Subsidy Uncertainty and Microfinance Mission Drift*

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Abstract

This paper shows that subsidy uncertainty contravenes the poverty-alleviation objective of microfinance institutions (MFIs) because it leads to mission drift. We present a model where a representative MFI's objective is to serve the maximum number of poor clients under self-sustainability and borrowing constraints. Fearing that subsidies can dry-up, the MFI has no choice but to build precautionary savings via serving wealthier clients thereby deviating from its poverty-alleviation mission. We thus offer a rationale for mission drift: It is a reaction to subsidy uncertainty by subsidy-dependent MFIs that struggle to preserve a pool of poor clients. To test our model's predictions, we use data collected from rating agencies. Our empirical results suggest that while more subsidies are associated with a larger portfolio of poor clients, subsidy uncertainty is positively correlated with higher interest rates, and negatively correlated with the number of poor clients being served.

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1. Introduction

Low-income households can access credit via microfinance institutions (MFIs). A vast majority of these institutions have themselves 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, from socially responsible investors. Quite independently of the source of such donations, subsidies have undeniably contributed to offer financial access to up to approximately 200 million clients (Daley-Harris, 2012). The effect of subsidized microfinance on poverty reduction, however, remains controversial.[2]

This paper focuses on the design of subsidies to microfinance. We argue that if the volume of subsidies delivered by donors – be these local governments, multilateral aid agencies or socially responsibly investors – take the form of credible commitments delivered under transparent and timely procedures, subsidies will have a stronger impact on the MFIs' poverty-alleviation objective. To this end, we follow a distinguished tradition on

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[1] See, for example, Armendáriz and Szafarz (2011) who report on the mission statements by the top ten MFIs. located in low-income and emerging market economies in Asia and Latin America, respectively.

[2] A typical case in point is small-sized loans demanded by women who account for 8 out of 10 loans extended by MFIs. Women score for as much as 70% of the world 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 (2012a) 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 have been seriously questioned empirically (see, for example, a comprehensive discussion based on field work in India by Banerjee and Duflo, 2011).

precautionary savings started by Friedman (1957) and Ando-Modigliani (1963). In particular, we construct a simple analytical framework of precautionary savings showing that supply-driven subsidy uncertainty can have detrimental effects on microfinance as poverty-alleviation tool. To our knowledge, this is the first framework in the literature on microfinance to pin-down that failed interventions might be supply-driven.

This paper shows that subsidy uncertainty contravenes the poverty-alleviation objective of microfinance institutions (MFIs) because it leads to mission drift. We present a model where a representative MFI's objective is to serve the maximum number of poor clients under self-sustainability and borrowing constraints. Fearing that subsidies can dry-up, the MFI has no choice but to build precautionary savings via serving wealthier clients thereby deviating from its poverty-alleviation mission. We thus offer a rationale for mission drift: It is a reaction to subsidy uncertainty by subsidy-dependent MFIs that struggle to preserve a pool of poor clients. To test our model's predictions, we use data collected from rating agencies. Our empirical results suggest that while more subsidies are associated with a larger portfolio of poor clients, subsidy uncertainty is positively correlated with higher interest rates, and negatively correlated with the number of poor clients being served.

Despite recent commercialization trends, the microfinance movement is either financially supported by local governments or is net recipient of subsidies from donor agencies.[3] (We henceforth refer to all institutional sources of subsidies as donors). Somewhat surprisingly, the literature on subsidies in microfinance and their impact on poverty alleviation is scarce.

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[3] González and Rosenberg (2006).

Some notable exceptions include the work by Hudon (2010), Nawaz (2010), and Hudon and Traça (2011). Their work, however, is not on microfinance and poverty alleviation directly. Instead, their focus is on the impact of subsides on efficiency. Hudon (2010) finds that subsidies have little impact on efficiency as far as the quality of MFIs' management is concerned. Nawaz (2010) and Hudon and Traça (2011), on the other hand, find that subsidies can have a positive impact on financial efficiency, albeit marginally.

In parallel to the nascent empirical literature on the impact of subsidies, a growing literature on mission drift has emerged (Ghosh and Van Tassel, 2008, Mersland and Strøm, 2010 and Armendáriz and Szafarz, 2011). Mission drift is defined as phenomenon where MFIs serve wealthier clients at the expense of poor clients.[4] Empirically, the divide between poor and wealthier clients is proxied by average loan size. Pioneering work by Cull *et al* (2007) shows that the commercialization movement is driven by MFIs offering loans that are larger on average when compared to those offered by non-governmental organizations (NGOs). It also shows that loans offered by commercial MFIs are biased against women. These findings are supported by Agier and Szafarz (2012) who report that women demand loans that are smaller in size relative to those of their male counterparts. The commercialization movement from a gender standpoint has prompted Mersland and Strøm (2010) to analyze mission drift by focusing on average loan size and the proportion of women served simultaneously. Their analysis suggests that commercialization and mission drift are

[4] According to Ghosh and Van Tassel (2008) mission drift should be viewed as a dynamic phenomenon driven by profit-oriented donors. The one-period model proposed by Armendáriz and Szafarz (2011) emphasizes the difference between mission drift and cross-subsidization.

intrinsically related both because poverty is proxied by average loan size and because women demand small loans relative to their male counterparts.

In this paper we assume away commercialization as a potential source of mission drift. Instead, based on qualitative interviews with microfinance practitioners at various MFIs, we focus on subsidies to MFIs, which are discretionary at best uncertain at worse -be these in terms of quantity or timing. We thus view mission drift as being rooted in the subsidy uncertainty faced by non-commercial MFIs, i.e., by subsidy-dependent financial institutions offering loans to unbanked individuals. We argue that supply-driven uncertainty leads to the following trade-off: Subsidy-dependent MFIs maximize utility by offering small loans to poor individuals on the one hand, but feel compelled to extend relatively larger loans to more profitable wealthier clients in order to build precautionary savings on the other.

Our analysis in this paper is closest in spirit to that in Agénor and Aizenman (2010) where poverty traps are induced by high aid volatility. Our focus is not on infrastructure, health and educational investments, however, but on the microfinance industry. Specifically, aid volatility in our paper triggers mission drift thereby hindering MFIs' ability to serve poor clients. Mission drift is triggered by donors. Not because donors are profit-oriented, as in Gosh-Van Tassel (2008), but because donors are not committed to delivering subsidies timely and under clear and transparent procedures to a vast majority of subsidy-dependent MFIs.

Our empirical analysis confirms that there is a link between uncertainty regarding the supply of subsidies by donors and mission drift: Higher subsidy uncertainty is positively correlated with higher interest rates.[5] And higher subsidy uncertainty is negatively correlated with the number of poor clients served. The policy implication of our findings is therefore straightforward: Considering that serving the poor is costly, if only because transaction costs are relatively high when compared to extending larger average loan sized loans to wealthier clients, donors should re-design subsidy delivery under clear rules and in a timely manner. Donors can then limit the scope for MFIs' sliding into serving wealthier clients so as to build precautionary savings.

The reminder of the paper is structured as follows. Section 2 delivers a quick review of the literature on the role of subsidies in microfinance. Section 3 displays a highly stylized model of precautionary savings. Through the lens of this set-up we are able for the to establish a link between subsidy uncertainty and mission drift. Section 4 describes the data and presents the empirical results. Section 5 concludes.

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[5] We interpret the hike in interest rate as a form of credit rationing à la Stiglitz andWeiss (1981). In the case of microfinance under 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).

2. Subsidies in Microfinance

It is impossible to dissociate microfinance from subsidies. This is true nowadays, and has also been true historically. Microfinance emerged and developed in the mid-1970s thanks to the generosity of visionary donor agencies such as the International Fund for Agricultural Development, the *Deutche Gesellshaft für Technische Zusammenarbeit* in Asia, and the United States Agency for International Development in Latin America.[6]

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. According to Morduch (1999)'s estimates, effective subsidies to the Grameen Bank were of approximately USD 175 million for the 1985-1996 period alone. Somewhat surprisingly, stories on subsidization have also been documented for the case of commercially-oriented MFIs in Latin America, most notably, on the transition from NGOs to commercial banks of BancoSol in Bolivia, and of Banco Compartamos in Mexico. (See González-Vega *et al,* 1996 on BancoSol, and Garric-Cagna and Santos, 2009, on Banco Compartamos)

Subsidies may help MFIs to reach their social objective, namely that of offering financial services to a large number of poor clients who demand small average loan sized amounts involving high transaction costs. A social objective, however, is not the only one donors expect MFIs to attain. Specifically, a large number of donors woud insist on MFIs reaching

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

a so-called “double bottom line” objective: reaching the largest number of poor *and* becoming financially self-sustainable (Conning, 1999; Copestake, 2007). Reaching a large number of very poor individuals can justify interventions and, in particular, subsidies (Zeller and Meyer, 2002). One argument is that serving the poor entails exceedingly large transaction costs. Implicit in the self-sustainability objective, on the other hand, is that donors would want MFIs not to rely on subsidies in the long run.

Transaction costs aside, another argument for intervention has been put forward by Armendáriz and Morduch (2010). They argue 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 for either the wealthy have other inputs of production (e.g., savvy business or higher levels of human capital) and/or because relative to the poor, the wealthy can obtain a higher return on capital because of economies of scale: The wealthy request large loan sizes which they manage to invest at a much higher rate of return relative to that of the poor whose businesses are tiny.

Suppose that intervention takes the form of subsidies to a particular MFI, and that subsidies help to bring interest rates down. Specifically, assume that the MFI in question can lower interest rates it charges to poor borrowers because part of its transaction costs are being covered by donors. Under this scenario, we can think of subsidies as acting in support of removing credit constraints faced by the poor and thereby reducing the incidence of MFIs deviating from their poverty-alleviation mission.[7]

[7] Heron we use “objective” and “mission” interchangeably.

Donors may however insist on self-sustainability as an additional objective. The problem then is how can donors make sure that subsidized MFIs will meet their dual objective, or, in the microfinance parlance, their double bottom line? Some donors might attempt to exercise some control rights on MFIs management. For example, donors might favour equity investments in MFIs so as to attract new private investors (Mersland, 2009). Other forms of subsidized resources flowing into MFIs do not provide real control over the MFIs' evolution through time, except in the case where donors make future disbursement of subsidies conditional on MFIs attaining their double bottom line.

Lack of control over the use of subsidies and control over managers' actions in subsidized MFIs can in turn lead to inefficiencies such as lax management practices, potential clients not being served when they should, and relatively high default rates to mention a few (Bhatt and Tang, 2001; Agier and Szafarz, 2012). This literature suggests that subsidization might be excessive at times, not that subsidies should be abolished. Note that the difference between the adjectives "excessive" and "inefficient" is purely semantic in this literature.

Efficient subsidy delivery is as old as the microfinance movement itself. Specifically, when the movement gained momentum in the 1980s, a lively debate emerged on how subsidies could be delivered more efficiently, and it was argued then that donors should implement the so-called "smart subsidies" (Morduch, 2005). Smart subsidies, it was contended, should address three issues, namely, the fact that subsidies must be transparent, rule-bounded, and, most importantly, time-limited. From a policy standpoint, donors were encouraged to focus on subsidizing start-up expenses, institutional capacity building, product development, and foreseeing a clear exit strategy. In sum, donors were told that they should promote competition among self-sustainable MFIs.

It was later recognized, however, that competition could be detrimental because microfinance clients can become over-indebted (Schicks, Forthcoming), particularly in the absence of credit bureaus. And, indeed, financing start-ups without appropriate credit bureaus, is increasingly perceived as counterproductive – contrary to what standard academic textbooks might suggests on efficiency in the advent of competition (Armendáriz and Morduch, 2010).

Arguably, it was not an excess of competition but the absence of it – probably due to the lack of smart subsidies – which might be at the root of some subsidized NGOs in Latin America transforming themselves into commercial MFIs. These are now partly benefitting from monopoly rents (e.g., BancoSol and Compartamos), and are often perceived as having drifted from their poverty-alleviation objective. These examples have shed light on poorly designed subsidies. And based on these and other examples from commercial MFIs in Asia, some observers have argued that subsidies to microfinance can be counterproductive at best detrimental at worse.

In section 3 below, we show that there is nothing wrong with subsidizing microfinance *per se*, for as long as donors do not generate uncertainty with regards to the amount and timing in the flows of subsidies into MFIs. We argue forcefully for subsidy delivery under clear rules and timing so as to eliminate residual uncertainty leading to undesirably mission drift. Our argument has solid theoretical underpinnings. Our principal objective being that moving the debate on subsidized microfinance forward. As far as we are aware, our precautionary savings approach below represents the first attempt at pinning-down the link between failed interventions via subsidies to the microfinance industry and failed attempts by MFIs to serve the largest possible number of poor clients.

From an empirical standpoint, the literature on subsidies in the microfinance industry is scarce. Cull *et al.* (2007) show that group lending MFIs, be these solidarity groups *à la* Grameen most prevalent in Asia or village banking institutions most common in Latin America, receive a lion's share of total subsidies. In contrast, individual lending MFIs benefit from a tiny fraction. Moreover, the authors report that NGOs tend to receive more subsidies than for-profit institutions. But what is the impact of subsidies on outcomes of interest? This question, clearly the most relevant one, has been somewhat addressed empirically. Data limitations have however been a major obstacle and the conclusions reached should therefore be taken cautiously.

Hudon (2010) finds that subsidies have little impact on the quality of management. Hudon and Traça (2011) report that subsidies have a positive impact on efficiency but only up to a certain threshold, above which the marginal effect of subsidies on efficiency becomes negative. Using non parametric analysis, Nawaz (2010) finds that subsidies contribute to MFIs' financial efficiency, albeit marginally. In contrast, Caudill *et al.* (2009) find that lower total subsidies and lower subsidy per loan are associated with higher cost reduction over time. In Section 4 below, we will contribute to existing empirical investigations through the lens of our model despite the fact that, just like previous empirical investigations,, severe obstacles were imposed on us by data availability.

3. The Model

In what follows we present a simple model of subsidies and mission drift. Consider a representative MFI serving two types of unbanked clients to whom it offers loans of type 1 and 2, respectively. Type-1 loans are offered to relatively poor clients. The size of these loans at time $t, s_1(t) \geq 0$ is chosen by the MFI.[8] Type-2 loans are available to relatively wealthier clients who require a minimum fixed size ($\forall t : s_2(t) > \underline{s}$) to invest in a project. These projects can only be financed by the MFI.[9] The interest rate charged on both loan types is exogenously fixed at ρ.

In period $t > 0$, the MFI receives a stochastic subsidy $K_t \geq 0$, and extends $N_1(t)$ loans of type 1 and $N_2(t)$ loans of type 2.[10] It faces transaction costs $f(N_1(t), N_2(t))$ depending

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[8] 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.

[9] 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.

[10] 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).

on the number and type of loan it extends. This cost function is assumed to be linear. Relative to wealthier clients, we assume that the poor are more costly 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 via offering them financial access. Otherwise stated, the MFI maximizes expected utility, which is an increasing function of the number or poor individuals it can afford to offer microloans. The MFI can control the size of each type of loan, $s_1(t)$ and $s_2(t)$. Ideally, the MFI would extend only $s_1(t)$ to the poor, 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 with an exponential factor:

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

where $U[.]$ is an increasing concave function.

Specifically, we assume that the subsidy, K_t, that the MFI receives from a donor is stochastic. The timing of events is as follows:

- At time 1, the MFI receives subsidy K_1, and allocates this subsidy by extending loans partly to poor clients ($N_1(1)$ or type 1 loans) and partly to wealthier clients ($N_2(1)$ or type 2 loans). The MFI maximizes expected utility, which delivers an optimal number of type 1 loans extended to poor clients, $N_1(1)$.

- At the end of period 1, all loans are reimbursed yielding return $\rho > 0$.
- At time 2 and beyond, the MFI is left with resources that are used to offer new loans. Such resources result from the sum of a new subsidy (e.g., K_2) plus the net profit from previous loans. These resources are used for lending to poor clients (i.e., $N_1(2)$ loans) and to wealthier clients (i.e., $N_2(2)$ loans) via expected utility maximization.

In sum, our representative MFI's problem can be written as follows:

$$\begin{aligned}
&\underset{s_1(t),s_2(t),N_1(t),N_2(t)}{Max} E\sum_{t=1}^{\infty}\beta^t U\left[N_1(t)\right] \\
&\text{s.t. } K_1 = s_1N_1(1)+s_2N_2(1)+\gamma_1N_1(1)+\gamma_2N_2(1) \\
&\quad K_{t+1}+(1+\rho)\left[s_1N_1(t)+s_2N_2(t)\right] = s_1N_1(t+1)+s_2N_2(t+1)+\gamma_1N_1(t+1)+\gamma_2N_2(t+1),\ t>0 \\
&\quad s_1(t)\geq 0;\ s_2(t)\geq \underline{s},
\end{aligned} \tag{3}$$

Let us now make the following assumptions:

Assumption 1: Lending to the poor is costly ($\gamma_1 > 1+\rho$) and lending to the wealthier is profitable ($\gamma_2 < 1+\rho$).[11]

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[11] Otherwise stated, 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 transactions costs are not too high. On the other hand, lending to the wealthier is profitable. If it wasn't, the MFI would never choose to issue loans of type 2 because offering loans to wealthier clients is not the MFI's objective.

It follows that, given that the number of poor individuals that are offered loans is the variable to be maximized, the MFI will always offer the smallest possible loan size to the poor: $\forall t : s_1^*(t) = 0$. Let us denote by C_t the cost of serving $N_1(t)$ poorer clients at time *t*:

$$C_t = \gamma_1 N_1(t) \tag{4}$$

and let us define:

$$U\left[N_1(t)\right] = V\left[C_t\right] \tag{5}$$

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

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

$$\forall t : s_2(t) = \underline{s} = 1 \tag{6}$$

Note that the latter assumption is purely technical. In the absence of it, the cost function $s_2(t)$ will become artificially large – the cost is per loan independently of its size.

Loans of type 2 appear as a profitable side-business which does not contribute to the MFI's objective directly. We should however note the subtle way in which loans of type 2 contribute to utility maximization. Specifically, loans of type 2 represent additional resources for offering loans to the poor in the future. The rate of return of this profitable business is constant. Indeed, by lending one dollar at the cost of γ_2 to a wealthier client the

MFI generates $(1+\rho)$ dollars. Consistent with assumption 1, the positive rate of return of this activity is:

$$\frac{1+\rho}{\gamma_2} = 1 + r \Leftrightarrow r = \frac{1+\rho-\gamma_2}{\gamma_2} > 0 . \tag{7}$$

Notice that rate *r* is used by the MFI for investing/lending, not for borrowing.

We can now re-write the MFI's objective function (3) above in the following manner:

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

where W_t represents the financial assets of the MFI at *t*, that is, after the subsidy but prior to lending to any borrower. Note that under specification (8), our model became strikingly similar to a standard intertemporal consumption model *à la* 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 the poor in the future.[12]

Our model suggests that a representative MFI wishing to maximize the number of poor clients served can finance its investment on poverty alleviation in two ways, namely, via

[12] 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.

subsidies from donors and/ or via launching a profitable "side-business." The latter could in principle involve any kind of profitable activity. It is natural, however, to assume that the MFI's side business is lending, because it can more easily reap economies of scale. Because lending to the unbanked wealthier clients involves a transaction cost, γ_2, the interest rate charged, ρ, is not a rate of return. The actual rate of return – net of transaction costs is:

$$r = \frac{1+\rho-\gamma_2}{\gamma_2}. \tag{9}$$

This rate is positive for as long as lending to wealthier clients is profitable.

Under the assumption of perfect capital markets, the same interest rate is applicable to lending and borrowing. A vast majority of unregulated MFIs such as financial NGOs, on the other hand, cannot legally borrow and/or intermediate clients' savings. Specifically, we assume away savings as a side-business activity.[13] 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.

In order to clearly discuss the outcome of the model, we first present the results when credit constraints are ignored. While we do this for the sake of clarity, we are fully aware of the fact that allowing for MFIs to be able to borrow is unrealistic because most MFIs, particularly subsidy-dependent NGOs can neither borrow in commercial banks nor raise capital via issuing shares in the stock exchange. We therefore impose credit constraints in a follow-up subsection 3.2.

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

3.1 The Model Without Credit Constraints

Let us first consider model (8) under the assumption that the MFI is allowed to either collect savings or borrow in commercial banks. Hence, our representative MFI charges all clients the (net) market interest rate, *r*. This is also the cost of borrowing from the MFI's standpoing. Under this assumption, the MFI's maximization problem becomes:

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

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

Following Hall (1988), the Euler equation for the above is:

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

At first sight, subsidies seem to have disappeared from the dynamics in (11). Note, however, that subsidies are still there, albeit indirectly, via expectations. However, the model becomes intractable, as far as deriving the optimal loan allocation is concerned, without making additional – rather strong — assumptions with regards to the dynamics of subsidies.[14]

Most models of this kind assume a random walk for process (K_t). In the context of our framework, this assumption means that subsidies at time *t* are equal to previous subsidies plus a white noise. Then, the mean subsidy is a constant and its variance is growing over

[14] see Zeldes (1989).

time. While disregarding the deterministic component of the model, such a random-walk assumption simplifies the analysis by enabling us to focus on the impact of subsidy uncertainty on the maximum number of poor borrowers to whom the MFI can offer microloans.

Under fairly general assumptions regarding the objective function (8) above, we show in Appendix 1 that when the MFI faces future subsidies which are uncertain, it will have a tendency to lower the number of loans it extends to the poor. Simultaneously, the MFI will extend loans to wealthier clients for precautionary savings reasons. That is, the MFI is compelled to lend to wealthier clients in order to ensure 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. By lowering the number of loans it extends to the poor, the MFI might seem as if it had drifted from its mission, when in fact it is actually adopting a cautious behaviour while at the same time preserving the conditions for the sake of perpetuating its long-term objective, namely, that of serving poor clients.[15]

3.2. The Model With Credit Constraints

The precautionary savings approach taken so far might be misleading. At first sight, it would appear realistic to assume that if and when an MFI has deviated from its poverty-

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[15] 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 at stake 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 not only care about the future of their institution, but also about their own career concerns.

alleviation mission, donors would have already detected it and consequently would have withdrawn their support. And, yet, this does not seem to be the case in reality for for a vast majority of MFIs who appeared as having deviated from their social objective. Moreover, donors such as the Inter-American Development Bank have helped NGOs to transform themselves into fully commercial MFIs as in the case of Bolivia's BancoSol. Why? Recall from Section 2 that donors often request that MFIs reach a double bottom line objective, namely that of serving the poor and that of becoming self-sufficient. Supporting efforts by MFIs to become free of subsidies in the long term might arguably be a way to help MFIs at attaining their dual objective.

A key working assumption in our analysis so far is that MFIs have the opportunity to either collect savings or borrow in the commercial banks at the prevailing market rates, which is clearly not the case for dozens of MFIs.[16]

Let us now introduce credit constraints. When these constraints 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 reach a lower level of utility than it would otherwise be the case.

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

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

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

where λ_t is the Lagrange multiplier associated to 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, one has a Lagrange multiplier $\lambda_t \geq 0$. If, at time *t*, this constraint is not binding, then $\lambda_t = 0$ and the results from our previous sub-section applies. 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 makes it impossible for the MFI to use future expected subsidies to "smooth" its current poverty-alleviation objective.

Borrowing from Schechtman (1976) we can show that, under fairly general conditions on stochastic subsidy - assuming zero interest rate and no discounting, the optimal number of poor served under credit constraints would be smaller at any time relative to the one without such constraints. In the same vein, Zeldes (1989) demonstrates that precautionary savings due to the uncertainty – in our case on future subsidies - are larger in the case of credit constraints.

Indeed, 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 so as to be able to have enough resources to save for the future. This will make the MFI to deviate from its certainty-equivalent optimal – just as it would reduce consumption in the Zeldes (1989) model. 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 behaviour. Note that this is a fairly standard result in intertemporal maximization models when agents (in this case MFIs) are risk averse. This approach, widely investigated in the consumption-smoothing literature, has somewhat surprisingly never been followed in the microfinance literature as far as we are aware. We now turn to testing the implications of our model in the following:

4. Empirical Results

4.1 Data Description and Estimation Method

Our empirical analysis attempts to establish a link between subsidy uncertainty and mission-drift variables for a worldwide sample of 230 MFIs active in 60 countries over the period 1999-2006.[17] Our dataset was obtained from assessment reports issued by external rating agencies. The main benefit of rating data is that reports have been compiled by a third party and therefore are less likely to be biased or 'upgraded' by the MFIs seeking, for example, to

[17] Appendix 2 provides information about the geographical composition of the sample by listing the number of MFIs and different types in each country.

secure future donations. For up to 53 percent of MFIs in our sample we have three years of data at our disposal; or 27.9% of them two years only. For a tiny fraction (0.4%) we have 4 or 5 years. The dataset contains a wide variety of MFI types with 114 that are reported as being NGOs (49.5%), 53 as non-bank financial institutions (23.04%), 46 as cooperatives (20%) and 17 as for-profit institutions (0.7%).

The MFIs in our sample are amongst the largest and best-managed institutions in the world and, given the well-established concentration of microfinance clients (Honohan, 2004), our sample should be representative of the universe of microfinance activities. In fact, basic statistics obtained from our sample appear to be similar to those appearing at the largest existing database in microfinance. For example, the 890 MFIs in the 17th MicroBanking Bulletin [MBB] (MicroBanking Bulletin, 2008) yield an average Operational Sustainability of 115% compared to ours of 117%. The average number of borrowers is 11,041 for the MBB compared to 10,232 in our database, the average nominal yield of is 30% in the MBB and 31% in our database. Moreover, the average staff productivity is 112 in the MBB compared to 132 borrowers per staff in our database.

Table 1 reports summary statistics. The median MFI is 7 years in operation and serves around 4,700 credit clients with a staff of 44 members. The total outstanding loan portfolio for the median MFI is 1,754 thousands US dollars, and the average loan granted is 398 dollars. The MFIs in the sample depend heavily on subsidies as can be seen from the ratio donated equity scaled by total equity which indicates that donated equity is roughly half the amount of total equity for the median MFI.

< Insert Table 1 here >

Subsidy uncertainty is defined as the standard deviation of the share of equity that is donated. This variable, which has a mean of 0.19 and ranges between 0 and 3.51, captures the dispersion in subsidies (or the uncertainty of) each MFI has had to confront in past years. The closer to zero, the less subsidies have fluctuated over time. Conversely, the larger the reported standard deviation obtained, the more subsidies have fluctuated over the observed sample period for which data is available.

Now, our approximation to an accurate measure of mission drift is far more challenging because a move from costly (very) poor clients towards profitable wealthier clients can be reflected in the MFI's reported data via various channels. First, mission drift can be expressed as the so-called "depth of outreach", that is, in terms of the number of poor borrowers served. Recall that our theoretical framework in the previous section differentiates between profitable loans that generate interests (with normalized size 1) and non-profitable loans that generate zero interests (with normalized size close to 0). The main prediction of our model is that subsidy uncertainty forces MFIs to reduce the number of costly loans it extends to poor clients – as proxied by average loan size. However, because our database shows the total number of loans, but not split into profitable and costly loans, we take the percentage change in number of active borrowers as a proxy for the variation in non-profitable loans. This variable has a mean of 0.19 and ranges between -0.81 and 0.90. This in turn suggests that, on average, the client-base is growing at 20 percentage points each year, whereas up to 15 percent of all MFIs in our sample suggest that there is a reduction in client-base. In section 4.2 we analyze the relation between subsidy uncertainty and changes in active borrowers.

Our model predicts that higher subsidy uncertainty is associated with smaller, or even negative, changes in active borrowers. This in turn suggests a crowding out of poor clients and a crowding in of wealthier clients. This phenomenon is indeed rooted in subsidy uncertainty, as our model above shows.

Mission drift could also lead to higher average loan sizes suggesting that MFIs are moving away from extending (costly) small loans and simultaneously getting closer to extending larger loans which are less costly. As Cull *et al.* (2009) argue MFIs can increase their profit margin significantly by cutting back on transaction costs related to small loans. We scale average loans by per capita gross national income (GNI) in order to make meaningful cross-country comparisons.

Lastly, mission drift could translate into higher interest rates charged on new or renegotiated loans. In this sense, a higher average annual interest rate charged on its loans portfolio may reflect MFIs' move towards wealthier yet unbanked clients. In section 4.3 we analyze the relation between subsidy uncertainties on the one hand, and average loans and interest rates charged on the other hand. We control for the dependence between average loans and interests by analyzing both variables simultaneously.

4.2 Subsidy Uncertainty and Variation in the Number of Poor Clients Served

Table 2 summarizes the results from regressing the change in the number of active borrowers on subsidy uncertainty and a set of controls, using pooled Ordinary-Least-Squares (OLS) as well as Random-Effects (RE). The hypothesis to be tested for is that higher subsidy uncertainty is associated with smaller growth in active borrowers. Indeed, our theoretical model predicts that the number of non-profitable clients declines when the MFI faces more subsidy uncertainty. The different columns displayed in table 2 correspond to different estimation methods and the subsequent inclusion of time and regional dummies. Standard errors are corrected for heteroskedasticity and autocorrelation, and are clustered at the MFI-level.

As far as control variables are concerned, we use the following:[18] MFI-type, age, size, a dummy indicating whether the MFI offers savings in addition to credit, portfolio-at-risk indicating the proportion of the loan-portfolio that is being repaid late. We add the level of subsidies scaled by equity as an extra control to isolate the effect of variation in subsidy uncertainty from the actual subsidization rate.

< Insert Table 2 here >

Table 2 indicates that more subsidy uncertainty significantly drives smaller increases in active borrowers, all other things equal. This result holds for pooled OLS (columns 1-3), and RE (columns 4-6) estimations, and regardless of the inclusion of time and/or regional dummies. Furthermore, the F-statistics (for OLS) and Wald χ^2-statistics (for RE) denote

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[18] These control variables are similar to the ones included in MFIs performance evaluations. See, for example, Yaron (1992) and Townsend and Yaron (2001).

joint significance of the overall model in all cases. This suggests that MFIs facing higher uncertainty with respect to subsidies have slower growth in the number of poor clients served, which is indeed in line with our theoretical prediction. As far as the controls are concerned, a higher growth in clients-base is obtained for for-profit institutions, which are also younger MFIs.

In Table 3, we display the results on the relationship between subsidy uncertainty and having a *positive-versus-negative* growth in clients. In our data, growth in clients is negative in 15% of the observations (each observation concerns one MFI and one year). Using Logit and Probit regressions, we investigate whether subsidy uncertainty is a significant predictor for the probability for an MFI to experience a positive outreach growth. The columns in Table 3 give the results for different estimation methods. In all instances, we include time and regional dummies. Standard errors are corrected for autocorrelation and heteroskedasticity.

< Insert Table 3 here >

Table 3 shows that higher subsidy uncertainty significantly reduces the chance of having positive changes in loanees. MFIs reviewing relatively higher uncertain subsidies have a higher probability of changing their existing portfolio of clients.[19] These results are in line

[19] An alternative explanation is that subsidy uncertainty triggers high dropout rates, not because clients leave voluntarily as in Karlan (2001) and Wright (2001), but because MFIs are unable to extend new loans to poor clients. The link between dropout rates and subsidies deserves further scrutiny in future research.

with the theoretical prediction that non-profitable loans are reduced when MFIs face uncertainty with respect to subsidies.

4.3 Subsidy Uncertainty, Average Loan Size, and Interest Rates

Albeit arguably, both average loan sizes and interest rates are used in the empirical literature in order to assess whether MFIs have drifted from their poverty-reduction mission. However, the interest rate charged on a loan is intrinsically linked to the average loan size and, consequently, both variables are jointly determined by the MFI. 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 loans. Therefore, rather than analyzing separately the relation between subsidy uncertainty and average loan size on the one hand, and the relation between subsidy uncertainty and interest rate on the other, we estimate a system of equations where we regress both variables simultaneously on subsidy uncertainty and on the controls. The main benefit of this approach is to take into account the endogeneity of average loan size and interest rate by allowing the errors of the different equations to be correlated.

Specifically we estimate the following set of equations:

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

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 for so that endogeneity is taken into account.

The parameters in (16) are estimated using the seemingly-unrelated-regression (SUR) procedure developed in Zellner (1962), Zellner and Huang (1962) and Zellner (1963). The columns displayed in Table 4 give the results when time dummies and regional dummies are added subsequently. Interestingly, the Breusch-Pagan test statistic for independence is always highly significant at the 5% significance level, hence rejecting the null hypothesis that both regressions in the system are uncorrelated. Interest rate and average loan size are simultaneously determined and modeling them jointly makes perfect sense.

< Insert Table 4 here >

In Table 4, the loadings of subsidy uncertainty are significantly positive in all interest-rate regressions, and insignificant in all average-loan-size regressions. This suggests that higher subsidy uncertainty is associated with higher interest rates, but subsidy uncertainty does not affect average loan size. The insensitivity of average loan size to subsidy uncertainty might seem surprising. However, albeit its frequent use in empirical studies, average loan size remains a poor indicator of mission fulfilment (Dunford, 2002; Armendáriz and Szafarz, 2011).

F-tests can now be jointly estimated across specifications. We report a joint F-test for the null hypothesis that both coefficients for subsidy uncertainty are jointly insignificant. In all specifications the test rejects the null hypothesis suggesting that there a positive and significant relation between the proxies for mission drift and subsidy uncertainty.

With respect to the control variables interesting results emerge. First, the regressions confirm that MFIs that depend more on donated funds usually offer smaller loans and charge lower interest rates. Second, MFIs that offer savings in addition to credit tend to provide larger loans. This is in line with the idea that voluntary savings are not being offered by MFIs focusing on the very poor. Third, larger MFIs as measured by the natural logarithm of equity offer larger loans and charge lower interest rates. Lastly, NGOs offer smaller loans, but there is no relation between MFI-type and the interest rate charged. Our results could indicate that existing results showing that interest rates are affected by the MFI-type (Mersland and Strøm, 2011; Robert, Forthcoming) could, at least partially, be attributed to model misspecification. Namely, failing to account for subsidy uncertainty could bring a missing-variable issue in interest-rate regressions. This hypothesis should, however, be further investigated.

4.4 Robustness Checks

We perform several robustness checks in order to test whether the observed relations remain robust after some modifications of the data and changing of set-up. The results are presented in Table 5.

Panel A is meant to check whether the previous results are driven by the measurement of subsidy uncertainty using standard deviations. Actually, the standard deviations of subsidies are computed on a limited number of observations per MFI. Hence, our results might be plague by measurement errors. We check the robustness of our results by replacing the standard deviation by the *spread* of donated equity scaled by total equity as an alternative measure for subsidy uncertainty. This spread is the difference between the maximum value and the minimum value for donated equity scaled by total equity. It is less sensitive to the number of observations.

The same issue is addressed in Panel B in a different way. Here, we re-estimate the system of equations for the case restring the sample to the MFIs for which data is available for more than three years. This sub-sample is made of of 53 percent of all MFIs in our data. Finally, in Panel C we adjust donated equity for donations in cash, in-kind subsidies and revenues from donations and use this adjusted subsidy-measure instead of donated equity to calculate the standard deviation.

< Insert Table 5 here >

Table 5 shows that the three modifications leave the baseline results unchanged. Namely, subsidy uncertainty has a significantly positive impact on the interest rate, and an insignificant impact on average loan size. Again, the Breusch-Pagan tests reject the null hypothesis that the equations of the system are unrelated. The joint F-tests indicate that the relation between mission drift and subsidy uncertainty is significant in the system. , Overall, the empirical analysis lends strong support to our theoretical result on higher subsidy uncertainty leading to mission drift.

5. Concluding Remarks

Historically, the dual objective of microfinance institutions has been that of alleviating poverty and attaining self-sustainability. Since it first emerged over thirty-five years ago the microfinance movement has benefited, and continues to benefit from subsidies.

Surprisingly, rigorous analyses on how subsidies support MFIs dual objective are missing from this literature on microfinance. In this paper we have attempted to bridge this gap.

We have argued that subsidy uncertainty is a contributing factor for MFIs deviating from their poverty-alleviation mission. Uncertainty forces MFIs onto building precautionary savings via serving wealthier clients. We suggest that donors deliver subsidies under clear, transparent rules, and in a timely fashion so that promises of future loans already offered to existing poor borrowers by MFIs are honored, and in order to ensure that the poor are increasingly included in MFIs' portfolios.

Future research should focus on pre-determined self-sustainability time-frames set by donors. Our conjecture is that under the fear that self-sustainability would not be attained under a particular time frame set *ex ante* by donors, may also drive MFIs onto mission drifting. Not establishing a self-sustainability time frame may on the other hand create a moral hazard problem.

Our analysis also opens venues for future research on the recent commercialization movement. Subsidy uncertainty migh accelerate transformation of NGOs into commercial MFIs. If this is desirable from the donors' standpoint, further empirical research is needed to fully assess the impact of commercialization on prices in general, and in particular, on interest rates.

Recall that our empirical analysis lends support to our theoretical framework: Subsidy uncertainty is associated with MFIs reviewing a slower growth of poor clients, and with higher interest rates. However, more theoretical research and better data is needed to establish the direct link between subsidy uncertainty and interest rates.

Finally, we note the following data limitations in hope that rating agencies, donors, and MFIs would take these on board to move research agendas forward. First, we had data on the total number of borrowers only. We therefore had no other choice but interpreting any decrease in the number of borrowers as a proxy for mission drift, relying on the implicit assumption that costly borrowers – the poor – are more numerous than profitable ones – the wealthier— all things equal. Future research should be directed at identifying profitable versus costly loans, and at isolating the impact of subsidy uncertainty on costly loans. This would require better data on cost per loan.

Second, subsidy uncertainty may be proxied via various channels, and the results pretty much depend on the venue empirical researchers decide to take. We used standard deviations. However, in the majority of cases we just had three observations. This made our rather rudimentary empirical research look distant from theoretical intertemporal analyses based on steady-states.

Finally, we advocate systematic documentation of qualitative assessments. In particular, keeping records of qualitative interviews with MFIs. And, in particular, on MFIs own views on subsidies in general, not just in the way these are delivered, can further shed light on policy prescriptions for donors.

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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 $N_1\left(t+1\right)$:

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

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

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

The stochastic process $\left(\varepsilon_t\right)$ is the martingale difference (see Broze *et al.,* 1985):

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

Equation (A5) exhibits the autoregressive structure of optimal outreach of which dynamics depends on the position of $\frac{1}{\beta\left(1+r\right)}$ with respect to unity. In particular, when $\beta\left(1+r\right)=1$, 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: $K_{t-i}\left(i \geq 0\right) \in I_t$. Equation (A7) also shows that uncertainty on future subsidies has a destabilizing impact through the error term $\left(\varepsilon_t\right)$, but no systematic impact.

Appendix 2: Sample Composition

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
Brasil	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
Guinee	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
Khazakhstan	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

Phillipines	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
Tunisie	1	1	0	0	0
Uganda	2	2	0	0	0
Zambia	1	0	1	0	0
Total	**230**	**114**	**53**	**46**	**17**