Subsidy Uncertainty and Microfinance Mission Drift*

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Abstract

We demonstrate that subsidy uncertainty in microfinance can lead to mission drift and defeat poverty alleviation efforts. Our model shows that microfinance institutions, fearing that subsidies may dry up, have no alternative but to build precautionary savings by serving wealthier clients, thereby deviating from their poverty alleviation mission. Using data from rating agencies, we find a positive relationship between subsidy uncertainty and the interest rate charged to borrowers. The policy prescription to donors wishing to maximize social impact is to deliver subsidies in a predictable and transparent way.

1. Introduction

Low-income households can access credit through microfinance institutions (MFIs). A vast majority of these have stated that poverty reduction is their *raison d'être*.[1] Donors' response to MFIs' poverty alleviation efforts has been generous. Ever since their inception in the mid-1970s, MFIs worldwide have benefitted from millions of subsidies from local governments, multilateral aid agencies and, more recently, socially responsible investors. Quite independently of the source of such donations, subsidies have undeniably contributed to offering financial access to approximately 200 million clients (Daley-Harris, 2012). However, the effect of subsidized microfinance on poverty alleviation remains controversial.[2]

This paper focuses on the design of subsidies to microfinance. We argue that MFIs can more easily meet their poverty alleviation objective if the volume and schedule of subsidies received from donor agencies are certain. Our argument is inspired by the theory of precautionary savings (Friedman, 1957; Ando and Modigliani, 1963). We construct a simple analytical framework showing that supply-driven subsidy uncertainty can have detrimental effects on microfinance when it is used as a poverty reduction tool. To our

[1] Armendáriz and Szafarz (2011) report on the mission statements from the top ten MFIs in Asia and Latin America.

[2] A case in point concerns microcredit to women, who account for eight out of ten loans extended by MFIs. Women account for as much as 70% of the world's poorest (UNDP Human Development Report, 1996). However, Garikipati (2008) and Guérin *et al.* (2009) have challenged the impact of microfinance on women empowerment by demonstrating that lending to women may increase intra-household strife, which is biased against women and renders them financially vulnerable. In a similar vein, Agier and Szafarz (2013a) argue that using gender as a proxy for poverty might be misleading since female borrowers can suffer from a glass-ceiling effect (i.e., *ceteris paribus* being granted smaller loans than men). More generally, the effects of microcredit on poverty reduction and empowerment have been seriously questioned empirically (see, for example, a comprehensive discussion based on field work in India by Banerjee and Duflo, 2011).

knowledge, this is the first microfinance model to show conclusively that failed interventions might be supply-driven.

We present a model where the MFI's objective is to serve the maximum number of poor clients under self-sustainability and borrowing constraints. Fearing that subsidies may dry up, the MFI has no alternative but to build precautionary savings by serving wealthier clients, thereby deviating from its poverty alleviation mission. Data collected from rating agencies is used to test the predictions of the model. Our empirical analysis suggests a positive relationship between subsidy uncertainty and interest rates charged to borrowers.[3]

Serving the largest possible number of poor clients is particularly important for an overwhelming majority of MFIs that are net recipients of subsidies from international donor agencies.[4] Surprisingly, however, the literature on subsidies in microfinance and their impact on poverty alleviation is scarce. Notable exceptions include recent work by Hudon (2010), Nawaz (2010), and Hudon and Traça (2011). Their focus is not on social mission, though, but on the impact of subsidies on managerial efficiency. For example, Hudon (2010) finds that subsidies do not have a positive impact on management quality. Similarly, Nawaz (2010) and Hudon and Traça (2011) find that subsidies have a marginally positive impact on financial efficiency. In contrast, Caudill *et al.* (2009) find that lower subsidies are associated with higher cost reduction over time.

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[3] In the case of group lending, higher interest rates might drive entire groups of poor individuals out of the credit market. Their exclusion is a form of credit rationing (Ghatak, 1999).

[4] See González and Rosenberg (2006). We henceforth refer to all institutional sources of subsidies to microfinance as "donors".

In parallel, a growing literature on mission drift has emerged (Ghosh and Van Tassel, 2008; Mersland and Strøm, 2010; Armendáriz and Szafarz, 2011). Mission drift is defined as MFIs serving wealthier clients at the expense of poor clients.[5] The empirical literature on mission drift is mainly devoted to its link with commercialization. Cull *et al* (2007) show that the relatively recent trend toward commercialization is driven by MFIs offering loans that are larger on average when compared with those offered by non-governmental organizations (NGOs). They also show that loans offered by commercial MFIs are biased against women. These findings are supported by Mersland and Strøm (2010), who focus on average loan size and the proportion of women served.

This paper adopts a different perspective on mission drift. Based on qualitative interviews with microfinance practitioners at several MFIs, we focus on the impact of subsidies on mission drift. Supply-driven uncertainty leads to a trade-off: subsidy-dependent MFIs maximize utility by offering small loans to poor individuals, but they also feel compelled to extend relatively larger loans to more profitable wealthier clients for precautionary savings purposes. We thus view mission drift as being rooted in the uncertainty faced by subsidy-dependent MFIs.

Our perspective is close in spirit to that in Agénor and Aizenman (2010), where poverty traps are induced by high aid volatility. The authors' analysis focuses on subsidies in infrastructure, health and educational investments. Ours deals with aid flowing into the microfinance industry. From a macro perspective, Neanidi and Varvarigos (2009) state that

[5] According to Ghosh and Van Tassel (2008) mission drift should be viewed as a dynamic phenomenon driven by profit-oriented donors. In contrast, Armendáriz and Szafarz (2011) emphasize that socially oriented donors often fail to distinguish between mission drift and cross-subsidization.

aid volatility can significantly hamper economic growth. Lensink and Morrissey (2000) find that the level of aid is not significantly related to growth whereas aid uncertainty is related to it, though negatively, of course.[6] Generally speaking, volatility is a problem because it makes objectives more difficult to reach.

In our analysis, aid volatility triggers mission drift. It restricts the number of poor individuals MFIs can serve, to the benefit of wealthier clients. Failed interventions in our paper are triggered by donors. This is not because donors are profit-oriented, as in Gosh and Van Tassel (2008), but because they are *not* necessarily committed to delivering subsidies in timely fashion and under clear, transparent rules.

The main policy implication of our findings is the following. Considering that serving the poor is costly, donors should re-design subsidy delivery by making credible commitments. Our results echo at the micro level the conclusion reached by Lensink and Morrissey (2000) that aid volatility reduces aid effectiveness. In both cases, enhanced quality of donations through reduced uncertainty is beneficial to the very purpose of those donations. Hence, donors must clearly specify the rules, volume and timing of disbursements.

The remainder of the paper is structured as follows. Section 2 delivers a brief review of the literature on the role of subsidies in microfinance. Section 3 presents a stylized model of precautionary savings. This set-up is used to establish the connection between subsidy

[6] Aid volatility is far from anecdotal. Bulir and Hamann (2007) show that it surpasses the volatility of domestic tax revenues. Moreover, aid volatility increases as the recipient country's natural and political environment becomes more volatile (Hudson and Mosley, 2006).

uncertainty and mission drift. Section 4 describes the data and presents the empirical results. Section 5 concludes.

2. Subsidies in Microfinance

Microfinance and subsidies are deeply intricate. Microfinance emerged in the mid-1970s thanks to the generosity of visionary donor agencies such as the International Fund for Agricultural Development, the *Deutsche Gesellschaft für Technische Zusammenarbeit* in Asia, and the United States Agency for International Development in Latin America.[7]

Arguably, one of the major recipients of foreign aid from multiple sources since the mid-1970s has been the Grameen Bank, the flagship of microfinance in Asia. Morduch (1999), for example, estimates that effective subsidies to the Grameen Bank amounted to approximately USD 175 million in the 1985-1996 period alone. Similar stories on subsidization have also been documented for the case of commercially-oriented MFIs in Latin America. BancoSol in Bolivia, for example, transformed itself from an NGO into a full commercial bank with the support of subsidies. Banco Compartamos in Mexico also benefitted from subsidies (González-Vega *et al,* 1996; Santos, 2009; Armendáriz and Morduch, 2010).

[7] The acronym for the *Deutsche Gesellschaft für Technische Zusammenarbeit* was GTZ (see Armendáriz and Morduch, 2010). It is now called *Deutsche Gessellschaft für Internationale Zusammenarbeit* (GIZ). This institution has financed dozens of replications of the Grameen Bank worldwide through donations of seed capital for start-ups and technical assistance.

Subsidies support MFIs in their efforts to offer financial services to the poor, who request small loans involving high operational costs (Conning, 1999; Copestake, 2007). In return, donors expect MFIs to reach the so-called "double bottom line" objective: serving the largest number of poor people *and* becoming financially self-sustainable. Another argument for intervention has been put forward by Armendáriz and Morduch (2010). They say that when the production function is not "conveniently" concave, capital will not naturally flow from rich to poor, as the standard neo-classical theory predicts. Loans will instead be granted to wealthy individuals, either because the wealthy have other production inputs (e.g., business savvy or higher levels of human capital) and/or because, relative to the poor, they can obtain higher returns on capital through economies of scale. The wealthy demand large loans, which they manage to invest at a much higher rate of return relative to that of the poor, whose businesses are small.

In practice, a simple way of analyzing the role of subsidies is to use interest rates. MFIs can indeed lower the interest rates they charge poor borrowers because transaction costs are partly covered by donors. The literature is however scarce on the impact of subsidies on microcredit interest rates. An exception is Hudon and Traça (2006), who find that higher subsidies drive lower interest rates and smaller average loan sizes. The level of interest rates in microfinance is a controversial issue. In particular, Muhammad Yunus considers that the interest rates charged by Compartamos, the largest – and now quoted — Latin American MFI, place it in the category of moneylenders. Interestingly, financial authorities in Bangladesh and India, the two countries with the largest microfinance industries, have recently set interest-rate ceilings. Subsidies therefore act in support of removing credit constraints faced by the poor. This in turn boils down to reducing the incidence of MFIs deviating from their poverty-alleviation mission.[8]

Donors may however insist on self-sustainability as an additional objective. The problem then is how donors can make sure that subsidized MFIs will meet their double bottom line. Some donors might attempt to exercise a right of control on MFIs' management. For example, donors might favor equity investments in MFIs so as to attract new private investors (Mersland, 2009). Lack of control over the use of subsidies might have a negative impact on managers' actions. Potentially eligible clients might not be served (Bhatt and Tang, 2001; Agier and Szafarz, 2013). These problems show that subsidization is poorly designed and even excessive at times. But existing literature on the subject does not convincingly suggest that subsidies should be slashed.

The debate on efficient subsidization is not new. When the movement gained momentum in the 1980s, donors were urged to implement so-called "smart subsidies" (Morduch, 2005). Smart subsidies, it was contended, should address three issues, namely, the fact that subsidies should be transparent, rule-bound, and, most importantly, time-limited. Donors were encouraged to focus on subsidizing start-up expenses, institutional capacity building, and product development, with an eye to designing an exit strategy within a particular time-frame.

It was later recognized that competition in microfinance could be harmful because of the risk of higher over-indebtedness (Schicks, 2012). Indeed, financing start-ups without appropriate credit bureaux is increasingly perceived as counterproductive. Paradoxically, it

[8] We use "objective" and "mission" interchangeably.

was not an excess of competition – but the lack of it – that might have prompted some subsidized NGOs in Latin America and Asia to convert themselves into commercial MFIs. This is a relatively recent occurrence. In the mid-2000s the commercialization of MFIs prompted researchers to revisit the subsidy design literature. Our empirical results in Section 4 show that arguments against subsidization of microfinance that are based on mission drift are misleading.

From an empirical standpoint, the literature on subsidized microfinance is scarce. Cull *et al.* (2007) show that group lending MFIs, whether solidarity groups such as Grameen – most prevalent in Asia – or village banking institutions – most common in Latin America – are net recipients of a disproportionate amount of subsides relative to those accruing to MFIs using individual lending methodologies. NGOs unsurprisingly receive a large amount of subsidies compared with commercial banks. The impact of subsidies on poverty alleviation, however, remains mostly unknown. Our theoretical analysis is intended to bridge the gap between subsidy design and mission drift.

3. The Model

This section presents a simple model of subsidies and mission drift. Consider an MFI offering two types of loans. Type-1 loans are offered to poor clients. The size of these loans at time $t, s_1(t) \geq 0$ is chosen by the MFI.[9] Type-2 loans are supplied to wealthier clients who

[9] Implicit in this assumption is that the MFI has all the bargaining power. This might be true for several large MFIs that have a considerable market share. An alternative justification is that the size of the loan offered by the MFI is incentive-compatible.

demand a minimal loan size ($\forall t: s_2(t) > \underline{s}$) to invest in a project. Both project types can be financed only by the MFI.[10] The interest rate charged on all loans is exogenously fixed at ρ.

In period $t > 0$, the MFI receives a stochastic subsidy $K_t \geq 0$, and extends $N_1(t)$ Type-1 loans and $N_2(t)$ Type-2 loans.[11] It faces transaction costs $f\left(N_1(t), N_2(t)\right)$ depending on the numbers and types of loans. This cost function is assumed to be linear. Relative to wealthier clients, we assume that the poor are costlier to serve:

$$f(N_1, N_2) = \gamma_1 N_1 + \gamma_2 N_2, \quad \gamma_1 \geq \gamma_2 > 0 \tag{1}$$

The MFI's objective is to maximize the number of poor individuals that can access finance. It maximizes expected utility, which is an increasing function of the number of poor individuals served. The MFI can control the size of each type of loan, $s_1(t)$ and $s_2(t)$. Ideally, the MFI would extend loans to the poor only, but it is subject to a budget constraint. Its expected utility is discounted by a factor $\beta \leq 1$. We assume that the MFI's utility is additive and that its expected utility is discounted exponentially:

$$U\left[N_1(1), \ldots, N_1(t), \ldots\right] = \sum_{t=1}^{\infty} \beta^t U\left[N_1(t)\right], \tag{2}$$

[10] Implicit in this assumption is that there is only one MFI serving all clients in the credit market. Our results will not be altered if we were to assume that the MFI is perfectly competitive. As long as the loan contract is incentive-compatible, both types of clients will face the same loan contracts from all MFIs operating in the market.

[11] For simplicity, we are assuming that both types of loans are offered individually and that clients self-select themselves into a contract depending on their type. Our results will not change if we were to assume group lending under joint liability and assortative matching as in Ghatak (1999).

where $U[.]$ is an increasing concave function. The assumption of concavity is key. It translates the MFI's dedication to its mission of poverty alleviation in an intertemporal perspective. In particular, the MFI would not stand serving poor borrowers in the present at the expense of being diverted from its mission in the future. Mission fulfillment should thus be understood as a sustainable long-term objective. Put differently, socially oriented MFIs are subject to a sustainability linked risk aversion that results from their very *raison d'être*.

At time *t*, the MFI benefits from a subsidy, K_t, which is stochastic. The timing of events is as follows. Initially, i.e. at time 1, the MFI receives subsidy K_1, and allocates it partly to finance poor clients ($N_1(1)$ of Type-1 loans), and the rest is used to finance wealthier clients ($N_2(1)$ of Type-2 loans). All loans are extended for one period with interest rate ρ and are reimbursed on time.[12] At time 2 (and beyond), the MFI cashes in subsidy K_2 and the loans granted in period 1 are repaid with interest. The total resources are used to grant loans to poor clients (i.e., $N_1(2)$ loans) and to wealthier ones (i.e., $N_2(2)$ loans). And so on.

In each period, the MFI fixes the numbers and sizes of both types of loan. The MFI maximization problem is:

[12] We could add the possibility for defaults in reimbursements. However, this would bring a second source of uncertainty and make the model unnecessarily more complex.

$$\underset{s_1(t),s_2(t),N_1(t),N_2(t)}{Max} E\sum_{t=1}^{\infty}\beta^t U\left[N_1(t)\right]$$

$$\begin{aligned}
&\text{s.t. } K_1 = s_1N_1(1)+s_2N_2(1)+\gamma_1N_1(1)+\gamma_2N_2(1)\\
&\quad K_{t+1}+(1+\rho)\left[s_1N_1(t)+s_2N_2(t)\right]=s_1N_1(t+1)+s_2N_2(t+1)+\gamma_1N_1(t+1)+\gamma_2N_2(t+1),\, t>0\\
&\quad s_1(t)\geq 0;\, s_2(t)\geq \underline{s},
\end{aligned} \tag{3}$$

We make the following assumptions.

Assumption 1: Lending to the poor is costly ($\gamma_1 > 1+\rho$ *), and lending to the wealthier is profitable (* $\gamma_2 < 1+\rho$ *).*

Assumption 2: Type-2 loans have a fixed (normalized) size:

$$\forall t : s_2(t) = \underline{s} = 1 \tag{4}$$

Assumption 1 implies that lending to the poor is similar to extending grants, thereby making the microfinance industry look like an aid agency. However, reimbursements by the poor make the lending activity less costly than giving grants, provided that transaction costs are not too high. In contrast, lending to the wealthier is profitable. Otherwise, the MFI would never issue Type-2 loans because serving wealthier clients is not its objective. Assumption 1 also implies that the MFI will always offer the smallest possible loan size to the poor: $\forall t : s_1^*(t) = 0$. In contrast, Assumption 2 is purely technical. It ensures that the cost function is well-behaved since costs are defined for each loan independently of its size.

Type-2 loans do not contribute directly to the MFI's objective. Rather, they represent a profitable side-business known as cross-subsidization. In sum, the MFI finances its loans to poor clients in two ways: through direct subsidies and cross-subsidization. Because lending to wealthier clients involves a transaction cost, γ_2, the interest rate charged, ρ, is not the rate of return. The actual rate of return from cross-subsidization – net of transaction costs – is:

$$r = \frac{1+\rho-\gamma_2}{\gamma_2}. \tag{5}$$

Importantly, rate *r* can be used by the MFI for investing/lending only, not for borrowing.

Let us denote by C_t the cost of serving $N_1(t)$ clients at time *t*:

$$C_t = \gamma_1 N_1(t) \tag{6}$$

and let us define:

$$U\left[N_1(t)\right] = V\left[C_t\right] \tag{7}$$

Function $V[\bullet]$ enjoys the same properties as $U[\bullet]$. Specifically, $V[\bullet]$ is increasing and concave, with: $V'[C_t] = \gamma_1 . U'\left[\gamma_1 N_t(t)\right]$.

Using Eqs. (4)-(7) we rewrite the MFI's problem (3) as:

$$\begin{aligned}
&\underset{C_t}{Max}\, E\sum_{t=1}^{\infty}\beta^t V\left[C_t\right] \\
&\text{s.t. } W_{t+1} = \left(W_t - C_t\right)\left(1+r\right) + K_{t+1},\, t>1 \\
&\quad C_t \geq 0,\, t>0 \\
&\quad W_t - C_t \geq 0,\, t>0
\end{aligned} \tag{8}$$

where W_t represents the budget of the MFI at time t to be allocated to loan granting. Under specification (8), our model becomes similar to the standard intertemporal consumption model of Hall (1988). Resources that are devoted to serving the poor add to the MFI's current utility while those resources lent to the wealthier support the MFI's efforts to serve the poor in future.[13]

Under the assumption of perfect capital markets, the same interest rate is applicable to lending and borrowing. However, a vast majority of unregulated MFIs cannot collect savings, and they face difficulties borrowing from commercial banks.[14] Most MFIs, particularly subsidy-dependent NGOs, can neither borrow from commercial banks nor raise capital by issuing shares on the stock exchange. In our model, credit constraints faced by the MFI are captured by the sign of the restriction $N_2(t) \geq 0$. This in turn implies that the risk of bankruptcy is nil.

For the sake of clarity, we organize the discussion on the outcome of the model into two steps. First, credit constraints are ignored in Subsection 3.1. Second, in Subsection 3.2, they are factored in.

3.1 The Model Without Credit Constraints

Let us consider model (8) under the assumption that the MFI is allowed to borrow from commercial banks. The MFI will therefore charge poor and wealthier clients the (net)

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[13] The parallel between our model and the intertemporal consumption model is not just formal as it relates strongly to the problem faced by charitable institutions, MFIs included. Just like consumption, lending to the poor is costly and therefore needs to be financed somehow.

[14] A similar restriction, called the "liquidity constraint," is considered as a factor that explains consumption smoothing (Flavin, 1985; Deaton, 1991).

market interest rate, *r*. This equals the MFI's cost of borrowing. Under a no-credit constraints assumption, the MFI maximization problem is thus:

$$\underset{C_t}{Max}\, E\sum_{t=1}^{\infty}\beta^t V\left[C_t\right]$$

$$\text{s.t. } W_{t+1}=\left(W_t-C_t\right)\left(1+r\right)+K_{t+1},\, t>1 \tag{10}$$

Following Hall (1988), the Euler equation in (10) above gives:

$$E_t V'\left(C_{t+1}\right)=\frac{1}{\beta\left(1+r\right)}V'\left(C_t\right) \tag{11}$$

Eq. (11) looks as if subsidies are no longer playing a role. But this is misleading since subsidies are part of our model, albeit indirectly, i.e. through expectations.

To derive optimal loan allocation, we make additional assumptions with regards to the dynamics of subsidies.[15] In line with most models in the same vein, we assume that subsidies follow a random walk. This means that a subsidy at time *t* is equal to a previous subsidy plus a white noise. Hence, the mean subsidy is a constant. This simplifying assumption enables us to disregard the deterministic component and focus instead on the impact of subsidy uncertainty on the maximum number of poor borrowers the MFI can serve.

Under fairly general assumptions regarding the objective function (8), we show in Appendix 1 that subsidy uncertainty reduces the number of loans to the poor and increases the number of loans to the wealthier. It does so for precautionary savings reasons. The MFI

[15] See Zeldes (1989).

is compelled to lend to wealthier clients as an insurance policy against being unable to extend loans to the poor in the future. Since the poor are costly to serve, the MFI must make sure it has enough resources to extend future loans to the poor once it has reached a certain threshold – in line with its intertemporal poverty alleviation objective.

Decreasing the number of loans the MFI extends to the poor while simultaneously serving a larger number of wealthier clients is the typical stigma of mission drift. Actually, the MFI is just being cautious: it wants to remain solvent in order to be faithful to its long-term objective, namely serving poor clients.[16]

3.2. The Model with Credit Constraints

A key assumption in our analysis so far has been that MFIs have access to finance, and hence can borrow from commercial banks at prevailing market rates. Alternatively, we could assume that MFIs' investments can be financed from savings. However, both assumptions are unrealistic. First, a vast majority of MFIs cannot borrow in the local or international markets. Second, for savings to be mobilized, microfinance NGOs have to be regulated, which is often not the case.[17]

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[16] As pointed out by Caballero (1991), the impact of precautionary savings may be huge. According to his estimation on US data, uncertainty on income can induce more than 60 percent of wealth devoted to precautionary savings. While the problem here is different, this number should not be taken at face value and specific estimations are required to assess the impact of precautionary savings in the specific case of MFIs. For instance, one may conjecture that MFIs are less concerned with their future activity than individuals are with their future consumption. Nevertheless, caution is a basic principle in firm management and MFIs' managers care not only about the future of their institution, but also about their own career.

[17] In practice, the situation is less clear-cut as subsidies to MFIs are sometimes provided in the form of cheap long-term credit.

Let us now introduce credit constraints. When these are binding, the poverty alleviation objective is further thwarted. When the unconstrained optimal number of poor served is no longer reachable due to tight credit ceilings, the MFI will fall to a lower level of utility.

More formally, consider model (8) with credit constraints. The MFI will allocate the resources available at time *t*. Following Zeldes (1989), the Euler equation becomes:

$$E_t V'\left(C_{t+1}\right) = \frac{1}{\beta\left(1+r\right)} V'\left(C_t\right) + \lambda_t , \tag{12}$$

where λ_t is the Lagrange multiplier associated with the non-negativity constraint: $W_t - C_t \geq 0$. Since the MFI is constrained in the amount it can borrow but *not* on the amount it can save, the Lagrange multiplier is $\lambda_t \geq 0$. If, at time *t*, this constraint is not binding, then $\lambda_t = 0$ and the results from our previous sub-section apply. However, when this constraint is binding $\lambda_t > 0$, the current poverty reduction maximization objective is lower but the future one is higher than in the previous scenario without credit constraints. Credit constraints make it impossible for the MFI to use future expected subsidies to "smooth" its current poverty alleviation objective.

Under fairly general conditions, Schechtman (1976) and Zeldes (1989) demonstrate that precautionary savings due to uncertainty are larger in the case of credit constraints. In our model, this means that an MFI that expects to be running short of cash at some point in the future will reduce its current lending to the poor and serve wealthier clients instead. The MFI will do so to save enough resources for the future. As a result, the MFI will deviate from its certainty-equivalent optimal. Mere observation of such deviations might in turn be misinterpreted as an *ex post* sign of mission drift. Even if the *observed* credit constraint is not binding, the MFI's decision to *ex ante* extend loans to wealthier borrowers could be attributable to rational optimization behavior. This phenomenon, widely recognized in the consumption-smoothing literature, has somewhat surprisingly never been mentioned in the microfinance literature.

At first glance, the application of precautionary savings to microfinance might seem questionable. One could reasonably object that donors detect in real time those MFIs that deviate from their poverty alleviation mission and react by withdrawing their support. Yet, this is not true in practice. Donors do shy away in the vast majority of cases where MFIs give the impression of having deviated from social objectives. Mission drift cannot be easily proven and control is costly. In fact, verifying compliance with social objectives is difficult if not impossible. Therefore, we argue that the intertemporal precautionary savings approach makes perfect sense in microfinance. We now turn to testing the implications of our model.

4. Empirical Results

Our empirical analysis aims at testing whether there is a relationship between subsidy uncertainty and mission-drift variables. We use data from 230 MFIs active in 60 countries over the 1999-2006 period.[18] Our data was obtained from assessment reports issued by external rating agencies. Being compiled by a third party, this data is less likely to be biased

[18] Appendix 2 provides information about the geographical composition of the sample by listing the number of MFIs of each type in each country.

than the self-reported data typically used in microfinance.[19] This is a notable advantage when it comes to studying subsidies. Conversely, we have a limited time span which hinders the measurement of subsidy uncertainty. More precisely, we have five years of annual data for 4% of the MFIs in the sample, four years for 15% of them, three years for 53%, and only two years for 28%.

The dataset contains a wide variety of MFIs (see Table 1): 50% are NGOs, 23% non-bank financial institutions, 20% cooperatives, and only 7% for-profit MFIs. To check the representativness of our sample, we compared some of the basic statistics with those from the 890 MFIs included in the 17th MicroBanking Bulletin (MBB, 2008). And we obtained similar figures.[20]

Table 2 presents descriptive statistics. The median MFI has been in operation for 7 years. Its total outstanding loan portfolio is USD 1,754k. Its average loan size is USD 398. In line with Hudon and Traça (2011), we measure subsidy (in %) by the share of donated equity in total equity.[21] As expected, the vast majority of MFIs in our sample depend heavily on subsidies. The median MFI enjoys a roughly 50% subsidization rate.

< Insert Table 1 here >

We measure subsidy uncertainty by the standard deviation of the subsidy. This variable ranges from 0 to 351%, its mean value is 19%. The closer the standard deviation of

[19] In self-reports, MFIs could purposely under-report donations and over-estimate social performances in order to secure future funding from international aid agencies.

[20] The average operational sustainability ratio is 115% in MBB (2008) and 117% in our database. The average number of borrowers is 11,041 in the MBB (2008) and 10,232 in our database. The average nominal yield is 30% in the MBB (2008) and 31% in our database. Last, the average staff productivity proxied by number of borrowers per staff member is 112 in the MBB (2008) and 132 in our database.

[21] We use a relative measure of subsidy in order to facilitate comparisons across MFIs.

the subsidization rate is to zero, the lower the subsidy fluctuations. For instance, unsubsidized MFIs as well as MFIs with a constant share of donated equity have zero subsidy uncertainty. Conversely, MFIs confronted with large standard deviations are subject to high subsidy fluctuations over the sample period.

Admittedly, unconditional standard deviations are rough proxies of expected volatility for future subsidies. They are computed over the whole sample period, and are therefore not usable as such by MFIs. Still, given the short available time span, we have no other option but to rely on some heroic steady-state assumptions on subsidy uncertainty and interpret our measure as the indicator used by MFIs to decide on the need for precautionary savings. Besides, this method raises the possibility of reverse causality. The MFI's decision-making can indeed make subsidies fluctuate. While subsidies are exogenous in our theoretical model, it is likely that, in the real-world, causations go both ways. Nevertheless, the risk of reverse causality is lower for subsidy uncertainty than for the subsidies themselves.[22]. We control for subsidies in all the regressions. Doing so helps separate the effect of subsidy uncertainty on mission drift from the effect of the subsidies, which may be endogenous. In addition, we will cautiously interpret our empirical results in terms of linkages rather than pure implication.

Measuring mission drift also turns out to be challenging. In our theoretical model, mission drift means that the MFI shifts from poor to wealthier borrowers. Unfortunately, direct data on clients' wealth is not available. As a consequence, we need to turn to proxies for mission drift.

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[22] Donors typically adapt their subsidies to the development of the MFI but it is unlikely that they purposely impose uncertainty on the MFI they wish to help.

In fact, MFIs can move from costly poor clients to profitable wealthier ones through various channels. A first variable that captures such a move is average loan size. MFIs typically grant very small loans to poor borrowers and relatively larger loans to wealthier ones. A higher average loan size thus suggests that MFIs are shifting from serving the poor to serving the wealthier. As Cull *et al.* (2009) argue, MFIs can increase their profit margins significantly by saving on transaction costs. We scale average loans by per-capita gross national income (GNI) to make meaningful cross-country comparisons.

Second, mission drift can be captured through the interest rates charged by MFIs. Higher interest rates might signal lower social concern. Accordingly, they might be associated with a move towards wealthier clients who can afford to pay more for potentially riskier loans whereas the poor cannot. Leaving aside shifts in clientele, the – sometime usurious – levels of interest rates charged by MFIs are often criticized as demonstrating the "ugly side" of an industry drifting away from its social mission (Hudon and Sandberg, 2013). This reason alone offers a strong motivation for scrutinizing the link between subsidies and interest rates.

In practice, donors and practitioners routinely use average loan size as the main indicator for assessing social performance. Their rationale is that larger loans would exclude the poorer segments of the population (Cull *et al*., 2007; Mersland and Strøm, 2009). However, viewing interest rate as a core part of the microfinance mission is gaining momentum. Yunus (2007, p. 1) considers that high interest rates indicate mission drift. His argument stems from the requirement that "a true microcredit organization must keep its interest rate as close to the cost-of-funds as possible".

Actually, the interest rate charged by an MFI is intrinsically linked to its average loan size. In fact, these variables are jointly determined. In our data, the overall sample correlation between portfolio yield and average loan size is -0.10, suggesting smaller loans are more costly than larger ones. Therefore, rather than analyzing separately the relationship between subsidy uncertainty and each of these two variables, we estimate a system of equations where we simultaneously regress both variables on subsidy uncertainty and control variables. This approach takes into consideration the endogeneity of average loan size and interest rates by allowing the error term of the two equations to be correlated.

Specifically we estimate the following system:

$$\begin{cases} \textit{interest rate}_{i,t} = \beta_0 + \beta_1 \textit{ subsidy uncertainty}_i + \beta' \textit{controls} + \varphi_{i,t} \\ \textit{average loan size}_{i,t} = \gamma_0 + \gamma_1 \textit{ subsidy uncertainty}_i + \gamma' \textit{controls} + \omega_{i,t} \end{cases} \tag{16}$$

where parameters β_0, β_1, and β' are estimated simultaneously with γ_0, γ_1, and γ', and correlation between $\varphi_{i,t}$ and $\omega_{i,t}$ is allowed so that endogeneity is taken into account.

We use the following control variables: MFI type, age, and size; a dummy indicating whether the MFI offers savings in addition to credit; and portfolio-at-risk (i.e. the proportion of loans repaid late). We also include subsidies in order to clearly disentangle subsidy uncertainty from its deterministic counterpart. Besides, we consider regressions with or without time and regional dummies.[23]

[23] Regional dummies are based upon classification of the country in which the MFI is active into the five main world-regions: Middle East and North Africa (MENA); Eastern Europe and Central Asia (ECA); Latin America and the Caribbean (LAC); Sub-Saharan Africa (AFR) and South-Asia (ASIA).

The parameters in (16) are estimated using the seemingly-unrelated-regression (SUR) procedure developed in Zellner (1962), Zellner and Huang (1962) and Zellner (1963). Interestingly, the Breusch-Pagan test statistic for independence is always highly significant at the 5% level, which rejects the null hypothesis that both regressions in the system are uncorrelated. In line with our conjecture, interest rates and average loan size are simultaneously determined.

< Insert Table 3 here >

Table 3 shows that subsidy uncertainty is significantly positive in the interest-rate regressions in all cases considered, but insignificant in all average-loan-size regressions. This suggests that higher subsidy uncertainty is associated with higher interest rates, but it does not affect average loan size. Interestingly, the results about the impacts of subsidies are the opposite. Specifically, subsidies reduce average loan size but their effect on interest rate is insignificant. Subsidies have thus a twin impact on social indicators: a direct one on average loan size, and an indirect one, channeled by uncertainty, on interest rates.

The insensitivity of average loan size to subsidy uncertainty might seem surprising. However, although frequently used in practice, average loan size is a poor proxy for mission drift (see, for example, Dunford, 2002; Armendáriz and Szafarz, 2011). This is mainly because average loan size is insensitive to the actual dispersion of loans within the population served. For instance, average loan size does not distinguish an MFI that grants approximately the same sized loan to all its borrowers from an MFI that serves two polar segments, such as the ones sketched in our theoretical model. Moreover, average loan size is silent on profitability. In contrast, our model starts from the assumption that large loans are profitable for the MFI while small loans are costly.

F-tests are jointly estimated across specifications. We report the F-test for the null hypothesis that both coefficients of subsidy uncertainty are jointly insignificant. In all specifications the test rejects the null hypothesis, suggesting a significantly positive relationship between the proxies for mission drift and subsidy uncertainty.

The loadings of the control variables also deliver interesting insights. First, the regressions confirm that MFIs depending more on subsidies tend to offer smaller loans (D'Espalier *et al.*, 2013). Second, MFIs that offer savings in addition to credit tend to provide larger loans.[24]. Third, MFI size (proxied by the log of equity) matters. Larger MFIs offer bigger loans and charge lower interest rates. Lastly, NGOs offer smaller loans, but there is no link between MFI type and the interest rate charged. This contrasts with previous findings showing that interest rates are affected by the MFI type (Mersland and Strøm, 2012; Dorfleitner *et al.*, 2012; Roberts, 2013). Our results could indicate that failing to account for subsidy uncertainty could bring a missing-variable issue in the interest-rate regression. This conjecture deserves further investigation.

Finally, we perform three robustness checks. First, Table 4 gives a glimpse of whether the previous results are driven by the measurement of subsidy uncertainty using standard deviation. Recall that the standard deviations of subsidies are computed on a limited number of observations per MFI. Hence, our results might be plagued by measurement errors. In

[24] This result is revealing. Most commercial or semi-commercial MFIs can legally collect savings. This service is offered to wealthier clients, however.

Table 4, we use the *spread* of donated equity scaled by total equity as an alternative measure for subsidy uncertainty. The spread is the difference between the maximum and minimum values. It is less sensitive than standard deviation to the number of observations.

< Insert Table 4 here >

Table 4 shows that the modification leaves the baseline results on subsidy uncertainty unchanged. Specifically, subsidy uncertainty has a significantly positive impact on the interest rate, and an insignificant impact on average loan size. The negative impact of subsidy itself on interest rate becomes significant. Again, the Breusch-Pagan tests reject the null hypothesis that the equations of the system are unrelated. The joint F-tests indicate that the relationship between mission drift and subsidy uncertainty is significant in the system.

< Insert Table 5 here >

Second, we re-estimate the model in Eq. (16) by restricting the sample to the MFIs for which three-year data is available. This sub-sample is made up of 53% of our original sample. The results in Table 5 deliver the same message as those from Table 3. The variability of the period of observation does not affect our findings to any great extent.

< Insert Table 6 here >

Last, in Table 6 we use an adjusted measure of subsidy. Specifically, we correct donated equity for donations in cash, in-kind subsidies and revenues from donations. This adjusted subsidy indicator is used by Morduch (1999b), for example. The adjustment does not modify the balance sheet total. Rather, it reflects the opportunity costs associated with the free or cheap services provided by the donors. The adjustment makes subsidy more conservative than the measure used in the baseline regressions. We use adjusted subsidy to calculate the standard deviation as well. Table 6 reveals that our results are robust with respect to the measurement of subsidy.

Overall, the empirical analysis lends support to our theoretical result that higher subsidy uncertainty leads to mission drift. Due to data issues, however, we were unable to run an empirical exercise perfectly in line with theory. In our model, the interest rate is exogenous and the MFI sets loan size. In our regressions, mission drift is captured through an increase in interest rates while average loan size does not seem to be affected noticeably by subsidy uncertainty. Despite these discrepancies, we believe the evidence is consistent with the intuition behind our model, namely that subsidy uncertainty is associated with mission drift. We argue that precautionary saving is the most probable explanation for this trend.

Our empirical results suggest that precautionary saving is observable through an increase in interest rates. Assessing the underlying mechanism empirically would, however, require a more comprehensive database including details on individual borrowers. For the time being, no such database is available to researchers. An alternative avenue could be to extend the theoretical model and endogenize interest rates. While this extension would undeniably make the model more realistic, it would also compromise its tractability.

In sum, our estimations confirm that MFIs are sensitive to subsidy uncertainty, a point never before raised in the literature. We are well aware that our empirical work is “heroic” in many regards. Still, it has the merit of being the first of its kind. As such, it inevitably bears the risks associated with exploring unvisited avenues. Therefore, despite the data-driven issues we face, we believe our results, though still preliminary, are insightful. They also lend credence to our theoretical model, which may in turn prove useful for designing subsidies in future.

5. Concluding Remarks

The dual objective of microfinance institutions consists in alleviating poverty and attaining self-sustainability. This objective has been and continues to be highly subsidized. Rigorous assessment on the role of subsidies is missing, however. With this paper we have moved the debate forward. We focus on subsidy design in a highly innovative theoretical model to address the following question: Can subsidies be more effectively designed to increase social impact?

The answer is yes, subsidies can be better designed. We have argued that subsidies can generate uncertainty. And uncertainty forces MFIs to build precautionary savings, which in turn defeats poverty alleviation objectives. In light of our analysis, the policy prescription to donors wishing to maximize social impact is to deliver subsidies credibly, specifying volume and delivery schedules clearly and transparently so that MFIs are not forced to concentrate on serving wealthier borrowers rather than on offering financial access to the poor.

Future research should focus on pre-determined self-sustainability time-frames. Our conjecture is that mission drift could also be caused by fear that self-sustainability would not be attained within a particular time frame set *ex ante* by donors. But by not establishing a clear, credible self-sustainability time-frame, donors create a moral hazard problem. Our analysis also opens avenues for future research into commercialization. Subsidy uncertainty might accelerate the trend toward commercialization in microfinance. The literature clearly mentions the risk of mission drift associated with commercialization (Copestake, 2007; Ghosh and Van Tassel, 2008). However, the specific dimensions of social performance that are most likely to be affected by commercialization are not fully elucidated. MFIs undergoing transformation may be tempted to focus on less poor clients, increase interest rates, or offer less flexible products. Meanwhile, commercialization also brings more competition into microfinance. In particular, the total impact on interest rates deserves further research.

Our approach is innovative, but it can undoubtedly be improved. First, subsidy uncertainty may be proxied through various channels. Here, we have used standard deviations. However, in many cases we had just three observations. This made our empirical research distant from our theoretical steady-state analysis. Second, future research should be directed at identifying profitable versus costly loans, and towards isolating the impact of subsidy uncertainty on costly loans. This would require better data on cost per loan.

More generally, our empirical findings lend support to our theoretical predictions. Subsidy uncertainty is indeed associated with mission drift. While our attempts to bridge the gap between theory and empirical work deliver useful insights, more empirical research using expanded data for a longer period of time is needed. We insist on these data limitations in the hope that rating agencies, donors, and MFIs would take them on board and move empirical research agendas forward.

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Appendix 1: Analytical Solution to Problem (8)

Consider problem (8) under the joint assumptions that the utility function is exponential with an absolute degree of prudence of $\eta > 0$:

$$V(C) = -\frac{1}{\eta}\exp(-\eta C), \tag{A1}$$

and the subsidy follows a random walk with i.i.d normal innovations:

$$K_t = K_{t-1} + \xi_t, \quad \xi \sim N\left(0, \sigma_\xi^2\right), \tag{A2}$$

In that case, under the assumption that $\beta(1+r) = 1$, the outreach follows the evolution given by:

$$E_t N_1(t+1) = N_1(t) + \frac{\eta\sigma_\xi^2}{2\gamma_1} \tag{A3}$$

Equation (A3) shows that the expected outreach grows with the variance of the noise σ_ξ^2 that affects the subsidies. This result is robust in wider contexts provided that the absolute degree of prudence of the utility function, $-\frac{V'''(C)}{V''(C)}$, is positive (Kimball, 1990).

However, some usual utility functions, like the quadratic function for which $V'''(C) = 0$, do not fulfill this requirement. When $V(C) = \frac{C^2}{2}$, equation (11) becomes:

$$E_t C_{t+1} = \frac{1}{\beta(1+r)} C_t . \tag{A4}$$

As $C_t = \gamma_1 N_1(t)$, the dynamics of outreach $N_1(t)$ is given by:

$$E_t N_1(t+1) = \frac{1}{\beta(1+r)} N_1(t) \tag{A5}$$

In order to solve the rational expectation model (A5), let us denote by ε_{t+1} the rational prediction error on $N_1(t+1)$:

$$\varepsilon_{t+1} = E_t N_1(t+1) - N_1(t+1) \tag{A6}$$

Replacing in (A5) and lagging by one period yields:

$$N_1(t) = \frac{1}{\beta(1+r)} N_1(t-1) + \varepsilon_t \tag{A7}$$

The stochastic process (ε_t) is the martingale difference (see Broze *et al.*, 1985):

$$E_t[\varepsilon_{t+1}] = 0 \tag{A8}$$

Equation (A5) exhibits the autoregressive structure of optimal outreach of which dynamics depends on the position of $\frac{1}{\beta(1+r)}$ with respect to unity. In particular, when $\beta(1+r) = 1$, the outreach is a random walk. Its stochastic increment is a martingale sequence to be seen as an unpredictable noise with a possibly variable variance, depending notably on the uncertainty on future subsidies. Indeed, the information set I_t to which ε_{t+1} is orthogonal is primarily including the past and current subsidies: $K_{t-i}(i \geq 0) \in I_t$. Equation (A7) also shows that uncertainty on future subsidies has a destabilizing impact through the error term (ε_t), but no systematic impact.

List of Tables

Table 1. Countries and statuses

We list the number of MFIs as well as different MFI-types in each country of the sample.

Country	# MFIs	# NGOs	# NBFIs	# coop	# for-profit
Albania	3	1	0	1	1
Armenia	2	0	2	0	0
Azerbaijan	6	0	6	0	0
Benin	7	5	1	1	0
Bolivia	9	8	1	0	0
Bosnia and Herzegovina	14	1	12	0	1
Brazil	12	10	0	1	1
Bulgaria	1	0	0	1	0
Burkina Faso	3	1	0	2	0
Burundi	1	0	0	1	0
Cambodia	5	0	4	0	1
Cameroon	2	0	1	1	0
Chad	1	0	0	1	0
Chile	3	0	0	1	2
Colombia	1	1	0	0	0
Croatia	1	0	0	1	0
Democratic Republic of Congo	1	0	0	1	0
Dominican Republic	1	1	0	0	0
Ecuador	17	8	0	8	1
Egypt	5	5	0	0	0
El Salvador	3	3	0	0	0
Ethiopia	7	2	4	1	0
Gambia	2	1	1	0	0
Georgia	3	0	3	0	0
Ghana	4	4	0	0	0
Guatemala	5	5	0	0	0
Guineau	1	0	0	0	1
Haiti	2	2	0	0	0
Honduras	7	5	0	2	0
Jordan	3	2	0	0	1
Kenya	4	3	1	0	0
Kazakhstan	3	0	3	0	0
Kosovo	5	3	2	0	0
Kyrgyz Republic	3	1	0	1	1
Madagascar	2	0	0	1	1
Malawi	1	1	0	0	0
Mali	1	0	0	1	0
Mexico	8	5	2	0	1
Moldova	2	0	2	0	0
Mongolia	1	0	0	0	1
Montenegro	1	0	1	0	0
Morocco	6	6	0	0	0
Mozambique	1	0	0	0	1
Nicaragua	7	7	0	0	0
Niger	1	0	0	1	0
Nigeria	1	0	0	0	1
Peru	14	10	1	3	0

Philippines	2	2	0	0	0
Romania	1	0	1	0	0
Russia	12	5	0	7	0
Rwanda	2	0	1	1	0
Senegal	6	0	0	6	0
Serbia and Montenegro	1	1	0	0	0
South Africa	1	0	0	0	1
Tajikistan	4	1	3	0	0
Tanzania	1	0	0	0	1
Togo	3	1	0	2	0
Tunisia	1	1	0	0	0
Uganda	2	2	0	0	0
Zambia	1	0	1	0	0
Total	**230**	**114**	**53**	**46**	**17**

Table 2. Descriptive statistics

This table reports the mean, median, standard deviation, minimum, and maximum for the variables used in our analysis.

Variable	Definition	n	Mean	Median	St. dev.	Min.	Max.
TLP	total outstanding loan portfolio in thousands USD	676	3991	1754	6153	8.47	51700
Age (in years)	number of years in operation	674	8.87	7.00	6.94	0.00	42.00
Equity (in kUSD)	total equity	676	2812	1032	1130	0	224000
Donated equity (in kUSD)	total donated equity	676	2140	459	1220	0	259000
Subsidy (in %)	donated equity as a percentage of total equity	676	0.71	0.53	0.94	0.00	6.08
Subsidy uncertainty (in %)	standard deviation of *subsidy*	676	0.19	0.07	0.44	0	3.51
ALS (in USD)	Average loan size defined as total loan portfolio divided by # borrowers	658	842	398	1587	10.17	22307
ALS / GNIcap	*ALS* scaled by per capital GNI	657	0.28	0.13	0.54	0.00	6.13
Interest rate	Interests paid on loans divided by total loan portfolio	676	0.31	0.27	0.15	0.00	0.67
PAR	portfolio at risk (30 days)	604	0.048	0.029	0.061	0.00	0.47
ROA	return on assets	662	0.02	0.01	0.11	-0.86	0.67
AROA	subsidy-adjusted return on assets	530	-0.04	-0.01	0.13	-1.18	0.22
OSS	operational self-sufficiency	525	1.17	1.14	0.35	0.09	2.61
FSS	financial self-sufficiency	562	0.96	0.97	0.30	0.12	2.22

Table 3. Joint estimation of interest rate and average loan size

We jointly regress the interest rate and average loan size scaled by per capita GNI on subsidy uncertainty and controls. We use the seemingly unrelated regressions (SUR) procedure. The Breusch-Pagan test asserts the null-hypothesis that the residuals of the separate regressions are uncorrelated. We also report a joint F-test that asserts the null-hypothesis that the coefficients for subsidy uncertainty are jointly significant. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	(1) Interest rate	*ALS / GNIcap*	(2) Interest rate	*ALS / GNIcap*	(3) Interest rate	*ALS / GNIcap*
Subsidy uncertainty	0.300	0.035	0.309	0.023	0.303	0.061
	(0.087)***	(0.083)	(0.086)***	(0.083)	(0.086)***	(0.083)
Controls						
Subsidy	0.016	-0.062	0.005	-0.064	0.018	-0.098
	(0.035)	(0.034)*	(0.035)	(0.034)*	(0.036)	(0.035)***
Equity (in log)	-0.049	0.038	-0.045	0.034	-0.044	0.025
	(0.017)***	(0.016)**	(0.017)***	(0.016)**	(0.017)***	(0.017)*
Age	-0.001	0.002	-0.002	0.002	-0.001	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
dumNONPROFIT	0.005	-0.091	0.013	-0.085	-0.024	-0.036
	(0.050)	(0.048)*	(0.050)	(0.048)*	(0.056)	(0.054)
dumSAVING	0.010	0.083	-0.021	0.074	0.021	0.036
	(0.054)	(0.052)*	(0.055)	(0.053)*	(0.062)	(0.060)
PAR	-0.002	0.005	-0.002	0.004	-0.001	0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)*
Regional dummies	excluded		excluded		included	
Time dummies	excluded		included		included	
n	573		573		572	
Breusch-Pagan for independence	3.409**		4.960**		3.053**	
Joint F-test for subsidy uncertainty	6.18***		6.61***		6.66***	

Table 4. Robustness check: Subsidy uncertainty measured by spread

We run the joint regressions of interest rate and average loan size scaled by per capita GNI on subsidy uncertainty and controls using SUR. We use the spread of donated equity scaled by total equity instead of the standard deviation as a measure for subsidy uncertainty. The Breusch-Pagan test asserts the null-hypothesis that the residuals of the separate regressions are uncorrelated. We also report a joint F-test for subsidy uncertainty that asserts the null-hypothesis that the coefficients for subsidy uncertainty are jointly significant. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	(1)		(2)		(3)	
	Interest rate	*ALS / GNIcap*	Interest rate	*ALS / GNIcap*	Interest rate	*ALS / GNIcap*
Subsidy uncertainty (spread)	0.287	0.013	0.289	0.006	0.284	0.027
	(0.045)***	(0.044)	(0.045)***	(0.045)	(0.045)***	(0.045)
Controls						
Subsidy	-0.051	-0.059	-0.061	-0.061	-0.048	-0.095
	(0.035)	(0.034)**	(0.035)*	(0.035)**	(0.036)**	(0.035)***
Equity (in log)	-0.035	0.037	-0.031	0.034	-0.032	0.025
	(0.016)**	(0.016)**	(0.016)**	(0.016)**	(0.017)**	(0.017)
Age	-0.002	0.002	-0.003	0.002	-0.002	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
dumNONPROFIT	0.003	-0.090	0.011	-0.086	-0.023	-0.036
	(0.049)	(0.048)**	(0.048)	(0.048)*	(0.045)	(0.054)
dumSAVING	-0.004	0.083	-0.035	0.074	0.001	0.036
	(0.053)	(0.052)**	(0.053)	(0.053)*	(0.061)	(0.060)
PAR	-0.001	0.005	-0.001	0.004	-0.001	0.005
	(0.002)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
Regional dummies	excluded		excluded		included	
Time dummies	excluded		included		included	
n	573		573		572	
Breusch-Pagan for independence	3.63**		5.16**		3.73**	
Joint F-test for subsidy uncertainty	19.97***		20.67***		20.22***	

Table 5. Robustness check: Subsample with 3-year data

We run the joint regressions of interest rate and average loan size scaled by per capita GNI on subsidy uncertainty and controls using SUR. We use the subsample composed of MFIs for which we have 3-year data (53% of the full sample) The Breusch-Pagan test asserts the null-hypothesis that the residuals of the separate regressions are uncorrelated. We also report a joint F-test for subsidy uncertainty that asserts the null-hypothesis that the coefficients for SD (donated equity/equity) are jointly significant. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	(1) Interest rate	(1) *ALS / GNIcap*	(2) Interest rate	(2) *ALS / GNIcap*	(3) Interest rate	(3) *ALS / GNIcap*
Subsidy uncertainty	0.071	0.070	0.071	0.079	0.060	0.073
	(0.029)***	(0.081)	(0.029)***	(0.081)	(0.029)**	(0.082)
Controls						
Subsidy	-0.038	-0.001	-0.040	-0.003	-0.032	-0.011
	(0.013)	(0.037)	(0.013)	(0.038)	(0.014)**	(0.039)
Equity (in log)	-0.021	0.025	-0.021	0.024	-0.016	0.026
	(0.006)***	(0.017)**	(0.007)***	(0.018)*	(0.007)**	(0.019)
Age	0.001	-0.002	0.001	-0.002	-0.001	-0.002
	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.005)
dumNONPROFIT	0.057	-0.139	0.053	-0.141	0.006	-0.156
	(0.020)***	(0.055)**	(0.020)***	(0.056)**	(0.024)	(0.069)***
dumSAVING	-0.076	0.187	-0.076	0.157	-0.096	0.089
	(0.023)***	(0.062)***	(0.023)***	(0.064)***	(0.025)***	(0.072)
PAR	0.003	0.004	0.004	0.002	0.003	0.002
	(0.001)	(0.004)	(0.002)**	(0.004)	(0.002)**	(0.004)
Regional dummies	excluded		excluded		included	
Time dummies	excluded		included		included	
n	312		312		312	
Breusch-Pagan for independence	10.76***		9.77***		10.938***	
Joint F-test for subsidy uncertainty	6.96***		4.54**		3.98**	

Table 6. Robustness check: Adjusted subsidy

We run the joint regressions of loan size and the interest rate on subsidy uncertainty and controls using SUR. We adjust subsidies for donations in cash, in-kind subsidies and revenues from subsidies. The Breusch-Pagan test asserts the null-hypothesis that the residuals of the separate regressions are uncorrelated. We also report a joint F-test for subsidy uncertainty that asserts the null-hypothesis that the coefficients for SD (donated equity/equity) are jointly significant. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	(1)		(2)		(3)	
	Interest rate	*ALS / GNIcap*	Interest rate	*ALS / GNIcap*	Interest rate	*ALS / GNIcap*
Adjusted-subsidy uncertainty	0.322	0.002	0.340	0.009	0.322	0.032
	(0.079)***	(0.075)	(0.078)***	(0.076)	(0.078)***	(0.076)
Controls						
Adjusted subsidy	0.006	-0.051	-0.006	-0.053	0.011	-0.089
	(0.031)	(0.030)**	(0.031)	(0.031)*	(0.032)	(0.031)***
Equity (in log)	-0.045	0.035	-0.040	0.031	-0.040	0.022
	(0.017)***	(0.016)***	(0.017)**	(0.016)*	(0.017)**	(0.017)*
Age	-0.001	0.002	-0.002	0.002	-0.001	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
dumNONPROFIT	0.007	-0.088	0.014	-0.084	-0.022	-0.032
	(0.050)	(0.048)**	(0.049)	(0.048)**	(0.056)	(0.052)
dumSAVING	0.014	0.083	-0.016	0.074	0.023	0.034
	(0.054)	(0.052)*	(0.054)	(0.053)*	(0.061)	(0.060)
PAR	-0.001	0.005	-0.002	0.004	-0.001	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.001)	(0.004)
regional dummies	excluded		excluded		included	
time dummies	excluded		included		included	
n	573		573		572	
Breusch-Pagan for independence	3.30***		4.76***		5.96***	
Joint F-test for subsidy uncertainty	5.41***		5.66***		3.96**	