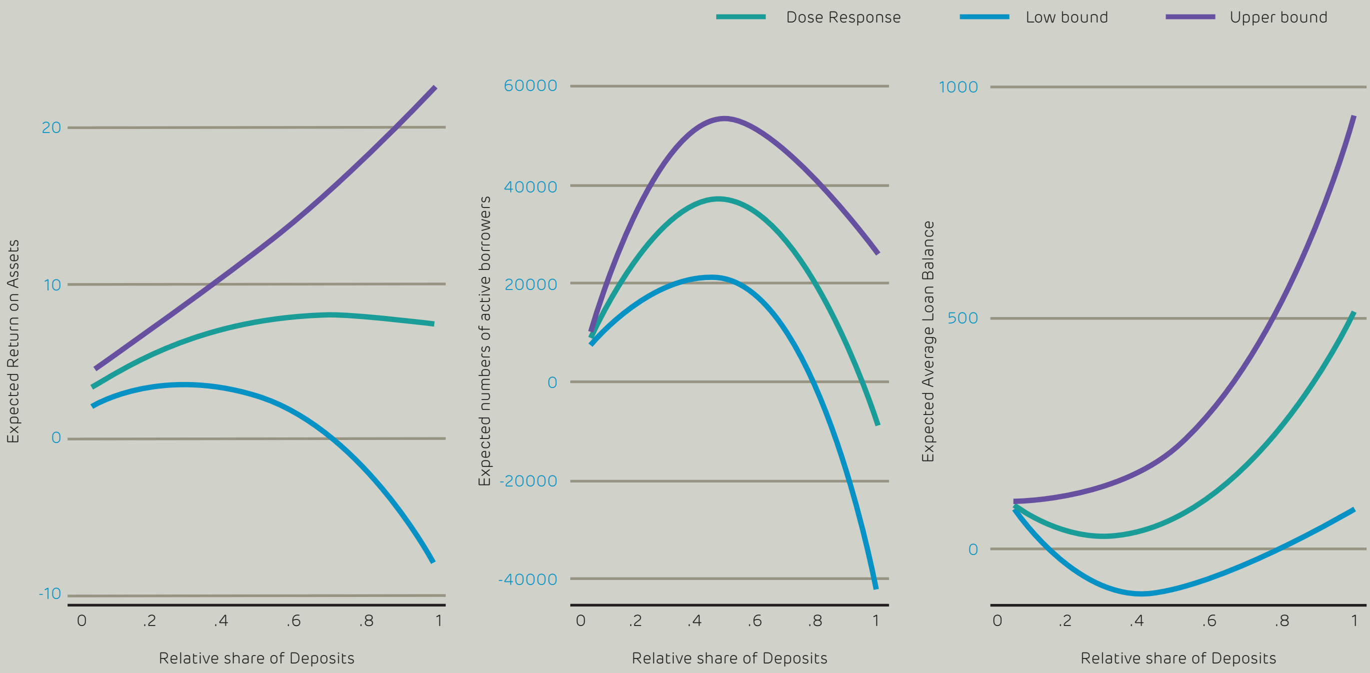


Share of deposit in capital structure (deposit taking MFIs only)

Since the data seem to indicate that either offering savings is an important part of MFI operations or it is just a small portion of the overall liabilities, it is prudent to address this heterogeneity of "treatment". To do that, instead of using a propensity score for a categorical variable, we estimate generalized propensity score appropriate for continuous treatment cases. We follow Guardabascio and Ventura (2014) who apply a generalized linear model instead of maximum likelihood estimator. This approach complements the one by used by Bia and Mattei (2008) and allows for non-normal distribution of the treatment variable. We estimate the dose response function for all of the outcome variables of interest, and the results are in line with the main findings and confirm that they are robust.
The dose response functions estimates of treatment effect are more reliable at lower end of continuous treatment variable, which is mostly explained by low number of matches at higher end of treatment level.[11] Interestingly, the effect of collecting savings on ROA is not dependent on the share of the deposits in the total capital, whereas for number of active borrowers we observe that number of borrowers is increasing with the increase in share of deposits up to a point and start dropping afterwards. This might indicate that MFIs with heavy reliance on deposits also prefer to work with relatively lower number of borrowers, possibly larger borrowers, which is also consistent with the main result on depth of credit outreach. The dose response function estimates for average loan balance to some extent confirms these observations as we note that at higher level of deposit shares the average loan balance is increasing, yet for the depth of credit outreach variable the predictive power remains an issue.

11. Note that treatment level is scaled with respect to MFI with highest share of deposits in total capital in our sample.

Figure 2. Dose Response Functions for outcome variables of interest



Note: Confidence Bounds at .95 % level, Dose response function = Linear prediction

Summarizing the results of PSM analysis and dose-response function estimations (Figure 2), we find that collecting savings has an impact both on financial performance and on social dimensions of MFI operations. Our findings support for the notion that in ECA region savings should be encouraged as a better instrument to serve the needs of the poor, to reach out to more customers and improve financial performance. Our results also suggest a positive relationship between mobilizing savings and the average loans size thus offering supporting evidence for a possible mission drift in ECA region. The results are overall consistent with previous findings on economies of scope (Hartarska et al., 2011; Delgado et al., 2015).

5. Conclusion

This study examines the extent to which MFIs performance is affected by combining loans with savings products. A dataset on MFIs from 19 countries in ECA was analyzed using propensity score matching method for the period of 2005-2009.

Our main findings suggest that the simultaneous delivery of loans and savings has a positive impact on MFIs financial performance and breadth of credit outreach. This is good news for the industry in the region because the ability to mobilize savings contributes to fulfilling the needs of the poor, together with an improved loan outreach, a reduced dependence on subsidies and a long term sustainability of MFIs (Karlan and Morduch, 2010). The result could be due to economics of scope from combining loan with savings as found in the emerging scope economies literature (Deldago et al., 2015; Hartarska et al. 2011). Cost-effectiveness in loan delivery, reduced transaction costs and enhanced communication channels can result from the spreading of fixed costs and cost complementarities when offering multiple services. The results are also likely due to scale economies. While our findings are consistent with scope economies, our work makes an important separate contribution because unlike previous scope economies studies, we control for the role of donations which have been found to be substitutes with savings collection. Another important contribution is our finding that the average loan size is larger in savings-collecting MFIs. This speaks to the on-going debate on MFIs mission drift, and is in line with D'Espallier et al. (2017) in the sense that savings mobilization may be eroding MFIs commitment to serving the more poor borrowers.

We acknowledge that combined microfinance services may not always be a winning option given that regulators tend to make it very costly for MFIs to provide savings, (and in some countries like Russia, MFIs collect only larger savings) so these savings are accessible only to a small fraction of the industry. One of the main reasons for MFI transforming is to mobilize savings, because in most countries, only regulated financial institutions are allowed to do so. In additional to this, providing saving requires additional managerial skills and various financial and operational risks for MFIs. The ability of MFIs to attract savings depends on conditions such as enabling macro-economy and some political stability, appropriate regulatory environment; public supervision of MFIs; accountable ownership, effective governance, and consistently good management of its funds.

References

- Abadie, A., & Imbens, G. W. (2011), Bias-corrected matching estimators for average treatment effects, Journal of Business & Economic Statistics 29(1), 1-11.
- Armendariz, B. and Szafarz, A. (2011), On Mission Drift in Microfinance Institutions. In B. Armendariz, B and Labie, M. ed. (2011), The Handbook of Microfinance, Toh Tuck Link, Singapore: World Scientific Publishing Co. Pte. Ltd, 341-366.
- Armendariz, B. and Morduch, J. (2010), The Economics of Microfinance, second ed. MIT Press, Cambridge.
- Augsburg, B., and Fouillet, C. (2010), Profit Empowerment: The Microfinance Institution's Mission Drift, Perspectives on Global Development & Technology 9 (3/4), 327-355.
- Bia, M., and Mattei., A. (2008), A Stata package for the estimation of the dose–response function through adjustment for the generalized propensity score. Stata Journal 8, 354–373.
- Bogan, V. L. (2012), Capital structure and sustainability: An empirical study of microfinance institutions, Review of Economics and Statistics 94(4), 1045-1058.
- Caliendo, M., & Kopeinig, S. (2005), Some Practical Guidance for the Implementation of PSM. IZA Discussion Paper No. 1588. The Institute for the Study of Labor. Bonn.
- Caliendo, M., & Kopeinig, S. (2008), Some practical guidance for the implementation of PSM, Journal of economic surveys 22(1), 31-72.
- Caudill, S. B., Gropper, D. M., and Hartarska, V. (2012), Microfinance institution costs: effects of gender, subsidies and technology, Journal of Financial Economic Policy 4(4), 292-304.
- Caudill, S., Gropper, D., Hartarska V. (2009), Which microfinance institutions are becoming more cost-effective with time? Evidence from a mixture model, Journal of Money, Credit, and Banking 41(4), 651-672.
- Cozarenco, A., Hudon, M., & Szafarz, A. (2016), What type of microfinance institutions supply savings products?, Economics Letters, 140, 57-59.
- Cull, R., Demirguc-Kunt, A., and Morduch, J. (2016), The microfinance business model: Enduring subsidy and modest profit, World Bank Policy Research Working Paper 7786.
- Cull, R., Demirguc-Kunt, A., Morduch J. (2009), Microfinance meets the market. Journal of Economic Perspectives 23(1), 167–192.
- Cull, R., Demirguc-Kunt, A., Morduch J. (2007), Financial performance and outreach a global analysis of leading MFIs. The Economic Journal 117, 107-133.
- Dehejia, R. H. and Wahba, S. (2002), PSM Methods for Nonexperimental Causal Studies, Review of Economics and Statistics 84, 151-161.
- Delgado, M. S., Parmeter, C. F., Hartarska, V., & Mersland, R. (2015), Should all microfinance institutions mobilize microsavings? Evidence from economies of scope, Empirical Economics, 48(1), 193–225.
- D'Espallier, B., Goedecke, J., Hudon, M., & Mersland, R. (2017), From NGOs to banks: Does institutional transformation alter the business model of microfinance institutions?. World Development, 89, 19-33.
- D'Espallier, B., I. Guérin, and R. Mersland (2011), Women and Repayment in Microfinance: A Global Analysis, World Development 39 (5), 758–72. doi:10.1016/j.worlddev.2010.10.008.
- Garrido, M. M., Kelley, A. S., Paris, J., Roza, K., Meier, D. E., Morrison, R. S., & Aldridge, M. D. (2014), Methods for constructing and assessing propensity scores, Health services research, 49(5), 1701-1720.
- Gonzalez, A., and R. Rosenberg (2006), The State of Microcredit: Outreach, Profitability and Poverty. Washington, DC: Microfinance Information Exchange (MIX), and the Consultative Group to Assist the Poor (CGAP).
- Guardabascio, B. and Ventura, M. (2014), Estimating the dose-response function through the generalized linear model approach, The Stata Journal, 14(1), 141–158
- Hartarska, V., X. Shen, and R. Mersland (2013), Scale Economy and Price Elasticities in Microfinance Institutions, Journal of Banking and Finance 37(1), 118–31.
- Hartarska, V.; Parmeter, C. and Nadolnyak, D. (2011), Economies of Scope of Lending and Mobilizing Deposits in Rural MFIs: a Semiparametric Analysis, American Journal of Agricultural Economics 93(2), 389-398.
- Hartarska, V., Parmeter, C., Nadolnyak and Zhou D. B. (2010), Economies of Scope for Microfinance: Differences Across Output Measures, Pacific Economic Review 15(4), 464–481.
- Heinrich, C., Blum, R., Gascón, S., Masserdotti, G., Tripathi, P., Sánchez, R., & Berninger, B. (2010), Directing astroglia from the cerebral cortex into subtype specific functional neurons. PLoS Biol, 8(5), e1000373.
- Hirano, K., & Imbens, G. W. (2004), The propensity score with continuous treatments, Applied Bayesian modeling and causal inference from incomplete-data perspectives, 226164, 73-84.
- Hermes, N., Lensink, R. and Meesters, A. (2011), Outreach and efficiency of microfinance institutions, World Development 39(6), 938-48.
- Hirschland, M. (2005), Savings Services for the Poor: An Operational Guide. Chapter 7. Savings products. Sterling, Va.: Kumarian Press.
- Holland, P. W. (1986), Statistics and Causal Inference, Journal of the American Statistical Association 81, 945-960.
- Hudon, M., Reichert, P., and Szafarz A. (2017), Public subsidies and private donations: A typology and application to

microfinance, mimeo.
- Hudon, M. and Traca, D. (2011), On the efficiency effects of subsidies in microfinance: An empirical inquiry, World development, 39(6), 966-973.
- Karlan, D., Ratan, A. L., and Zinman, J. (2014), Savings by and for the poor: A research review and agenda, Review of Income and Wealth 60(1), 36-78.
- Karlan, D., and Morduch, J. (2010), Access to Finance. Chapter 2 in Dani Rodrik and Mark Rosenzweig, eds., Handbook of Development Economics, vol. 5. Amsterdam: North-Holland.
- Khachatryan, K., Hartarska, V., & Grigoryan, A. (2017), Performance and Capital Structure of Microfinance Institutions in Eastern Europe and Central Asia, Eastern European Economics 5(55), 395-419.
- Lensink, R., Mersland, R., Vu, N. T. H., & Zamore, S. (2017), Do microfinance institutions benefit from integrating financial and nonfinancial services?, Applied Economics, 1-16.
- Leuven, E. and Sianesi, B. (2003), psmatch2: Stata module to perform full Mahalanobis and PSM, common support graphing, and covariate imbalance testing.
- Malikov E., Hartarska, V. (2017), Endogenous scope economies in microfinance, Working Paper, Auburn University.
- Quaye, F. M., & Hartarska, V. (2016), Investment Impact of Microfinance Credit in Ghana, International Journal of Economics and Finance, 8(3), 137.
- Rossel-Cambier, K. (2012), Can Combined Microfinance Boost Economic Results? An Empirical Cross-sectional Analysis, Review of Economics & Finance 2(3), 79-94.
- Schicks, J. (2007), Developmental Impact and Coexistence of Sustainable and Charitable Microfinance Institutions: Analysing Bancosol and Grameen Bank, European Journal of Development Research 19 (4), 551–568.
- Sheremenko, G., Escalante, C. L., & Florkowski, W. J. (2017), Financial Sustainability and Poverty Outreach: The Case of Microfinance Institutions in Eastern Europe and Central Asia, The European Journal of Development Research, 29(1), 230-245.
- Strom, R., D'Espallier, B., and Mersland, R. (2014), Female leadership, performance, and governance in microfinance institutions, Journal of Banking & Finance 42, 60-75.
- Stuart, E.A., and Rubin, D.B. (2008), Best Practices in Quasi-Experimental Designs: Matching Methods for Causal Inference. In J.W. Osborne (Ed.), Best Practices in Quantitative Methods (pp. 155–176). Thousand Oaks, CA: Sage.
- Van Tassel, E. (2004), Household bargaining and microfinance, Journal of Development Economics, 74(2), 449-468.