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Abstract

The majority of microfinance impact studies focus on finding their effect on a specific group of beneficiaries, in contrast we aim to identify the impact on whole economies (economic growth, and financial sector development and reductions in income inequalities), which is an important policy concern, not previously addressed. To address heterogeneity across countries, we group countries into three broad clusters delineated by a set of macro-institutional determinants. We find long-term evidence of a significant ability of microfinance to affect broader economies. Moreover, the impact and dynamics differ substantially by macro-institutional environment; the microfinance effect is more pronounced in weaker environments.

JEL Classification: C5, G2, O1 and O4
Keywords: development, economic growth, income inequality and microfinance

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1. Introduction

Access to credit for low-income populations has proven to be a key enabling them to invest in productive assets, which results in greater investments in human capital, increased productivity, and improved standards of living (Wolfensohn and Bourguignon, 2004). Microfinance emerged in the 1970s, with its primary mission aimed to reduce poverty by means of improved access to finance for low-income households. Since then microfinance has transformed vastly and has become a global and self-sustaining industry of more than 3,500 reported microfinance finance institutions (MFIs) serving 205 million clients (Maes and Reed, 2012). Today, microfinance is no longer perceived as a "magic bullet", automatically lifting poor people out of poverty through microenterprise. Rather, it focuses on the graduation from poverty of low-income households by delivering a variety of good-quality financial services, actively addressing the various forms of the poverty penalty (Mendoza, 2011).

The microfinance landscape is currently undergoing dramatic changes which are driven by two important phenomena. First, there is a growing trend of mature MFIs transforming from NGOs to licensed and regulated financial institutions, thus integrating more closely with established national financial systems. Second, perceived profitability and a new market niche lure commercial banks into the microfinance segment. All of these factors signal that microfinance is no longer an isolated marginal sector of informal means of financing, but rather constitutes a separate, lower-end segment of broader financial systems.

Despite the fundamental changes in the microfinance, little is known about the aggregate impact of microfinance expansion on national economic growth rates and national-level poverty rates, as acknowledged by Morduch (2013)[1]. While there have been numerous idiosyncratic and isolated studies measuring the impact of microfinance in various settings, a lack of systematic evidence at an aggregate level identifying general patterns across countries remains. The net contribution of microfinance to the broader economy is ambiguous because of its complementary and competitive relationship with commercial banks and also its long-run redistributive effects (Ahlin et al. 2011; Buera et al. 2012). Further, economic theories provide conflicting predictions

[1] For an overview of literature on financial development and inequality, see Claessens and Perotti (2007).

concerning the relationship between financial development and both income distribution and poverty alleviation (Levin, 2004).[2]

The degree to which microfinance fulfills its promise of promoting financial sector development and poverty reduction at the macro level remains unclear. More important, most recognized impact studies focus on measuring the impact of microfinance on limited groups of beneficiaries, while the general effect on larger population remains unstudied.[3]

This motivates our study of the impact of microfinance at aggregate country level, considering the spillover effect on a national population, in a dynamic setting which enables us to trace the evolution of the impact over time. The aim of this paper is therefore to provide a set of stylized empirical findings on the impact of microfinance to broad economies and reduction in income inequality at cross-country level. We analyze both dimensions of the impact - through microfinance loan portfolios and the number of borrowers.

To address potential parameter heterogeneity in a dynamic panel, we divide countries into three broad clusters based on economic development, income inequality, financial sector development, and measured levels of corruption.[4] Such clustering also enables us to address the external environment for microfinance, which is multidimensional. Finally, we perform impulse response functions to predict the evolution of the shock generated at the bottom from microfinance to macro fundamentals.

In general, the results indicate an important and significant impact of microfinance in a macro context. In particular, the expansion of microfinance is found to be positively and significantly associated with economic growth. We further find support for the impact of microfinance on financial sector development captured by broad money circulation in economies. Effect of microfinance on both economic growth and financial sector development is found to be stronger in developing and more stable environments. This is in line with Ahlin et al.'s (2011) findings that greater financial depth is strongly associated with lower default and

[2] On the one hand, alleviating credit constraints allows the poor to exploit investment opportunities. This improves the allocation of capital and has a disproportionately beneficial impact on the poor (e.g. Banerjee and Newman, 1993; Galor and Zeira, 1993; Aghion and Bolton, 1997). On the other hand, in the early stages of economic development, primarily the wealthy and well-connected benefit from financial development (e.g. Lamoreaux, 1994; Haber 1991, 2004, and 2005]. Further, Greenwood and Jovanovic (1990) argue a non-linear relationship between finance and income distribution. First the wealthy benefit from the development of the financial system and later, with aggregate growth, more people can access the financial markets and thus take advantage of its opportunities.

[3] For a typology and various definitions of microfinance impacts, see e.g., Zohir and Matin (2004).

[4] We benefit from the earlier established empirical findings of Ahlin et al. (2011), Armendáriz & Vanroose (2009), Hermes & Meesters (2011) that identify the nature of microfinance as being complementary or competitive to a number of macro-institutional indicators.

operating costs for MFIs. Finally, we find a positive impact of microfinance in reducing income inequality. The results are stable for sample integrity of the Gini coefficient and trimming for outliers.

Overall results indicate that microfinance plays a significant role and provide evidence of its potential to affect broader economies. The impact and transfer dynamics of microfinance, however, differ substantially by the macro-institutional environment of countries.

This paper is constructed as follows. Section 2 describes the background literature. Section 3 explains the methodology. Section 4 presents the data and descriptive statistics. Section 5 presents the analysis and section 6 concludes.

2. Literature Review

2.1. Economy-Wide Effect of Microfinance: Theory and Empirics

The positive contribution of financial sector development to economic growth through banks and equity markets is proven and has been widely tested at the cross-country, industry and firm levels (King & Levine, 1993; La Porta et al., 1998; Rajan & Zingales, 1998; Beck, Levine & Loayza, 2000). While the main role of the financial sector is to reduce information, enforcement and transaction costs, Levine (2004) outlines five functions that a financial system serves in facilitating growth: savings mobilization, provision of investment information, monitoring/governance, risk management and facilitation of goods and service exchange. Through these functions, the financial sector not only promotes private sector development, but also supports the public sector, infrastructure and the ability of households to invest in human capital and smooth consumption. Karlan & Morduch (2010) claim that the general empirical linkages between finance and growth cannot be directly projected to the expansion of household financial access, which is different than with firms, including the spread of microfinance. However, considering the fact that, in some developing countries microfinance already has significant penetration, we could potentially draw reasonable inferences about its broad

economy-wide impact. The contribution of microfinance to the economic growth at a country level could be measured through production created by small entrepreneurship, improvements in human development indicators (health, nutrition, education) and reduction in poverty (Ravallion, 2001).

The second important aspect of financial expansion is related to its distributional impact affecting poverty and inequality[5] (Hermes & Lensink, 2011). Loury (1981) develops a model of intergenerational transmission of inequality, where redistribution due to financial deepening can improve economic efficiency. The basic result is that borrowing constraints reduce efficiency and exacerbate inequality by diverting capital from low-income households with high-return investments. Greenwood & Jovanovic (1990) build a model in which financial development can increase inequality as richer segments of a population invest in financial infrastructure first. Over time, a broader segment of the economy benefits, so that inequality first widens then narrows with financial development. Other mainstream theoretical literature explores the aggregate and distributional impacts of financial intermediation in models of occupational choice and financial frictions (Lloyd-Ellis & Bernhardt, 2000; Erosa & Hidalgo Cabrillana, 2008). According to the theoretical predictions of these studies, improved financial intermediation leads to more entry into entrepreneurship, higher productivity and investment, and increases in wages - which is considered a general equilibrium effect in the long-run.

As regards direct application of microfinance, Buera et al. (2012) develop a model to analyze the economy-wide effect when microfinance programs are first introduced. They claim that in the long run, a scale up of microfinance programs will have only a small impact on per-capita income. Despite this, the vast majority of a population will be positively affected by

[5] See Karlan & Morduch (2010, pp. 4713-4714) for a detailed review of theoretical models on financial deepening and poverty reduction.

microfinance through an increase in equilibrium wages (Buera et al. 2012). The bottom line of the theoretical model and calibration is that introduction of typical microfinance programs can have significant aggregate and distributional impacts economy wide.

The empirical evidence testing the general effect of microcredit expansion is based mainly on two experimental studies. First, Kaboski and Townsend (2012) evaluate the short- and long term impact of Thailand's "Million Baht Village Fund" program. This has been found to increase short-term credit, consumption, agricultural investment and income growth, but to decrease overall asset growth. There is also evidence of (localized) general equilibrium effects in terms of positive impacts on village-level wages. Second, Banerjee et al. (2010) conducted one of the largest randomized expansions of "Spandana" MFI branches in the new urban market of Hyderabad, India. The study indicates a positive and significant effect of microfinance economy-wide, including both program participants and non-participants.

The theoretical models and experimental studies to date indicate a significant effect of microfinance at the aggregate level. The effect, however, is expected to differ in short- and long-run contexts. We therefore empirically estimate the economy-wide effect of microfinance on the whole sample of countries, thus capturing regions that are heterogeneous in microfinance evolution and socio-economic development.

2.2. Macroeconomic Determinants of Microfinance Performance

Analysis of macroeconomic factors determining the uneven distribution of MFIs and the impact of country-level aggregates is an emerging trend in the literature.

Macro economy: The most relevant study to date is by Ahlin et al. (2011), and is based on data from 373 MFIs, determining their success based on macroeconomic and macro-institutional features. Evidence is found of complementarity between MFI performance and broader

economy. MFIs are more likely to cover costs when economic growth is stronger. Both the level of growth and its composition matters: microfinance loans grow faster where the share of the manufacturing sector is high, foreign direct investment is large, and labor force participation is extensive (Ahlin et al. 2011; Leegwater & Shaw, 2008). On the contrary, a rivalry or substitutability is also observed. In particular, higher workforce participation is associated with slower growth in MFI outreach. MFIs are also found to have better outreach in countries that receive more donor aid and where population density is high. Based on stylized facts, Armendáriz & Vanroose (2009) find that, contrary to the original poverty eradication mission of microfinance, the outreach of MFIs is more developed in regions that are relatively less poor such as Latin America and in fast-growing South Asian countries.

Financial sector development: The maturity of the financial sector is an important determinant of MFI performance. Hermes et al. (2009) investigate the direction of causality between a country's financial development and the efficiency of MFIs through cost reduction. They find that a stronger financial environment tends to generate more efficient MFIs, as intense banking competition provides incentives for MFIs to improve their operational efficiencies. Ahlin et al. (2011) find that greater financial depth is strongly associated with lower default and operating costs of MFIs. Hermes & Meesters (2011) confirm a clear and robust association of MFI cost efficiency with economic growth and financial sector development. However, a trade-off exists between the outreach to the poor and cost-efficiency of the MFI, suggesting difficulty in trying to achieve the two goals simultaneously (Abate at al., 2013).

The market failure hypothesis suggests that microfinance is normally a good complement to mainstream banking, as it fills the gaps where standard banking services are not used. Cull et al. (2009) find positive and robust evidence of competition from formal banks pushing micro-banks. The intensity of the competition is associated with micro-banks serving poorer markets and more

women. Vanroose & D'Espallier (2009) empirically test the market failure hypothesis and find that MFIs reach more clients and are more profitable where access to a formal financial system is low. In addition, Vanroose & D'Espallier (2013) claim that MFIs are less profitable when interest rates and inflation are high, which indicate their dependency on banking systems for external financing and the stability of formal financial system.

Formal institutions and their quality: The institutional environment and its quality is an important determinant of a business and microfinance development. Hermes and Meesters (2011) define the following measures of institutional environment as relevant to microfinance: rule of law, establishment of property rights, regulatory quality, government effectiveness and control of corruption and political stability. Ahlin et al. (2011) also include a set of "ease of doing business" indicators based on the World Doing Business survey dataset. The influence of the institutional environment on microfinance operations can go in two directions. On one side, an environment with well-developed institutions and controlled corruption is favorable for business activity and hence ensures sufficient demand for microfinance products. On the other side, a strong environment reflected by effective government implies a significant number of regulations imposed on business owners, which in turn translates into an increase in their cost of operations. Due to this, there may be less demand for MFIs in a well-developed and controlled environment (Crabb, 2007; Hermes & Meesters, 2011; Ahlin et al. 2011).

Age of microfinance and industrialization stage: Based on their analysis of stylized facts and empirical findings, Armendáriz & Vanroose (2009) claim that the age of microfinance is an important determinant when trying to explain the scale, scope and rapid growth of microfinance activity. They show that there is a potential country-wide learning curve which could explain the growth of the microfinance sector. Complete industrialization of microfinance is a long process and requires substantial public reforms, enormous subsidies, and deep transformations in

government decision-making. It also requires an acceptance of microfinance as a separate segment, which is in contrast to the concept of heavily subsidized lending or extensive reliability on donor funds (Morduch, 1999; Hulme & Moore, 2005. There is, however, no evidence of the performance of this microfinance-dominated financial sector or, more importantly, there is no evidence of its impact on growth and sustainable development.

Drawing the bottom line, existing empirical findings and stylized facts suggest that the external environment is an important factor in explaining the performance of microfinance institutions. Most studies, however, focus on the role of the external environment on microfinance performance. Conversely, in this paper we aim to find the reverse effect - the impact of microfinance itself on a broad economy. Most related studies merely represent a correlation analysis or set of qualitative studies. The causal inference at aggregate country level remains unstudied. We therefore aim to draw a Granger-type causal link from microfinance on main macroeconomic fundamentals such as economic growth, financial deepening and inequality that are also linked to the original mission of microfinance. Moreover, the myriad of macro-institutional determinants, coupled with various industrialization stages of microfinance segment, suggest that countries are heterogeneous based on multidimensional characteristics. We therefore group countries into clusters based on identified macro-institutional determinants and try to capture unobserved heterogeneity. We also consider a dynamic setting as opposed to cross-country analysis, which enables us to trace the evolution of the impact of microfinance over time.

3. Methodology

3.1. Linking Economic Fundamentals and the Extent of Microfinance Development.

VAR Model using Dynamic Panel Data

The primary objective is to estimate the causal link running from microfinance to macroeconomic fundamentals and reversely. Therefore, we estimate the following four vector autoregressive model (VARs) in the following dynamic panel data settings.

$$GDP_{it} = \sum_{j=1}^{p1} \propto_{1j} GDP_{i,,t-j} + \sum_{j=1}^{p2} \propto_{2j} BMoney_{i,,t-j} + \sum_{j=1}^{p3} \propto_{3j} Microfin_{i,,t-j} + \epsilon_{1,it} \quad (1)$$

$$BMoney_{it} = \sum_{j=1}^{q1} \beta_{1j} BMoney_{i,,t-j} + \sum_{j=1}^{q2} \beta_{2j} GDP_{i,,t-j} + \sum_{j=1}^{q3} \beta_{3j} Microfin_{i,,t-j} + \epsilon_{2,it} \quad (2)$$

$$Microfin_{it} = \sum_{j=1}^{r1} \gamma_{1j} GDP_{i,,t-j} + \sum_{j=1}^{r2} \gamma_{2j} BMoney_{i,,t-j} + \sum_{j=1}^{r3} \gamma_{3j} Microfin_{i,,t-j} + \epsilon_{3,it} \quad (3)$$

.....

$$Gini_{it} = \sum_{j=1}^{s1} \delta_{1j} Gini_{i,,t-j} + \sum_{j=1}^{s2} \delta_{2j} GDP_{i,,t-j} + \sum_{j=1}^{s3} \delta_{3j} Microfin_{i,,t-j} + \epsilon_{4,it} \quad (4)$$

where $i = \{1, \ldots, N\}$, $t = \{1, \ldots, T_i\}$, and ϵ_{it} are i.i.d.

Equations (1) and (2) specify the dynamic effects of microfinance on real economy growth and the development of the financial sector respectively. Equation (3) describes the reverse effect of these two key macroeconomic fundamentals on the microfinance itself. Finally, equation (4) is used here to study a link from microfinance at a country level.

We will discuss definitions of variables in more detail in Section 4 (Data), but let us note here that we will measure economic growth [*GDP*] by the real GDP per capita[6] and financial sector development by the real broad money per capita [*broad money*]. Though broad money is

[6] We employ GDP per capita in levels and not in growth rates for consistency measures with other equations and the methodology employed.

partly a decision making choice of Central Banks in domestic economies, we nevertheless use this indicator to capture the financial sector development. This is based on earlier findings of Rousseau and Wachtel (2000). Broad money (M3), as opposed to ratio of private credit to GDP, is a comprehensive measure of financial depth and includes currency, demand deposits, all time deposits, and the liabilities of money market mutual funds. Further, *Microfinance* will be captured by either the percentage of microfinance borrowers (in relation to total population) or by the gross loan portfolio of MFIs scaled by the real GDP.

To find evidence of a link from microfinance to economic growth (1) we test the null hypothesis H_0: $\propto_{3j} = 0$, jointly for j=1, ..p_3. Similarly, to study the effect of microfinance on financial sector development (2), we test the null hypothesis H_0: $\beta_{3j} = 0$, jointly for j=1, ..q_3. Reverse effects, i.e. a link from macroeconomic fundamentals to microfinance (3) can be studied and tested via coefficients γ_{1j} and γ_{2j}, respectively. Finally, the effect of microfinance development on income inequality (4) can be tested by the null hypothesis H_0: $\delta_{3j} = 0$, jointly for j=1, ..s_3.

In a dynamic model such as this, with fixed effects, classical estimation techniques yield biased (inconsistent) estimates. The magnitude of bias can be quite large for short time series with strong dynamic effects (Nickel, 1981). In order to obtain consistent estimates, we employ a dynamic panel-data model following Arellano and Bover (1995), Blundell and Bond (1998), and Blundell, Bond, and Windmeijer (2000).[7] Therefore, to find the existence of a link from microfinance and estimate equations (1)-(4) we use the Arellano-Bover/Blundell-Bond system estimator with two lags of dependent variables included as regressors, covariates treated

[7] Building on the work of Arellano and Bover (1995), Blundell and Bond (1998) proposed a system estimator that applies moment conditions in which lagged differences are used as instruments for the level equation, in addition to the moment conditions of lagged levels serving as instruments for the differenced equation.

endogenously and robust variance-covariance matrix. This is a linear dynamic panel-data estimation implemented through "xtdpd" command in Stata 12.

Tests for validity of instruments used as well as specification-type test for equations (1)-(4) including the lengths of lags *p, q, r* or *s* will be conducted using the Sargan test (Overidentifying restriction test; e.g., Sargan, 1958; Hansen, 1982).[8] Estimation results revealed that, at most, the second lag was significant. Therefore, we present estimation results for all equations for two lags.

3.2. Unobserved heterogeneity and clustering

Given that the objective is to examine the size and direction of the dynamic relationship between microfinance and macro fundamentals, we employ panel data vector autoregressions as mentioned in the previous subsection. This focus on the nature of transition paths is more advantageous than a cross-section approach as it is more informative about identification of the causal link running from microfinance (Rousseau & Wachtel, 2000). Despite this fact, application of the panel data implies a potential bias driven by parameter heterogeneity (Hsiao, 1986). As a result, there is a high probability of the Sargan test to reject the null hypothesis and find appropriate instruments. In addition, countries differ not only by income level; many other macroeconomic and institutional characteristics define the external environment. Therefore, we group the countries in homogeneous clusters based on similar macro-institutional determinants. This grouping enables us to address unobserved heterogeneity in a dynamic panel and capture multidimensional external environments for microfinance. To identify the variables for clustering, we benefit from the established empirical findings of Ahlin et al. (2011), Vanroose

[8] The null hypothesis in this case is that instruments used in equations (1)-(4) are exogenous. The Sargan test is therefore a test for overidentified restrictions.

(2007; 2008), Hermes & Meesters (2011), Vanroose & D'Espallier (2013). We select the following seven indicators for clustering:

[1] Macroeconomic growth [captured by real GDP per capita]. Overall economic growth in countries is a strong predictor of microfinance performance, suggesting complementarity between the two (Ahlin et al.2011).

[2] Financial depth [captured by domestic credit to the private sector, as a percent of GDP]. The microfinance sector is part of the broader financial system and financial depth is also strongly associated with lower default and operating costs of microfinance institutions. This in turn translates into lower interest rates rather than into greater MFI self-sufficiency. Ahlin et al. (2011) claim that this suggests that (potential) financial market competition is good for micro-borrowers, if not MFIs. MFIs are found to reach more clients and are more profitable where access to formal financial systems is low (Vanroose & D'Espallier, 2013).

[3] Foreign Direct Investment [captured by FDI, net inflows, as a percent of GDP]: the overall business environment is a strong predictor of the competitive climate in which MFIs operate. As such, inflow of foreign direct investment reflects the business climate and the competiveness of local economy. In addition, Ahlin et al. (2011) find that microfinance loans grow faster where there is more FDI. Vanroose & D'Espallier (2013) find that more FDI is associated with higher microfinance outreach and profitability. This in turn implies that more open countries develop larger microfinance markets.

[4] Industry share [captured by industry value added, as a percent of GDP]: certain macroeconomic determinants are substitutes or rivals for microfinance. As such, Ahlin et al. (2011) find that the industry share of GDP is a negative predictor of extensive growth of MFIs captured by number of borrowers.

[5] Inequality [captured by the Gini coefficient]: the original mission of microfinance is to reduce poverty and income inequality. Empirical evidence of the relation of poverty and microfinance is supported by Ahlin et al. (2011). In particular, higher inequality is found to be associated with much higher default and operating costs, higher interest rates, and lower MFI sustainability.

[6] Level of corruption [captured by control of corruption index]. In terms of microfinance, Ahlin et al. (2011) show that MFIs grow their clientele more slowly where there is more corruption. Vanroose and D'Espallier (2013) find that countries with less corruption have higher microfinance outreach and higher profitability.

[7] Stability [captured by estimates of political stability and the absence of violence/terrorism]: Microfinance institutions often serve more clients living in economically unstable environments, which is an indicator of the difference between MFIs and formal financial institutions (Vanroose, 2007).

Overall, we divide all countries in the sample into more homogeneous groups with respect to their economic development and quality of institutions using clustering around the mean values of [1]-[7] identified variables. In particular, we employ *kmeans* command in Stata 12. Since the results of clustering serve as a basis for further estimation, they will be presented early in Section 5 (results). The number of clusters may range from three to more. In our setting, we identify three main broad clusters that distinguish the external environment of microfinance: rich, stable, controlled corruption defined as "rich" (cluster 1), developing or moderate (cluster 2), and underdeveloped, unstable environment and with high corruption entitled "poor" (cluster 3).

To visualize the effect of microfinance on macroeconomic fundamentals, we complement our empirical analysis by plotting impulse response functions to identify the transmission of the

shock coming from microfinance. The impulse response functions represent the following autoregressive AR(p) process:

$$y_{it} = \mu + \alpha_1 y_1 + \cdots + \alpha_p y_{t-p} + \varepsilon_t \quad (5)$$

Consider $y_t = [y_{1t,} y_{2t,} \ldots y_{kt}]$ and application of the same model will result in the following vector autoregression model (VAR), where instead of coefficients, we have matrices of coefficients:

$$y_t = m + A_1 y_{t-1} + \cdots + A_p y_{t-p} + \varepsilon_t \quad (6)$$

Therefore, we estimate the VARs by clusters for the three main dynamic equations: growth, broad money, and microfinance, and we will use their interactions in the impulse response function.

4. Data, Descriptive Statistics and Data Cleaning

4.1 Data sources

Microfinance data: was downloaded from Microfinance Information eXchange (in September 2012). This is a global microfinance platform and captures 1292 MFIs, in 101 countries for 1995-2011. We use two main indicators to capture microfinance: [i] gross loan portfolio of MFIs scaled by real GDP in USD to unify the currency and [ii] number of borrowers scaled by country population. We also collect institutional determinants of MFIs including age, legal, regulatory and profit status, share of microfinance operations, and data quality captured by diamonds marks[9].

Macroeconomic data: [i] Economic growth is captured by real GDP per capita, PPP in constant 2005 international USD, and was retrieved from the World Development Indicators

[9] In this version of the paper we do not distinguish between MFI institutional and legal status. Respective sensitivity analysis could be performed further, which remains as a focus for further research.

(September 2012 release). [ii] Financial sector development is proxied by broad money in constant USD, retrieved from World Development Indicators (September 2012 release). [iv] Income inequality measures is based on the Gini coefficient. We use the UN World Income Inequality Database and World Development Indicators (September 2012 release) to create the balanced coefficient for entire sample. Further, we employ a linear interpolation of the Gini coefficient within the sample to ensure a sufficient number of observations.

Institutional data: [i] Foreign Direct Investment is captured by FDI, net inflows, as a percent of GDP is based on World Development Indicators (September 2012 release). [ii] Industry share is captured by industry value added, as a percent of GDP is based on World Development Indicators (September 2012 release). [iii] Levels of corruption are captured by control of corruption index (-2.5 to 2.5) from World Governance Indicators. [iv] Stability is captured by estimate of political stability and low levels of violence/terrorism (-2.5 to 2.5) from World Governance Indicators. Summary statistics of these variables are presented in Table 1.

INSERT TABLE 1 ABOUT HERE

4.2 Data cleaning

To ensure the homogeneity of the sample and to minimize the impact of outliers, we perform two types of data cleaning. First, we drop observations where the percentage of microfinance borrowers is lower than 0.05% of the whole population in an economy. This ensures that there is a certain “critical mass” of microfinance borrowers in an economy, which is also justified by the self-reported nature of MFIs into the MIX database. Second, acknowledging the multi-dimensional nature of clusters, we performed a procedure to identify outliers in multivariate data. The procedure is based on identification of multiple outliers in multivariate data, using the blocked adaptive computationally efficient outlier nominators algorithm proposed

by Billor, Hadi, Velleman (2000).[10] We performed identification of the outliers based on 5-10% trimming. Different trimming levels can serve as a sensitivity analysis and also improve the power of the underlying Sargan test.

5. Results, Discussion and Implications

5.1. Cluster analysis

Based on the methodology of clusters presented in section 3.2., we provide descriptive statistics (Table 2). Countries grouped in stable environments (cluster 1) are characterized by having USD 10,941 real GDP per capita. In comparison, in "moderate" countries (cluster 2), mean GDP is USD 5,422 while in "poor" (cluster 3) countries, it is USD 1,722. Clusters differ substantially in terms of the stability of environment and control of corruption. Table 3 summarizes the difference across clusters in terms of macro-institutional factors and their interpretation.

INSERT TABLE 2 ABOUT HERE

INSERT TABLE 3 ABOUT HERE

We also visualize clusters by plotting the mean value of macro-institutional determinants (Figure 1). As can be seen, for each individual variable there is a clear separation by three clusters. This in fact ensures that countries in the sample are grouped appropriately and clusters

[10] The algorithm is implemented in Stata 12 as a procedure BACON (Stata Journal, 2010). The procedure typically creates a new variable equal to 1 if an observation is an outlier and equal to 0 otherwise. As a parameter *p* we set a maximum percentage of outliers to be potentially identified. As shown in Stata Journal (2010), the BACON procedure is scale-invariant, which is a necessity when dealing with variables of different magnitudes or with different units.

are homogenous, which ensures the validity of methodology and clear identification of a link to microfinance.

INSERT FIGURE 1 ABOUT HERE

We also characterize the clusters in terms of geographical coverage (Table 4) and income group (Table 5). As can be seen, most countries in a stable environment are in East Asia and the Pacific and South Asia regions. In contrast, Cluster 2 (moderate) includes mostly the emerging economies of Europe and Central Asia, and Latin American countries.

INSERT TABLE 4 ABOUT HERE

INSERT TABLE 5 ABOUT HERE

As can be seen from the descriptive analysis, there is clear and definite identification of clusters, which ensures that they are homogenous and correctly grouped. The latter is important for econometric identification and further panel data estimation.

5.2. Dynamic panel estimation of the VAR components

We present estimation results of panel VARs based on (1) – (4) equations: growth, broad money, microfinance and inequality. We provide both extended version of results reporting coefficients for all lags, as well as corresponding equilibrium relationship.

Given that the whole sample combines various countries with different levels of macro-institutional development, there is a potential significant unobserved heterogeneity (Table 6a). This is particularly observed in the example of growth equation as instruments are weak. Therefore, we control unobserved heterogeneity by grouping the countries into the clusters described in the previous section 5.1.

5.2.1. Economic growth

At first glance, there is evidence of a link running between microfinance and economic growth. The effect is more pronounced through extensive margin [borrowers] compared to intensive margin [portfolio]. A 1% increase in the share of MF borrowers in the country leads to a USD 365 increase in real GDP per capita, which is equivalent to 8.4% of mean GDP per capita of the whole sample (Table 6).

INSERT TABLE 6 ABOUT HERE

The effect clearly differs across clusters. In relative terms, an increase in the percent of microfinance borrowers leads to an increase of mean GDP per capita for each cluster: USD 826 or 7.5% of cluster mean GDP in cluster 1 [rich-stable-controlled corruption] and USD 66.2 or 3.8% of cluster mean GDP in cluster 3 [poor-unstable-corrupt]. The effect of microfinance is therefore stronger when measured in terms of loan portfolio, in developing and more stable environments: cluster 1 and cluster 2. The result is consistent with Vanroose (2008) and Armendáriz & Vanroose's (2009) stylized facts that microfinance is more developed in regions such as Latin America and fast-growth South Asia countries. In fact, cluster 1 and cluster 2 in our sample include countries from these regions such as Argentina, Brazil, Peru, Chile, Bolivia, Colombia and Venezuela (See Section 2 for detailed list of countries in each cluster).

The dynamics of microfinance transfer also differs across clusters. In poorer and more corrupt environments [cluster 3] where microfinance was originally born and where demand for it is stronger, its impact is transferred through the second lag. In countries with more stable and developed institutions, the effect dies out, as the transfer occurs in the first lag [cluster 1 and 2].

5.2.2. Financial Sector Development

Given the original mission of microfinance to improve access to finance, we estimate the promised impact on financial intermediation captured by broad money circulation in the

economy. Results are presented in the Table 7 below. Microfinance has a positive and significant effect on broad money, both through extensive [MF borrowers] and intensive [MF portfolio] margins.

INSERT TABLE 7 ABOUT HERE

Disentangling the impact by clusters, we observe that microfinance outreach is more pronounced in more stable and developed environments, i.e. cluster 1. Overall, in relative terms a one percent increase in microfinance borrowers causes a USD 24.5 [equivalent to 0.9% of cluster mean value] increase in broad money in cluster 1, USD 40.9 [equivalent to 0.8% of cluster mean value] in cluster 2, and USD 31.2 in cluster 3 [equivalent to 6.5% of cluster mean value]. The results are consistent with Ahlin et al.'s (2011) findings that greater financial depth is strongly associated with lower default and operating costs for MFIs, which is ultimately beneficial for micro-borrowers.

The impact of microfinance through intensive margin (MFI portfolio) is found to be mainly driven by cluster 2 [USD 31.4] and cluster 3 [USD 271], i.e. less developed and weaker environments. This finding is line with market failure hypothesis and related findings of Vanroose and D'Espallier (2013) that MFIs flourish where the formal financial sector fails.

5.2.3. Microfinance

Table 8 presents the estimation result of reverse effect and the impact of macroeconomic fundamentals [GDP, broad money] on microfinance itself. First, the observed significant coefficient of microfinance first lag indicates a potential auto regression or diffusion effect.

INSERT TABLE 8 ABOUT HERE

The impact of the financial sector development [broad money] is mostly negative, which could be interpreted as indicating that a stronger financial sector has negative effects on

microfinance performance, both in terms of depth [MF portfolio] and outreach [MF clients]. The effect becomes smaller when it reaches cluster 3. The finding is consistent with the initial hypothesis that in more developed and stable environments where formal institutions are strong, there is limited scope for microfinance.

The impact of economic growth on microfinance is clearly heterogeneous across clusters. A positive and significant coefficient of GDP per capita implies that stronger economic growth fosters the development of microfinance.

The patterns clearly differ across clusters. In this regard, one can potentially draw a concave curve of microfinance evolution as a function of a country's macro-institutional economic development. Microfinance is born in mostly weak and unstable environments [cluster 3], reaches its peak in moderately developed economies with high growth potential [cluster 2], and dies out when reaching the richer and more stable environments where formal financial institutions are assumed to be strong and mature [cluster 1].

5.2.4. Income inequality

Finally, we estimate the keystone "microfinance promise" of reduction in income inequality[11]. Tables 9a and 9b report estimation result of microfinance impact on income inequality captured by the the Gini coefficient[12]. To ensure comparable units with income inequality measure, the impact of microfinance is captured in terms of borrowers only and not in loan portfolio. Given the low number of available observations, we use both versions: raw data and linear interpolation of the Gini coefficient for missing years and countries within the sample. We present two

[11] To estimate the impact of microfinance on poverty and thus to derive stronger statements on poverty reduction, one should use direct poverty measures, which is beyond the scope of this paper and remains for further research.

[12] For interpretation of coefficients, a low Gini coefficient indicates a more equal distribution, with 0 corresponding to complete equality, while a higher Gini coefficient indicates more unequal distribution, with 1 corresponding to complete inequality. In our case, the Gini coefficient is expressed in percents varying from 0 to 100.

versions of results: first, those of the whole sample without any procedures for outliers and second, those derived from multidimensional trimming using BACON at 5%, given the potential effect of influential observations (Billor et al. 2000).

The microfinance effect on reduction of income inequality is presented in Table 9, below. Observed negative coefficients on lagged values of the Gini coefficient indicate lessening of income inequality.

INSERT TABLE 9 ABOUT HERE

Negative and significant coefficients in GDP per capita imply that, as countries strive for better economic growth, they experience lessening of inequality. There is evidence of microfinance driving reductions in income inequality. The overall impact varies from -0.946 [linear interpolation of the Gini coefficient] to -2.324 [linear interpolation of the Gini coefficient], reflecting sensitivity to sample. The results are robust to trimming procedures where the poverty reduction effect is more pronounced when using the BACON procedure.

5.3. Impulse response functions

As a conclusion to the empirical analysis, we visualize the impact of microfinance by plotting impulse response functions (Figures 2, 3 and 4). The initial level of the impulse of microfinance is set at 5% lasting for 12 periods. We visualize the effect of microfinance disenabling across three clusters. Given that the effect of microfinance is primarily captured through its outreach, we present the impulse response functions for microfinance borrowers only. We also model the microfinance market as finite and assume a saturation point at around 3% of the population.

Figure 2 represents the impact of microfinance shock on economic growth measured in terms of real GDP per capita. Figure 3 - the impact on financial sector development captured by broad money per capita, and finally the effect of microfinance itself (Figure 4).

We observe that there are similar patterns in the same cluster across equations. We observe strong growth potential of microfinance in clusters 1 and 2. This is in line with earlier findings of Ahlin et al. (2011), Vanroose (2008), Armendáriz & Vanroose (2009) that the outreach of MFIs is more developed in stable countries and operational costs are recovered when economic growth is stronger.

The most interesting situation is observed in cluster 3, which captures countries with weak and unstable environments. In this group of countries, the evolution of microfinance is transferred through a concave function and "dies out" after a certain critical point. This might potentially indicate two effects. First, it might be that in weaker environments microfinance does not have sufficient capacity to grow and expand. Second, it could be due to potential "mobility" across clusters as developing countries grow, and "graduate" from cluster 3 to cluster 2. Ahlin and Jiang (2008) developed a model examining the long-run effects of micro-credit on development in an occupational choice model. According to theoretical predictions, microcredit could raise or lower long-run GDP, inequality and poverty. In this regard, the key to microcredit's long-run effect is "graduation rate", defined as the rate at which self-employed workers build up enough wealth to start full-scale firms.

A concave response to microfinance shock to economic growth might potentially indicate its cyclical or countercyclical influence in times of macroeconomic crises. For example, microfinance acted as a shock-absorber amidst severe economic collapse in Indonesia between 1998–2000, while there was an opposite situation in Bolivia, where microfinance declined even more severely than the national economy during hard times (Marconi & Mosely 2005).

INSERT FIGURE 2 ABOUT HERE

In particular, the rapid growth of microfinance sector observed and its impact on financial sector development (Figure 3) in clusters 1 and 2 is connected to a relation between conventional

financial institutions (commercial banks) and MFIs, which may be co-operative or competitive depending on the competition on the market. Cull et al. (2009a) finds positive and robust evidence of competition from conventional banks pushing MFIs to serve poorer markets and more women. In this regard, our findings indicate a potential saturation point where microfinance clients grow and "graduate" to become clients of conventional financial institutions.

INSERT FIGURE 3 ABOUT HERE

Finally, the observed diverse impact of microfinance across clusters could potentially be explained by the "age" of microfinance activity as proxied by the number of years since the sector was introduced in a country (Armendáriz & Vanroose, 2009). As they claim, there is a potential country-wide learning curve which could explain growth and expansion of the microfinance sector (cluster 1 and 2).

INSERT FIGURE 4 ABOUT HERE

Impulse response analysis indicates that a further avenue for research could be identification of the state under which the microfinance shifts from being a complement to being a substitution. This could potentially be done using a non-parametric discrimination analysis, where countries are placed in three types of environments and the nature of microfinance as a complement or substitute is identified.

6. Conclusion

Motivated by limited knowledge of the economy-wide effects of microfinance, we aimed to measure its impact on economic growth, financial sector development and income inequality. We believe this constitutes an important contribution to the literature, as it is the first evidence of measurement of the aggregate effects of microfinance including those on non-recipients of

microfinance programs. Acknowledging the multidimensional nature of the external environment of microfinance, we divide countries into three broad clusters based on macro-institutional determinants established in previous literature. Our study finds that generally, microfinance has a significant positive effect at the macro level. MFI expansion is positively linked to economic growth, most strongly in developing and more stable economies when measured in terms of loan portfolios, consistent with Ahlin et al.'s 2011 findings.

We further find support for the impact of microfinance on financial sector development captured by broad money circulation in economies. A one percent increase in the numbers of microfinance borrowers in a country leads to a USD 314 increase in broad money per capita, which is equivalent to 13.8% of mean value for the whole sample. The effect clearly differs across clusters. Greater microfinance outreach is found in more stable and developed environments. This is in line with Ahlin et al.’s (2011) findings that greater financial depth is strongly associated with lower default and operating costs for MFIs. In contrast, the effect through loan portfolio is more pronounced in less developed and weaker environments. This is in line with the market failure hypothesis that MFIs flourish where formal financial institutions are weak.

Finally, we find a positive impact of microfinance in reducing income inequality. The results are stable for sample integrity of the Gini coefficient and trimming for outliers. The results are consistent with Ergungor (2010) showing that the favorable effects of bank branch presence become stronger when the branch is located closer to a (poor) neighborhood. More research is needed to make a stronger claim on any direct poverty reduction effect of microfinance. Nevertheless, we believe that our findings provide evidence of a positive impact on income inequality at aggregate impact.

Overall our results indicate that microfinance plays a significant role and provide evidence of its potential to affect broader economies. The impacts of microfinance on macro level and transfer dynamics, however, differ substantially by the macro-institutional environment of countries.

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Table 1. Summary statistics of the variables

Category:	Name:	Description:	N	Mean	Std. dev.	Minimum	Maximum
Microfinance	Portfolio	Loan portfolio/real GDP in USD	1091	7.8	15.6	0.0	147.5
	Borrowers	Percent, number of borrowers/population[c]100 people	1091	1.26	2.26	0.0	16.18
Macroeconomic	Economic growth	Real GDP per capita in constant prices	1069	4331	3891	248	24080
	Poverty	Gini coefficient	781	43.0	8.7	22.3	67.4
	Financial depth	Ratio of private credit to GDP	802	30.4	26.0	0.8	162.0
	Financial development	Broad money per capita, real USD	1043	2277	3236	12.0	29763
Institutional	FDI	Foreign direct investment, net inflows (% of GDP)	1070	4.1	5.2	-14.4	46.8
	Industry share	Industry, value added (% of GDP)	1009	29.8	10.6	10.8	77.4
	Lack of corruption	Control of corruption index (-2.5 to 2.5)	800	-0.6	0.5	-1.8	1.6
	Stability	Political Stability and Absence of Violence/Terrorism: Estimate (-2.5 to 2.5)	802	-0.6	0.8	-3.1	1.1

Source: authors' computation
N stands for a number of observations.

Table 2. Summary statistics of clusters

		Real GDP	**Stability**	**Control of corruption**	**Gini**	**Private Credit**	**FDI**	**Industry share**
Cluster 1 Stable	N	14	14	14	14	14	14	14
	min	8373	-1.11	-0.97	27	15	1.31	17
	mean	10941	0.02	0.02	45	45	4.37	31
	max	15122	0.89	1.39	61	135	10.57	50
Cluster 2 Moderate	N	22	22	22	22	22	22	22
	min	3784	-1.75	-1.21	30	9	1.51	19
	mean	5422	-0.43	-0.49	44	40	3.95	33
	max	7744	0.54	0.30	67	114	12.2	53
Cluster 3 Poor	N	48	48	48	48	48	48	48
	min	414	-2.51	-1.62	28	3	0.13	12
	mean	1722	-0.83	-0.75	41	17	3.29	28
	max	3534	0.62	-0.04	58	59	11.86	75
Total	N	84	84	84	84	84	84	84
	min	414	-2.51	-1.62	27	3	0.13	12
	mean	4228	-0.58	-0.55	42	28	3.65	30
	max	15122	0.89	1.39	67	135	12.21	75

Source: authors' computation
N stands for a number of observations.

Table 3. Interpretation of clusters

	Cluster 1 - Stable	**Cluster 2 - Moderate**	**Cluster 3 - Poor**
Real GDP	rich	developing (less rich)	poor
Stability	stable	moderate stable	unstable
Control of corruption	controlled	less controlled	uncontrolled
Inequality	greater inequality	greater inequality	moderate inequality
Private Credit	banking is developed	banking is less developed	banking is underdeveloped
FDI	developed business environment/ country openness	less developed business environment/ country openness	underdeveloped business environment/ country openness
Industry share	industrialized	most industrialized	less industrialized

Source: authors' computation

Table 4. Clusters by geographical regions

	Cluster 1 - Stable	Cluster 2 - Moderate	Cluster 3 - Poor	Total:
Other		22 (1)		22 (1)
East Asia and the Pacific	51 (4)	3 (1)	46 (4)	100 (9)
Europe & Central Asia	30 (1)	56 (5)	65 (6)	151 (12)
Latin America & the Caribbean	14 (1)	97 (9)	107 (8)	218 (18)
Middle East & North Africa	8 (1)		66 (6)	74 (7)
South Asia	65 (5)		9 (1)	74 (6)
Sub-Saharan Africa	281 (25)	16 (2)	33 (3)	330 (30)
Total:	449 (37)	194 (18)	326 (28)	969 (83)

Source: authors' computation

Notes: The table reports the total number of observations per country and year and total number of countries in 2009 (in parentheses).

Table 5. Clusters by income groups

	Cluster 1 - Stable	Cluster 2 - Moderate	Cluster 3 - Poor	Total:
High income: OECD		15 (2)		15
High income: non-OECD		7 (1)		7 (1)
Low income	276 (22)			276 (22)
Lower middle income	173 (15)		207 (18)	380 (33)
Upper middle income		172 (17)	119 (10)	291 (27)
Total:	449 (37)	194 (18)	326 (28)	969 (83)

Source: authors' computation

Notes: The table reports the total number of observations per country and year and total number of countries in 2009 (in parentheses).

Table 6. Economic Growth equation, equation (1).

	Cluster 1 - Stable		**Cluster 2 - Moderate**		**Cluster 3 - Poor**	
	MF borrowers	MF portfolio	MF borrowers	MF portfolio	MF borrowers	MF portfolio
GDP p.c. $_{-1}$	-0.787[b]	-0.038	0.562	0.671[a]	0.426[b]	-0.313
	(0.377)	(0.286)	(0.373)	(0.172)	(0.183)	(0.239)
GDP p.c. $_{-2}$			-0.918[b]	-0.010		
			(0.439)	(0.186)		
Microfinance $_{-1}$	**826[a]**	**-1.8**	**67.5**	**35.6[a]**	**-80.4[c]**	**268[a]**
	(280)	(4.02)	(125)	(8.89)	(45.7)	(67.5)
Microfinance $_{-2}$		**11.3[c]**	241		**146.6[b]**	
		(6.326)	(151)		(59.3)	
BMoney p.c. $_{-1}$	1.102[a]	1.027[a]	0.925[a]	0.459[b]	0.432[c]	0.688[a]
	(0.374)	(0.314)	(0.286)	(0.205)	(0.225)	(0.233)
BMoney p.c. $_{-2}$		-0.329	0.001	-0.608[a]	-0.046	
		(0.341)	(0.341)	(0.207)	(0.229)	
Constant	11745[a]	982[a]	3795[a]	1645[a]	560[a]	9217[a]
	(2071)	(267)	(1230)	(301)	(159)	(1369)
No of obs.	*104*	*246*	*210*	*210*	*246*	*96*
Sargan test, value	*15.4*	*9.6*	*16.5*	*25.7*	*17.6*	*25.4*
Sargan test, p-value	*0.162*	*0.380*	*0.056*	*0.262*	*0.610*	*0.185*

Notes: The table reports estimation results from the Arellano-Bover/Blundell-Bond system estimator with two lags of dependent variable included as regressors, endogenous covariates and a robust variance-covariance matrix based on equation (1). The dependent variable is real GDP per capita in constant prices. Data was cleaned, limiting microfinance borrowers at minimum 0.05% and using the identification procedure for outliers (BACON) with a maximum trimming to be less than 5% in last two columns. a, b, and c denotes statistical at 1%, 5% and 10% significance levels, respectively.

Table 7. Development of Banking sector (Broad money), equation (2)

	Cluster 1 - Stable		**Cluster 2 - Moderate**		**Cluster 3 - Poor**	
	MF borrowers	MF portfolio	MF borrowers	MF portfolio	MF borrowers	MF portfolio
BMoney p.c. $_{-1}$	0.558[a]	-0.291	0.774[a]	0.359[b]	0.758[a]	0.462[a]
	(0.092)	(0.317)	(0.055)	(0.156)	(0.076)	(0.120)
BMoney p.c. $_{-2}$		-0.235				
		(0.268)				
Microfinance $_{-1}$	**24.57[c]**	**-0.26**	**40.9[b]**	**31.4[b]**	**31.2**	**271[a]**
	(13.6)	(1.9)	(18.0)	(12.3)	(24.4)	(87.3)
Microfinance $_{-2}$				**-7.2**		
				(14.0)		
GDP p.c. $_{-1}$	0.261[a]	0.474[b]	0.078	0.125	0.116[c]	
	(0.085)	(0.232)	(0.055)	(0.161)	(0.070)	
GDP p.c. $_{-2}$		0.768[b]		0.188		
		(0.340)		(0.174)		
Constant	-148[b]	-911[a]	195	-143	69.1	2402[a]
	(73.9)	(291.9)	(186.6)	(303.4)	(242.7)	(440)
No. of obs.	*291*	*246*	*239*	*210*	*212*	*96*
Sargan test, value	*78.3*	*10.2*	*87.4*	*34.5*	*46.2*	*20.0*
Sargan test, p-value	*0.184*	*0.329*	*0.103*	*0.043*	*0.063*	*0.520*

Notes: The table reports estimation results from the Arellano-Bover/Blundell-Bond system estimator with two lags of dependent variable included as regressors, endogenous covariates and a robust variance-covariance matrix based on equation (2). The dependent variable is real GDP per capita in constant prices. Data was cleaned, limiting microfinance borrowers at minimum 0.05% and using the identification procedure for outliers (BACON) with a maximum trimming to be less than 5% in last two columns. [a], [b], and [c] denotes statistical at 1%, 5% and 10% significance levels, respectively.

Table 8. Microfinance equation, equation (3)

	Cluster 1 - Stable		**Cluster 2 - Moderate**		**Cluster 3 - Poor**	
	MF borrowers	MF portfolio	MF borrowers	MF portfolio	MF borrowers	MF portfolio
Microfinance $_{-1}$	**0.490**[c]	**0.081**	**1.740**[a]	**1.309**[a]	**1.225**[a]	**0.350**[b]
	(0.255)	(0.276)	(0.388)	(0.167)	(0.258)	(0.164)
Microfinance $_{-2}$		**0.461**[b]	**-0.628**[c]		**-0.410**	
		(0.180)	(0.332)		(0.270)	
BMoney p.c. $_{-1}$	-0.006[a]	-0.002	0.004[c]	-0.001	-0.001[b]	-0.018
	(0.002)	(0.002)	(0.002)	(0.008)	(0.000)	(0.032)
BMoney p.c. $_{-2}$	0.001			-0.006		-0.093[a]
	(0.003)			(0.006)		(0.036)
GDP p.c. $_{-1}$	0.005[c]	0.001	-0.003[c]	-0.003	0.001[b]	0.072[c]
	(0.003)	(0.002)	(0.002)	(0.004)	(0.000)	(0.041)
GDP p.c. $_{-2}$	0.002			0.003		0.042
	(0.002)			(0.007)		(0.036)
Constant	-5.7[b]	-2.3	6.3	13.6	-3.9[c]	-92.7[a]
	(2.3)	(10.7)	(4.7)	(10.2)	(2.2)	(27.4)
No. of obs.	*246*	*81*	*210*	*210*	*88*	*246*
Sargan test, value	*20.6*	*7.1*	*12.9*	*6.0*	*14.7*	*11.1*
Sargan test, p-value	*0.421*	*0.621*	*0.226*	*0.810*	*0.677*	*0.265*

Notes: The table reports estimation results from the Arellano-Bover/Blundell-Bond system estimator with two lags of dependent variable included as regressors, endogenous covariates and a robust variance-covariance matrix based on equation (2). The dependent variable is real GDP per capita in constant prices. Data was cleaned, limiting microfinance borrowers at minimum 0.05% and using the identification procedure for outliers (BACON) with a maximum trimming to be less than 5% in last two columns. [a], [b], and [c] denotes statistical at 1%, 5% and 10% significance levels, respectively.

Table 9. Inequality equation, equation (4)

	No trimming for outliers			**Trimming at 5%**	
	Gini	**Linear interpolation of Gini**		**Gini**	**Linear interpolation of Gini**
	MF borrowers	MF borrowers		MF borrowers	MF borrowers
Gini $_{-1}$	-1.345[a]	-0.869[a]		-1.369[a]	-0.904[a]
	(0.330)	(0.185)		(0.349)	(0.184)
Gini $_{-2}$	-1.143[a]	-0.724[a]		-1.155[a]	-0.789[a]
	(0.297)	(0.165)		(0.307)	(0.171)
Microfinance $_{-1}$	**6.719**	**5.083[b]**		**6.957**	**4.488[b]**
	(4.273)	(2.373)		(4.263)	(2.223)
Microfinance $_{-2}$	**-9.043[c]**	**-6.029[b]**		**-9.432[b]**	**-5.306[b]**
	(4.623)	(2.862)		(4.689)	(2.689)
GDP p.c. $_{-1}$	0.005	-0.001		0.006	-0.000
	(0.005)	(0.003)		(0.005)	(0.003)
GDP p.c. $_{-2}$	-0.007	-0.000		-0.008	-0.002
	(0.006)	(0.004)		(0.006)	(0.004)
Constant	11.854	5.507		12.848	6.217[c]
	(9.325)	(3.482)		(8.968)	(3.252)
No. of obs.	*183*	*582*		*180*	*571*
Sargan test, value	*5.360*	*9.691*		*4.842*	*14.389*
Sargan test, p-value	*0.718*	*0.287*		*0.774*	*0.072*

Notes: The table reports estimation results from the Arellano-Bover/Blundell-Bond system estimator with two lags of dependent variable included as regressors, endogenous covariates and a robust variance-covariance matrix based on equation (4) The dependent variable is the Gini coefficient. Data was cleaned, limiting microfinance borrowers at minimum 0.05% and using the identification procedure for outliers (BACON) with a maximum trimming to be less than 5% in last two columns. [a], [b], and [c] denotes statistical at 1%, 5% and 10% significance levels, respectively.

Figure 1. Comparison of clusters, mean values

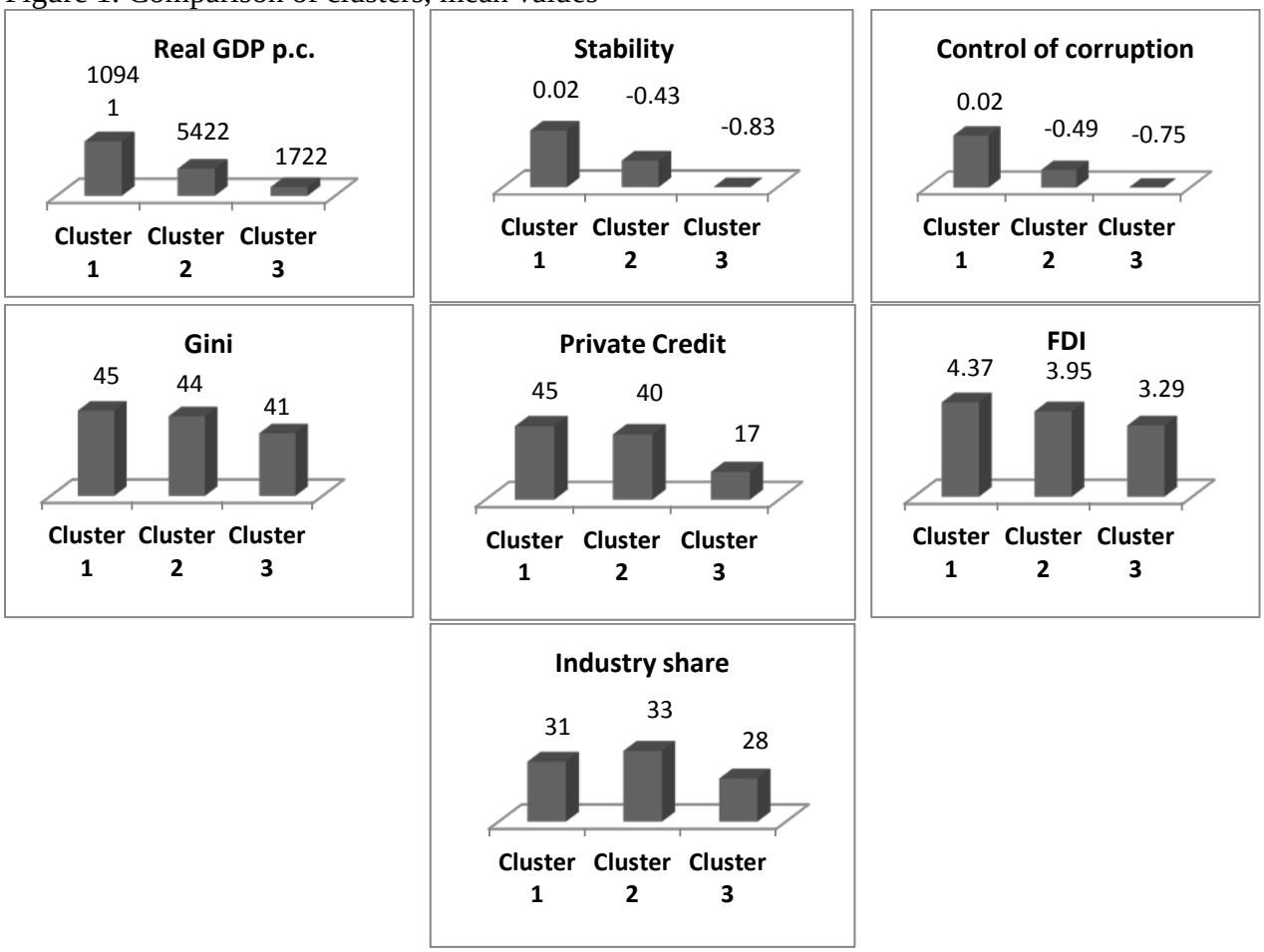
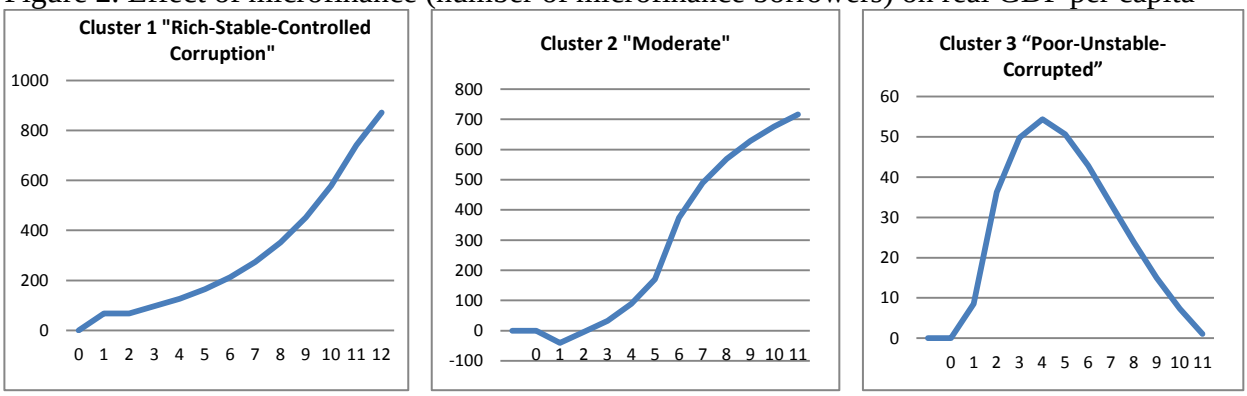
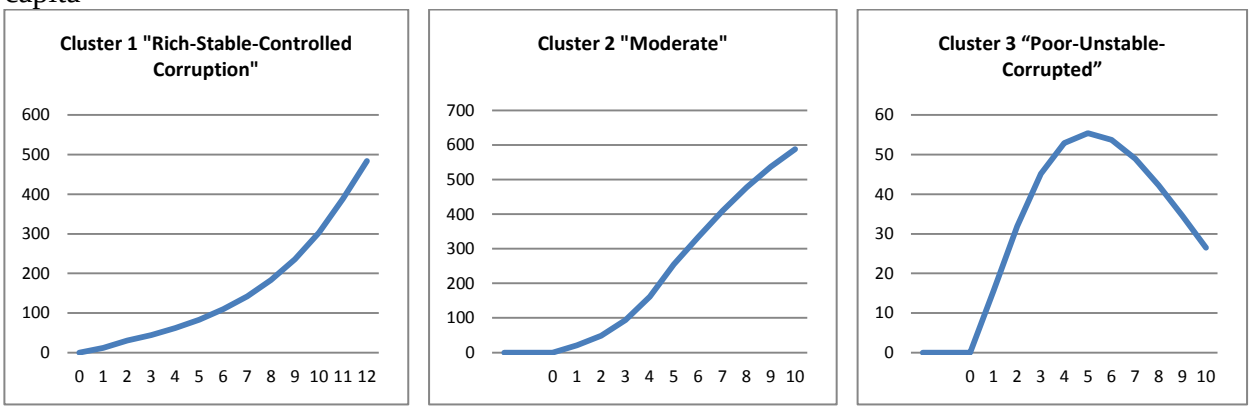


Figure 2. Effect of microfinance (number of microfinance borrowers) on real GDP per capita



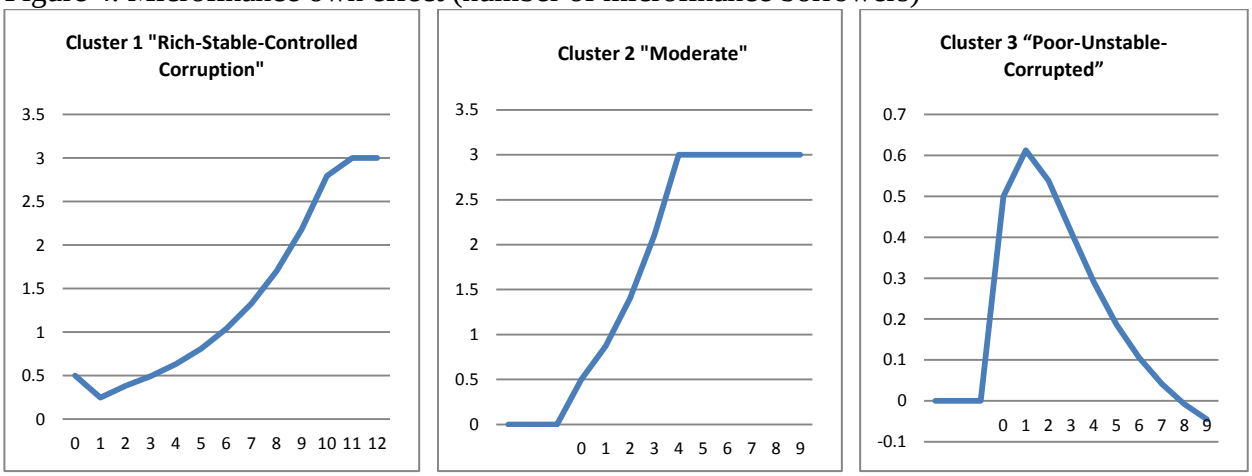
Notes: the figure represents impulse response functions of the shock from microfinance at 0.5%. Additional modeling is made so that there is a potential saturation of microfinance market at 3%.

Figure 3. Effect of microfinance (number of microfinance borrowers) on broad money per capita



Notes: the figure represents impulse response functions of the shock from microfinance at 0.5%. Additional modeling is made so that there is a potential saturation of the microfinance market at 3%.

Figure 4. Microfinance own effect (number of microfinance borrowers)



Notes: the figure represents impulse response functions of the shock from microfinance at 0.5%. Additional modeling is made so that there is a potential saturation of the microfinance market at 3%.