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Revisiting the Effects of IMF Programs on Poverty and Inequality

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Abstract

Investigating how lending programs of the International Monetary Fund (IMF) affect poverty and inequality, we explicitly address model uncertainty. We control for endogenous selection into IMF programs using data on 86 low- and middle income countries for the 1982-2009 period and analyze program effects on various poverty and inequality measures. The results rely on averaging over 90 specifications of treatment effect models and indicate adverse short-run effects of IMF agreements on poverty and inequality for the whole sample, while for a 2000-2009 subsample the results are reversed. There is evidence that significant short-run effects might disappear in the long-run.

JEL codes: O11, O15, O19, C31. **Keywords:** Poverty and income distribution, IMF lending programs, model uncertainty, treatment effects, cross-country analysis, developing countries

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1 INTRODUCTION

Although the International Monetary Fund (IMF) was created to provide assistance to all of its members, its field of action shifted towards the support of developing countries especially since the outbreak of the debt crisis in 1982. This shift in the IMF's clientele created demand for a change in the Fund's adjustment policies and new, concessional lending facilities emerged. As rumors grew loud that the Fund's adjustment programs worsened the situation of the poor in recipient countries,[1] the Fund departed from its neutral position on poverty issues and included poverty alleviation in its agenda (Collier & Gunning 1999, IMF 2012a, Polak 1991). This raised the question whether IMF programs contribute to reducing poverty, or, by contrast, if IMF critics are justified. In this study we apply a quantitative approach to clear that question and evaluate the effects of the IMF's lending facilities on poverty rates and income distribution in participant countries.

Although a big body of literature deals with analyzing the determinants of poverty and income inequality, a unique theoretical framework is missing.[2] This leads to the inclusion of very heterogeneous sets of explanatory variables in different studies and empirical findings that are hardly unanimous in supporting a particular argument. One reason therefore might be the absence of universal causal mechanisms as there is no guarantee that the economic processes and its interactions with poverty and inequality are the same across countries or regions (Kenny & Williams, 2001). Due to data constraints research in this field of developing economics, however, usually relies on cross-country or large-n panel-data evidence. Time series analyses that would give scope for more detailed structural investigations are seldom possible. Hence, the findings of empirical work might be conditioned on the sample of countries (and the time period) covered by the study. But also the set of explanatory variables included in the regressions could drive the results.

Despite of the big number of regressors used in different studies it is common in the empirical literature to regress a usually small number of variables on poverty or income distribution, neglecting factors that have been proposed as determinants of poverty and inequality by other authors. This motivates the concern for taking into account model uncertainty, which is present in both the choice of explanatory variables and the resulting estimates connected to it, in order to unveil universally applicable relationships that are not conditioned on a particular regressor set. As estimates obtained from selecting one model do not take uncertainty into account, the precision of the resulting coefficients is overestimated, thus, leading to a too confident interpretation of a variable as being significant (Fernández *et al.* 2001).

To the knowledge of the author, Ghura *et al.* (2002) provide so far the only study that explicitly controls for model uncertainty in finding robust determinants of poverty. The work investigates the effect of 36 variables on average income in the lowest quintile of the income distribution in a Bayesian Averaging of Classical Estimates (BACE, Sala-i-Martin *et al.* 2004) analysis. Six out of the 36 variables are identified as robustly related to poverty—gross domestic product (GDP) *per capita* growth, inequality, inflation, educational achievement, financial development, and government size—thus point-

[1] See Abugre 2000, Cavanagh *et al.* 2000, Hertz 2004, and Lundberg & Squire 2003, Vreeland 2002.

[2] For studies on the determinants of poverty see Adams (2004), Collier & Dollar (2002), Ghura *et al.* (2002), Morduch (1994), Mosley *et al.* (2004), Nissanke & Thorbecke (2006), for inequality see Adams (2004), Deininger & Squire (1998), Kuznets (1955), Meschi & Vivarelli (2009).

ing towards the universal applicability of their effects. In this study we aim to identify patterns concerning the impacts of program participation on poverty and inequality that are common to a big group of countries. To provide a comprehensive picture we look at six poverty indicators: The number of people living below the poverty line of 1.25$ or 2$ per day (headcount ratios), their income shortfall from these poverty lines (poverty gaps), and income equality before and after redistribution (Gini indexes).[3] As the focus of this paper is to identify treatment effects, we take a slightly different approach to Ghura *et al.* (2002). Instead of sampling over the whole model space (that is allowing for every combination of explanatory variables) we restrict some of the variables to be included in each regression. We estimate 90 model specifications for each poverty indicator and perform model averaging over the results of the regressions. An explanation of the procedure can be found in Section 3(b).

The contribution of this study is twofold. On the one hand we provide an empirical study on a large group of countries (86 low- and middle income countries, from 1982 to 2009) taking both poverty and distributional aspects into account while controlling for endogenous selection into IMF programs. On the other hand we explicitly account for model uncertainty to work out to what extend this uncertainty puts the robustness of the effect of program participation under strain. This kind of robustness analysis about the consequences of IMF agreements for poverty and income inequality is the primary concern of this research rather than identifying robust determinants of those indicators. We find empirical evidence for adverse short-run effects of IMF agreements on the number of people living in poverty, as well as on the severity of poverty (measured by the income shortfall from the poverty line). Income inequality (both, when measured before and after redistribution) is found to rise with program participation—when estimating the effects of concessional programs only, however, an improvement in inequality is detected. Our results also indicate that the inclusion of poverty alleviation in the IMF's agenda turned out to be successful as restricting the estimations to the 2000-2009 period the results are in many cases reversed.

The paper is structured as follows. Section 2 provides an overview of IMF programs, their theoretical implications for poverty and inequality, as well as a short review of the findings of more recent empirical studies. The estimation framework is outlined in Section 3. It describes the methodologies of treatment effect regressions and model averaging, followed by a summary of the model specifications. In Section 4 we report data-based analyses and regression results. Finally, Section 5 concludes.

2 IMF PROGRAMS

(a) Types of IMF programs

This study addresses both concessional as well as non-concessional programs of IMF lending. Concessional loans carry zero interest payments (through the end of 2013) and are available for low-income countries only while non-concessional loans are subject to the IMF's market related interest rate, called the rate of charge[4] (IMF 2012b).

[3] Kanbur (1987) and Sen (1979) provide information about the construction of poverty indicators and a discussion of their adequacy for measuring poverty. Concerning data quality, it is widely recognized that data on poverty and inequality suffer from measurement problems and comparability constraints. Deaton (2001) provides a summary about potential problems underlying the measurement of poverty. For an overview of caveats concerning inequality data see Atkinson & Brandolini (2001) and Solt (2009).

[4] The rate of charge is based on the SDR interest rate, which is revised weekly to take account for changes in short-term interest rates in major international money markets.

The non-concessional loans we consider are provided through Stand-By Arrangements (SBA) and the Extended Fund Facility (EFF). SBAs are short-term agreements, which typically last from one to two years and imply higher conditionality than other types of IMF lending programs. They are designed to help countries with severe disequilibria to respond quickly to their external financing needs. The greatest amount of IMF resources is provided under SBAs. The EFF was established to help countries with severe disequilibria to address medium-term balance of payment problems which require fundamental economic reforms. The typical EFF program lasts for three years (IMF 2011c, and IMF 2011d). The three concessional programs that form part of this study are the Structural Adjustment Facility (SAF), which was established in 1986, the Enhanced Structural Adjustment Facility (ESAF) founded in 1987, and the Poverty Reduction and Growth Facility (PRGF), which replaced the ESAF in 1999. The SAF and the ESAF are longer-term programs with lower conditionality. Programs under the SAF normally imply less stringent conditionality than ESAF programs and mostly antecede ESAF programs. The PRGF is based on country-owned Poverty Reduction Strategy Papers, which are prepared by the government of the country concerned. The largest number of IMF loans has been implemented through the PRGF in recent years (IMF 2011e, and IMF 2011f).[5] Although these program types differ in terms of duration, size, and loan conditions, the underlying objectives are the same (Polak 1991, Przeworski & Vreeland 2000). Thus, in the main analysis of this article we follow conventional practice and investigate the effects of participation in any of these programs.[6]

The above mentioned lending facilities are connected to conditionalities. Conditionalities cover both policy requirements that a country has to fulfill in order that a tranche of the loan gets disbursed, as well as tools used to monitor progress towards the goal outlined in the program. These loan conditions are supposed to help to solve balance of payments problems and ensure that the country will be able to repay the Fund (IMF 2011b). Typical conditionalities include policies concerning trade liberalization, fiscal policy reforms and privatization, as well as financial reforms. These conditions affect poverty either directly or as a channel for impacting on it. Although a detailed discussion concerning all direct and indirect effects of these policies is beyond the scope of this paper, we provide a short summary in the following.[7]

(b) Theoretical impacts of IMF programs on poverty and inequality

[5] As a reaction to the global financial crisis the IMF reshuffled the structure of lending facilities in 2009. The concessional lending facilities were rearranged and new non-concessional lending facilities emerged. The new concessional facilities include the Extended Credit Facility (ECF), which replaced the (PRGF), the Standby Credit Facility (SCF), and the Rapid Credit Facility (RCF), both replacing the Exogenous Shock Facility, which was established in 2008 (IMF 2011a, IMF 2011g). The Flexible Credit Line (FCL) and the Precautionary Credit Line (PCL) emerged in 2009 and 2010 respectively as new non-concessional lending facilities (IMF 2011h, and IMF 2011i). These recently created facilities, however, are not the focus of this study as it addresses IMF programs up to the end of the year 2009. In the rest of the paper we will use the terms *programs* and *agreements* for referring to IMF lending programs.

[6] In order to find out if this simplification is justified we perform cluster analysis, taking into account economic and financial indicators apart from poverty and inequality indicators. We fail to detect clustering according to participation in different agreements, suggesting that focusing on aggregate program participation is reasonable. Although most clusters include all program types, concessional programs seem to be similarly distributed between clusters. The same is true for non-concessional programs. Hence, we disaggregate program participation in concessional and non-concessional lending programs in an additional robustness check. I thank one anonymous referee for pointing out the potential difference in the effects of program types and Octavio Fernández-Amador for suggesting to perform cluster analysis.

[7] For a more detailed theoretical overview of the effects of conditionalities on poverty see also Cashin *et al.* (2001). For an overview of the results of empirical studies see Hajro & Joyce (2009).

Trade liberalization has two potential opposite effects on poverty. On the one hand, sectors that were protected before the liberalization contract, leading to lower incomes in these areas. On the other hand, according to the Stolper-Samuelson theorem, trade liberalization leads to increased demand and higher wages for unskilled workers in countries that are relatively abundant in unskilled labor (Handa & King 1997). Thus, the theoretical effect of trade liberalization on poverty is ambiguous and depends on production, trade, and consumption patterns (Gunter *et al.* 2005).[8] Most of the work in the recent empirical literature about the effects of trade liberalization on poverty shows that trade liberalization has a positive impact on poverty reduction but leads to higher inequality. Looking at the effects of trade on inequality in more detail there is evidence that trade with high income countries worsens the income distribution of middle income countries while it has no effect on the income distribution of low income countries (Meschi & Vivarelli 2009).

A country under IMF agreement typically is obliged to decrease its budget deficit, which can be achieved through an augmentation of fiscal revenue or a decrease in public expenditure. The re-distributional effects of such reforms depend on the budgetary policy that the government implements. Usually reductions in public expenditure imply cuts in social spending, public sector wages, and public sector employment. The resulting rise in unemployment and the lower wages in this sector tend to increase poverty levels and worsen income distribution. Fiscal revenue can be increased with privatization of state-owned enterprises (mostly implying layoffs of public sector employees) or reform of the tax structure. Tax reform often implies a bigger focus on expenditure taxes and a simplification of income taxes and, therefore, leads to a deterioration of the after-tax income distribution.[9] There is no consensus in the literature concerning whether participation in IMF programs results in a decrease in social expenditure.[10]

Financial reforms include currency devaluation, liberalization of the financial sector, as well as an adjustment of the banking sector. Although there is no clear-cut conclusion about the relationship between devaluation and poverty (Gunter *et al.* 2005), devaluation is connected to negative associations in developing countries (such as increased costs of servicing foreign debt or capital flight of foreign investors). Theoretically, the effect of currency devaluation is a decrease in the price ratio of non-tradable to tradable goods which gives some scope for import substitution. Whether poor people benefit from a devaluation depends on the composition of the economy and on consumption patterns.[11] Financial liberalization is often connected to weaknesses in the domestic banking sector and currency crises, leading to an increase in poverty. Therefore, such a liberalization needs to be accompanied by sound economic policies and legal and regulatory underpinnings to improve economic performance (Bird & Rajan 2001). Bank reforms leading to higher interest rates or more restrictive bank-reserves requirements, as well as the introduction of credit ceilings, reduce the access to domestic credit and make it easier for large companies to get credits in contrast to small and medium-sized firms. Also, the urban sector is favored over the rural sector, resulting in rising inequality (Johnson & Salop 1980, cited by Vreeland 2002). Most of these fiscal and financial reforms (credit

[8] Nissanke & Thorbecke (2006) provide a comprehensive overview of the channels through which globalization might affect poverty.

[9] See Handa & King (1997), and Johnson & Salop (1980), cited by Vreeland (2002).

[10] See Handa & King (1997) and Nooruddin & Simmons (2006) for evidence that participation in IMF programs leads to a decrease in social expenditure, and Martin & Segura-Ubiergo (2004) for evidence against it.

[11] See Bourguignon *et al.* (1992), Garuda (2000), Kanbur (1987), and Pastor (1987) for more details about the effects of financial reforms on poverty.

restraints, budgetary cuts, higher levels of taxation, and reductions in real wages) are very likely to reduce domestic demand. The resulting contraction of spending is most probable to decrease the welfare of people whose main source of income is labor income and people living in poverty (Heller 1988).

The policies implemented under IMF agreements are supposed to lead to a reduction of inflation and restore economic growth. Economists broadly agree that high levels of inflation have negative consequences on economic growth and poverty. Some studies, however, find that countries that maintain macroeconomic stability do not necessarily gain significant improvements in economic growth and poverty reduction.[12] Theoretically the effect of inflation on income distribution depends on how rigidly income adjusts to prices for each group of the population. If poorer individuals face longer adjustment lags than wealthier ones, a higher inflation rate will raise income inequality (Garuda, 2000). While it is not clear whether growth affects inequality in one way or the other, most authors agree that economic growth is fundamental for poverty reduction. Some point out that the sectoral composition of growth and its distributional effects matter for poverty alleviation. This highlights the need for appropriate politico-economic programs that create conditions for the poor to benefit from growth.[13] The empirical evidence on whether participation in IMF programs leads to a higher rate of economic growth is ambiguous. Some studies find that IMF lending reduces economic growth, whereas others find beneficial effects of IMF support on growth.[14]

The possibilities for implementing IMF programs are broad and imply different consequences for poverty and income distribution. Political power plays an important role in determining the design of the program and to which extent conditionalities are fulfilled. It is likely that IMF programs are carried out in a way that does not hurt politically powerful groups, frequently at the expense of the poor. Furthermore, participation in a program makes it easier for policymakers to tackle painful reforms as they can blame the Fund for "forcing" them to do so.[15]

(c) Empirical findings

Investigating the impacts of IMF agreements on the distribution of income most studies find that program participation is connected to higher inequality. More recent large-n studies that control for sample selection as opposed to many earlier investigations in this

[12] Easterly & Fischer (2001), Ghura *et al.* (2002), and Meschi & Vivarelli (2009) agree on the negative consequences of high levels of inflation, while Gunter *et al.* (2005) find no significant improvement in economic growth and poverty reduction in periods of macroeconomic stability.

[13] Information about the effects of economic growth on inequality is provided by Deininger & Squire (1998), Dollar & Kraay (2004), Ghura *et al.* (2002), and Ravallion & Chen (1997). While Adams (2004), Dollar & Kraay (2002), Fanta & Upadhyay (2008), and Ghura *et al.* (2002) provide general evidence for the effect of growth on poverty, Cashin *et al.* (2001), Garuda (2000), Hajro & Joyce (2009), Loayza & Raddatz (2010), and Stiglitz (2002) point out that certain conditions have to be met in order for poor people to benefit from economic growth.

[14] Atoyan & Conway (2006) point out the ambiguity of the effect of IMF lending on economic growth. For evidence that IMF lending reduces growth see Barro & Lee (2005), Bordo & Schwartz (2000), and Przeworski & Vreeland (2000), for evidence of the beneficial effects of IMF programs for growth see Dicks-Mireaux *et al.* (2000), Evrensel (2002), and Hutchison (2004). Ul Haque & Kahn (1998) and Steinwand & Stone (2008) provide a more detailed summary about the effects of participation in IMF programs on macroeconomic variables such as economic growth, inflation, balance of payments, and current account deficits.

[15] Arpac *et al.* (2008), Garuda (2000), Pastor (1987), and Vreeland (2002) recognize that political power plays a role both for program design and compliance with conditionalities. Collier & Dollar (2002), Dreher & Walter (2010) state that the IMF exerts a scapegoat function for implementing unpopular reforms.

field include the work of Garuda (2000) and Vreeland (2002). While Garuda's study suggests that IMF programs lead to a deterioration of the income distribution in countries with severe external imbalances but to a relative improvement in distributional indicators if imbalances are small, Vreeland concludes that program participation lowers the labor share of income in the manufacturing sector thus contributing to rising inequality. In contrast to Garuda's study that relies on propensity score group comparisons covering 39 countries over the 1975-1991 period, Vreeland's work is based on a dynamic version of Heckman's (1979) selection model for 110 countries over the 1961-1993 period. More recent studies that investigate the effects of program participation on poverty find that, both, IMF and World Bank programs lower the response of poverty levels to changes in economic growth (Easterly 2001). However, neither infant mortality nor the Human Development Index, as proxies for poverty, are found to be significantly different in countries that participate in an IMF agreement (Hajro & Joyce 2009). While the results of Easterly's work are based on instrumental variable regressions for 65 countries, the study of Hajro & Joyce does not explicitly control for self-selection but performs fixed effects regressions for a sample of 82 countries.[16]

3 ESTIMATION FRAMEWORK

In the empirical analysis we are confronted with several kinds of statistical challenges. First, there is a problem of unobservability of the counterfactual outcome. We can perceive what happens to countries that took part in an IMF agreement after program participation, but we cannot observe what would have happened to them otherwise. Second, we are confronted with an endogeneity problem as the choice of a country whether to participate in a program is not made randomly. Countries which are more likely to join an IMF agreement generally face specific macroeconomic conditions that make them eligible for participation in programs (Przeworski & Vreeland 2000). These differences, which could themselves influence poverty and/or income distribution, have to be controlled for, otherwise leading to biased estimates of the effect of program participation. Finally, we also face a problem of model uncertainty as it is not clear which factors are robust determinants of program participation and poverty indicators.

In order to address the first two issues and obtain unbiased estimates, we deal with program evaluation as a particular case of a treatment effects setup. Although it is impossible to observe the counterfactual outcome, the task is to match countries that participate in an IMF program with countries that face similar conditions but do not form part such a program. While some of these conditions are observable some, like political will, might be not. Treatment effect regressions remove the effects of non-random selection taking into account both observable and unobservable factors. The remaining difference in poverty or inequality between countries that form part of IMF agreements and countries that do not is the inherent effect of IMF programs (Vreeland 2002, 2003). In order to address model uncertainty, we estimate various treatment effect regressions with country fixed effects based on different sets of explanatory variables that could potentially be driving factors of program participation and poverty measures. We test for the presence of selection bias in each of the model specifications. If there is no evidence for such bias, we estimate OLS regressions with country fixed effects additionally to the treatment effect regressions. Based on the results we perform model averaging, placing more importance on models with higher explanatory power. For constructing the model

[16] For a summary of earlier research dealing with the effect of IMF programs on poverty and inequality see Hajro & Joyce (2009).

weights, we use both Bayesian (Schwarz 1978) and frequentist (Akaike 1973) information criteria. Subsequently, we get an insight about which factors affect the poverty indicators used, independent of model specification and free of selection bias, and are able to evaluate the robustness of program effects.

(a) Treatment effects model

We are interested in estimating

$$y_{it} = x'_{it-1}\beta + \delta D_{it-\tau} + \xi_i + \epsilon_{it} \tag{1}$$

where y_{it} is alternatively one of the six poverty indicators used in this study—the natural logarithm of poverty gaps and poverty headcount ratios both at the poverty line of 1.25$ and 2$ per day, and Gini indexes of gross and net income inequality—measured in period t for country i, x_{it-1} is a vector of variables that likely affect poverty or income inequality, and β is the corresponding parameter vector. $D_{it-\tau}$ is a dummy variable which is equal to one if country i is participating in an IMF program at time $t-\tau$ and zero otherwise.[17] Its coefficient δ reports the effect of program participation on poverty and income distribution. ξ_i is the time invariant country fixed effect of country i and ϵ_{it} is the random error term. As we cannot test for reverse causation due to data limitations, all of the explanatory variables enter with one year time lag in order to avoid contemporaneous feedback effects.[18]

Estimation results relying on specification (1) are potentially subject to bias due to endogenous selection into program participation, as countries do not make their choice whether to ask the IMF for help randomly but depending on their macroeconomic conditions and other (unobservable) factors. Therefore, it is not possible to tell if the effect on poverty or income inequality arises due to program participation or those differences, unless controlling for non-random selection.[19] To take this into account we make use of treatment effect models, which allow to estimate the impact of program participation on poverty and income distribution consistently. Treatment effect models rely on an instrumental variable approach in which the endogenous program participation D_{it} is instrumented as

$$D^*_{it} = w'_{it-1}\gamma + z'_{it-1}\alpha + u_{it}, \tag{2}$$

and depends on a set of variables w_{it-1} which explain program participation, and at least one exclusion restriction z_{it-1}, which should be correlated with D_{it} but uncorrelated with y_{it} in (1). The validity of the exclusion restriction is essential for effective bias correction. γ and α are the coefficient vectors for these two sets of variables, and D^*_{it} is a latent variable with its observable counterpart D_{it} that is generated by

$$D_{it} = \begin{cases} 1 \text{ if } D^*_{it} > 0 \\ 0 \text{ otherwise} \end{cases}$$

The system formed by (1) and (2) assumes bivariate normal distributed error terms u_{it} and ϵ_{it} and homoscedasticity, with $Var(\epsilon_{it}) = \sigma^2$, $Var(u_{it}) = 1$, and $Cov(\epsilon_{it}, u_{it}) = \rho\sigma$,

[17] In the empirical section of the paper τ ranges from 0 to 2.

[18] The same data limitations make us dependent on using cross country information for investigating the effects of IMF programs although the possibility exists that causal mechanisms differ across countries. By allowing for country fixed effects we take into account differences in levels of poverty and inequality.

[19] See Conway (1994), Dreher & Walter (2010), Goldstein & Montiel (1986), Przeworski & Vreeland (2000), and Vreeland (2002).

and can either be estimated in two stages or jointly by maximum likelihood. Although computationally less expensive, the two stage estimator is inefficient compared to maximum likelihood. Therefore, the latter approach is used in this paper (Heckman 1974, Nelson 1984). As the treatment effects model accounts for endogeneity, δ is free of bias and can be interpreted as the effect of program participation on poverty or income distribution, respectively.[20]

With this theoretical framework in mind, the researcher has to specify potential determinants, x, of the poverty measures in equation (1)—what we will refer to as the outcome equation—and the variables included in w and z that explain program participation in equation (2)—what we will call the selection equation. The empirical literature on the determinants of participation in IMF programs proposes quite a lot of different sets of explanatory variables driving such a decision.[21] To the knowledge of the author, Sturm *et al.* (2005) provide the first attempt to address model uncertainty including a very broad set of explanatory variables which potentially influence the probability of obtaining an IMF credit. Moser & Sturm (2011) update the work of Sturm *et al.* (2005) for the post-Cold War period. Both studies make use of the Extreme Bounds Analysis proposed by Leamer (1983, 1985) and Levine & Renelt (1992) to identify robust determinants of IMF programs and analyze the entire distribution of the coefficient estimates as proposed by Sala-i-Martin (1997). While Sturm *et al.* (2005) find that mostly economic variables play a role in IMF lending decisions, Moser & Sturm (2011) suggest that also political variables matter.

Addressing model uncertainty in the selection equation (2) as outlined here, as well as in the outcome equation (1) as sketched out in Section 1, we estimate a broad range of alternative models including different sets of regressors and instruments. Then, we perform averaging of the coefficients obtained from those model specifications using Bayesian and frequentist information for constructing model weights. The primary aim of applying this method is to ensure that a significant coefficient of the program dummy is not the result of model selection, but is robust to model specification.

(b) Model averaging

The importance of sensitivity analyses for empirical studies has already been emphasized by Leamer (1983, 1985) who proposes a method for testing the robustness of variables, which he calls Extreme Bounds Analysis (EBA). EBA consists of running a battery of regressions including variables that are common to each specification (*free variables*), and additional explanatory variables (*doubtful variables*) that enter in any linear combination in the model. In order to classify a variable as *robust*, the minimum and the maximum of its coefficient have to be statistically significant and of the same sign. The EBA has been regarded to impose too strong conditions on the variable coefficients in order to be considered as robust, however, and new methods for dealing with model uncertainty have developed (Fernández et al. 2001, Sala-i-Martin 1997, Sala-i-Martin *et al.* 2004).

[20] For further details on treatment effect models consult Cameron & Trivedi (2009, pp. 869-871), Greene (2008, pp. 889-890), Heckman (1978), or Maddala (2008, pp. 117-125).

[21] Studies that deal with the participation decision in IMF programs include Andersen *et al.* (2006), Atoyan & Conway (2006), Barro & Lee (2005), Bird & Rowlands (2001), Broz & Hawes (2006), Dreher *et al.* (2009), Dreher & Walter (2010), Dreher & Sturm (2012), Eichengreen *et al.* (2008), Elekdag (2008), Garuda (2000), Harrigan *et al.* (2006), Moser & Sturm (2011), Przeworski & Vreeland (2000), Sturm *et al.* (2005), and Vreeland (2002).

This paper builds on the Bayesian Averaging of Classical Estimates (BACE) proposed by Sala-i-Martin *et al.* (2004), which relies on averaging ordinary least squares (OLS) coefficients across models with model weights being proportional to the Bayesian Information Criterion, BIC (Schwarz, 1978). Applying model averaging in the context of program evaluation, the method we use differs from BACE in the way that we do not apply a sampling algorithm. Rather, we specify what Leamer (1985) calls free variables and sequentially include other variables which are believed to have an influence on the dependent variable. The resulting models form part of the averaging process. We prefer this approach to a full BACE approach because of two main aspects. In terms of variable selection we allow, on the one hand, only for model specifications which are theoretically reasonable, on the other hand, we can explicitly take care of the handling of exclusion restrictions, which we introduced in Section 3(a). Also, in terms of efficiency, sampling over the whole model space would entail a huge computational expense, as Maximum Likelihood estimations of treatment effect models are rather time consuming.

We follow Buckland *et al.* (1997) in using model weights which are obtained from information criteria like the Akaike Information Criterion, AIC (Akaike, 1973), and the BIC.[22] The weight for model k is calculated as

$$w_k = \frac{exp(-I_k/2)}{\sum_{j=1}^{K} exp(-I_j/2)} \tag{3}$$

where I is the information criterion and K is the number of model specifications. Following Sala-i-Martin *et al.* (2004) we derive the model averaged coefficients, $\hat{\beta}$, and their variance, $Var(\hat{\beta})$, as

$$\hat{\beta} = \sum_{j=1}^{K} w_j \hat{\beta}_j \tag{4}$$

$$Var(\hat{\beta}) = \sum_{j=1}^{K} w_j Var(\hat{\beta}_j) + \sum_{j=1}^{K} w_j (\hat{\beta}_j - \hat{\beta})^2, \tag{5}$$

where $\hat{\beta}_j$ and $Var(\hat{\beta}_j)$ are the coefficient and variance estimates from the treatment effect regression with the regressor set that defines model j.

(c) Model specifications

The results of this paper rely on averaging over 18 specifications of the outcome equation (1), which are combined with five different specifications of the selection equation (2). This leads to 90 treatment effect models being averaged for each poverty indicator. Table 1 shows the five specifications of the selection equation. The variables Vote in line with $G7_{t-1}$, Countries under $program_t$, and Past program $years_t$ serve as exclusion

[22] Raftery (1995) provides a formal derivation of the BIC approximation to the Bayes factor, the latter being used to construct model weights in a fully Bayesian context. Clyde (2000) gives a justification for model weights based on both the BIC and the AIC. The BIC is biased in favor of parsimony over fit while the AIC often tends to overestimate the number of parameters needed (Clyde 2000, Raftery 1995). Therefore, we perform model averaging with model weights based on either one of the two. The results based on the AIC, which are qualitatively the same as the ones obtained by the use of the BIC, are not reported here but are available from the author upon request.

restrictions, z.[23] Appendix B discusses the model specifications in more detail and provides an overview of studies using the explanatory variables that are also included in the here presented work. Since the primary purpose of this paper is to investigate the effects of IMF programs on poverty and inequality, I refer to the studies mentioned in the appendix for a discussion of the effect of the explanatory variables.[24]

Insert Table 1 here.

Table 2 reports the 18 specifications of the outcome equation. A base of variables is included in each estimation which, additionally to variables proposed in the literature like the logarithm of GDP *per capita*, a democracy index, and the Gini coefficient, also includes country dummies and three time trends to control for common developments before participation in a program, during program participation and after the termination of an agreement. The reason for the three exclusion restrictions to be included in all specifications is to allow the assessment of their validity.[25] We request at least one exclusion restriction to be valid in order to use the estimation results for inference about program effects. The country dummies are included in order to control for individual effects that are time invariant. As shown in Table 2 each of the model specifications adds different variables to the common base.[26]

Insert Table 2 here.

Estimating the 90 treatment effect models for each of the six poverty indicators allows us to test for statistically significant error correlation between the residuals of the selection equation and the ones from the outcome equation, $\rho\sigma$ (see Section 3(a)). A statistically insignificant error correlation suggests that there is no bias arising from endogenous selection of countries into a program and the equation could be estimated by OLS. For these cases (where ρ turns out to be statistically insignificant) we also estimate OLS regressions with country fixed effects. We include the same variables that form part of the selection and the outcome equation in the OLS regressions, leading to a maximum number of 90 model specifications also here. In order to gain insight on whether program participation affects poverty and income distribution upon impact, we include the instrumented program participation dummy in the same year, t, in which the poverty outcome is observed. Additionally, we estimate specifications in which program participation is included with one ($\tau = 1$), or two ($\tau = 2$), time lags respectively. The results are shown in Section 4.

[23] Voting behavior in the UN General Assembly serves as a proxy for a country's political proximity to the G7 countries who have some degree of influence over IMF decisions. Voting in line with G7 countries is found to be connected to a higher probability of obtaining a loan and better terms from the IMF. The number of countries under agreement in a certain year can be seen as a proxy for world conditions—as world conditions are bad, more countries turn to the Fund. Alternatively, the more countries turn to the Fund, the less costly the sovereignty costs may be perceived to be, so more countries apply for a program (Sturm *et al.* 2005). The number of years a country spent under IMF agreement is included because countries that participated already in IMF programs are more likely to do so again. This happens as the political cost may be lower if a country has already participated in an IMF program before, as compared to the first agreement with the Fund (Vreeland 2003).

[24] See Steinwand & Stone (2008) for a more complete survey about factors determining participation in IMF programs.

[25] Like already mentioned in Section 3(a), exclusion restrictions should be significant in explaining the country's participation decision in IMF programs but should not be correlated with the dependent variable of the outcome equation.

[26] We drop individuals with less than two data points available. Note that the estimation of all model specifications is based on same number of observations (Akaike 1973, Schwarz 1978).

4 DESCRIPTIVES, RESULTS, AND ROBUSTNESS

(a) Data and descriptive statistics

For investigating the effects of IMF programs empirically, we combine various databases to construct an (unbalanced) panel dataset covering the period 1982-2009 and including 86 low- and middle income countries. Details about variables, data sources, and descriptive statistics concerning the variables used, as well as a list of countries included in this study, can be found in *Appendix A*.

To provide a first, descriptive overview of the six poverty indicators that are the focus of this study, we form five classes according to the program participation status of countries. This leads to groups of countries which were *never* under IMF agreement in the time period from 1982 to 2009, *before* the first program participation, currently participating in a *program*, *between* two IMF programs and *after* the last IMF program that has been implemented in the country as long as data are reported. Summary statistics—number of observations, means, medians, standard deviations, minima, and maxima—for poverty gaps and headcount ratios can be found in Table 3. The distribution of all four indicators is positively skewed. Thus, focusing on the median values of the indicators, poverty is the lowest for countries of our sample which *never* participated in an IMF program, and the highest for countries *before* their first participation and during the agreement. *After* the last program participation poverty turns out to be lower again.

Insert Table 3 here.

Table 4 shows summary statistics for Gini indexes of gross and net income inequality—the former measuring income inequality before taxes and transfers, the latter income inequality after redistribution. Both indexes are the highest for countries that never adopted an IMF program, indicating higher income inequality in those countries. They are the lowest after the last program participation.

Insert Table 4 here.

(b) Empirical specification

For illustrative purposes, coming to the specifications of the treatment effects models, Table 5 shows the results of probit estimations of the selection equations. It reports marginal effects at means of the variables. In our sample most of the regressors turn out to be significant predictors of participation in an IMF programs with their coefficients showing the expected sign. The natural logarithm of GDP *per capita* is found to have a significant non-linear relationship with IMF program participation.[27] The probability of receiving an IMF program initially increases with GDP *per capita* but later decreases. The estimated coefficients imply that the switch occurs at a GDP *per capita* between \$983.5 (column 1) and \$1187 (column 2)[28], which lies below the sample mean and the sample median of the datasets used. The natural logarithm of GDP and its square, as

[27] Ln(GDP pc) and its square are jointly significant with a p-value of 0.000 for each of the five specifications. The same is true for ln(GDP) and its square, where the p-values for the joint significance lie between 0.0157 (specification 2) and 0.0261 (specification 5), respectively. When dropping the squared terms from the specifications, the coefficients of ln(GDP pc) and ln(GDP) turn out to be negative and significant, each. The results that are reported in Table 6 and Table 7 are robust to this specification change.

[28] That corresponds to a ln(GDP pc) between 6.891 and 7.079.

well as the current account balance, turn out to be insignificant in predicting program participation. Voting behavior in the UN General Assembly and trade are only weak determinants of the adoption of an IMF agreement for the countries in our dataset. A possible reason for the insignificant or significantly negative trade coefficient in our sample is the lack of controlling for the composition of trade, for which unfortunately there are not data available.

Insert Table 5 here.

We do not show the estimation results of each of the treatment effects models as this would go beyond the scope of this paper due to space limitations. Rather we provide the results of the averaging across all models in the next subsection.

(c) Averaging results and robustness

Table 6 reports the results of the averaging over the model specifications described earlier, for poverty gaps and headcount ratios as dependent variables. Because of space constraints we report only the results that are based on the BIC for constructing model weights.[29] Which poverty indicator has been used as the dependent variable is visible in the head of the table. The table provides information about the contemporaneous program effect on the poverty indicator (seen in the panel labeled $\tau = 0$), as well as program effects of one ($\tau = 1$), or two years time lag ($\tau = 2$). For which time lag the results are reported can be seen in the first column. The second column indicates, for each time lag, how many and which exclusion restrictions have been satisfied in order to include a model in the averaging process. Also the results of the averaging over OLS fixed effects regressions are reported. Finally, the outcome of the averaging process can be found in the cells of the last four columns. Each cell reports the mean of the posterior distribution of the program participation coefficient with the significance level attached to it, as well as the posterior standard error (in parentheses) below. The number of model specifications included in the averaging process is reported at the bottom of each cell. In the case of treatment effects, it is the number of models (out of the 90 models estimated) which fulfill the respective exclusion restriction. In the case of fixed effects, it is the number of models for which no endogeneity bias was detected. The percentage in parentheses next to it indicates its fraction of the overall 90 model specifications.[30]

Insert Table 6 here.

Table 6 reveals a clear-cut impact of program participation on poverty gaps and headcount ratios, measured at the poverty lines of 1.25$ and 2$ per day for our sample. As already mentioned, the results shown in the table rely on averaging the coefficients over different treatment effect regressions with country fixed effects (the values in the rows labeled OLS fixed effects are an exception).[31] According to the treatment effect results, program participation increases both, the number of people living in poverty (poverty headcount ratios), as well as their income shortfall from the respective poverty

[29] The results do not change quantitatively if we use the AIC instead of the BIC.

[30] The high values of the percentages (for one fulfilled exclusion restriction) indicate that the reported outcome relies on a big number of averaged models and is not the result of only a few model specifications.

[31] Like pointed out in Section 3(a), treatment effect regressions control for differences in economic conditions in countries prior to their participation in an IMF program and selection bias arising from it. As OLS regressions are just computed for model specifications for which treatment effect regressions show an insignificant error correlation of the residuals, $\rho\sigma$, the results relying on OLS fixed effects should not be influenced by selection bias to a big extent.

line (poverty gaps). All poverty indicators worsen in the year the program is in force ($\tau = 0$), as well as in the following year ($\tau = 1$). Two years after program participation has been observed, the undesirable effect of participation in an agreement on most poverty measures vanishes ($\tau = 2$). Generally, the poverty augmenting effect of program participation is stronger when poverty is measured at the lower poverty line of 1.25$ per day, meaning that the poorest members of the economy are hit the most by unfavorable program effects. Quantifying the effects, according to our data program participation has the biggest contemporaneous impact on the income shortfall of poor people from the 1.25$ poverty line followed by the number of people living with an income below this line. The effects of IMF programs on the two poverty indicators measured at the 2$ poverty line, are somewhat smaller.[32] The magnitudes of the program effects on poverty should be taken with care, however, as the measurement of poverty is not without problems (Deaton 2001). For most indicators the detrimental effect on poverty diminishes as we include more time lags between program participation and the poverty index, until the program effect becomes insignificant.[33] Turning to the OLS fixed effects regressions the averaging leads to statistically insignificant effects of program participation in almost all cases. The only exception is the favorable slightly significant effect of program participation on the number of people living in poverty (measured at the lower poverty line of 1.25$ per day).[34] [35]

Due to space constraints, we do not show the averaged coefficients of the other variables forming part of the regressions but summarize the results shortly.[36] In line with theory and previous studies, higher GDP *per capita*, as well as a higher level of democracy, and a more equal distribution of income are found to significantly lower poverty as measured by our four poverty indicators.[37] The time trends indicate that poverty increases in the time the program is in force.[38] In some cases, the number of countries that are participating in an IMF program in a certain year, which could serve as a proxy for world conditions (Vreeland 2002), turns out to be significantly correlated to higher poverty, measured at the 2$ per day poverty line. Including the natural logarithm of GDP *per*

[32]The results suggest that the income shortfall from the 1.25$ poverty line more than doubles due to program participation, the shortfall from the 2$ line rises by up to 44%. The number of people living below the 1.25$ line increases by about 68%, or up to 39% considering the higher poverty line. Recall that for obtaining these numbers the program coefficient has to be transformed as $\%\Delta y = [exp(\delta) - 1] \times 100$.

[33]One exception is the income shortfall of people from the poverty line of 2$ per day, which is found to be stronger affected as we increase the time between program participation and its impact on poverty. The effect of program participation (included with two years time lag) on this indicator remains significant only when the averaging is based on a small number of specifications (2% of total).

[34]This finding should be treated with caution, however, as it relies on a relatively small number of model specifications (3% of total) for which sample selection bias has not been detected. In the other 97% of model specifications for this indicator, sample selection bias has been found to be present. For contemporaneous effects of program participation selection bias has been detected in each specification, therefore no OLS fixed effects results are reported.

[35]Running separate regressions for three income-group subsamples we confirm the poverty increasing effect of IMF agreements for low-income and lower-middle income countries. In upper-middle income countries we fail to detect statistically significant results although the program coefficients have a positive sign. The insignificance of the program effects in upper-middle-income countries might stem from the lower number of observations in each subgroup. I thank one anonymous referee for suggesting to include this analysis in the paper.

[36]In the following we denote a variable as having an effect on poverty if it is statistically significant at least at the 10% level.

[37]These results are in line with Adams (2004), Fanta & Upadhyay (2008), Ghura *et al.* (2002), Mosley *et al.* (2004), and Nissanke & Thorbecke (2006). As opposed to our findings Ghura *et al.* (2002) did not find democratic institutions being a robust determinant of the income share of the lowest quintile.

[38]There is slight evidence that the number of people living with less than two dollars per day has been increasing before program participation and has been decreasing afterwards. This, however, cannot be confirmed for other poverty indicators.

capita squared, we find an interesting pattern. Its coefficient is found to be positive and significant in explaining 1.25$ line poverty indicators (the coefficient of ln GDP *per capita* becomes more negative), while it is negative and significant in explaining the 2$ line poverty indicators (the coefficient of ln GDP *per capita* becomes insignificant or positive). This result suggests that as the level of *per capita* income increases, its marginal impact on poverty at the 1.25$ line decreases, while the poverty reducing effect for poverty measured at the 2$ line becomes stronger. Other factors that are found to be significantly lowering poverty include domestic credit to the private sector (as suggested by Morduch 1994), which mostly affects poverty measured at the poverty line of 2$ per day, and currency devaluation (Gunter *et al.* 2005, and Kanbur 1987). A hyper devaluation, however, (measured as a devaluation of more than 200% within one year) is found to lead to an increase in poverty. There is also some, but limited, evidence that a higher average in years of schooling, higher life expectancy, and urbanization are significantly correlated to lower poverty rates, while hyperinflation leads to a rise in poverty.[39] The data suggest that the general development over time has been a decrease in poverty.[40] Variables whose effect on poverty remains unclear are trade openness and population growth. Their coefficients are insignificant in most cases and, if significant, the direction depends on the specification of the estimation. Investment, government consumption, GDP *per capita* growth, a country's natural resource rents, and the value added in agriculture are not found to be significant determinants of poverty.[41]

Providing further details, *Appendix C* gives an overview of the treatment effect models that enter with the highest weights in the averaging process. For each poverty and income inequality indicator it reports the estimation results of the tree "best" model specifications, where program participation enters without time lag in the model.[42]

Insert Table 7 here.

Table 7 is built up in a similar way to Table 6 and shows how IMF programs affect income inequality in our sample. The results based on treatment effect regressions indicate that program participation is connected to higher income inequality measured both before redistribution (Gini gross), and afterwards (Gini net).[43] While program participation seems to have a stronger contemporaneous effect on income inequality after taxes and transfers, the reverse is true if the program dummy enters the estimations with one year time lag. The increase in the Gini indexes as a result of program participation lies between 2.5 and 3.5 points. The same caution as before in interpreting magnitudes also applies here. Including program participation with two years time lag, the significant

[39]The findings concerning education and life expectancy are in line with Easterly & Fischer (2001), Fanta & Upadhyay (2008), Ghura *et al.* (2002), and Nissanke & Thorbecke (2006). Theoretically however, higher urbanization is suggested to lead to an increase in inequality, and therefore also results in higher poverty (see Kuznets 1955, and Nissanke & Thorbecke 2006), what cannot be confirmed by this study.

[40]This finding is in line with Mosley *et al.* (2004) and Ravallion & Chen (1997).

[41]Ghura *et al.* (2002) identify GDP *per capita* growth as a robust determinant of poverty, what is opposed to our result.

[42]The results for the inclusion of program participation with one or two years time lag can be obtained from the author upon request.

[43]The results here rely on a smaller number of model specifications because for many specifications none of the three exclusion restrictions is fulfilled. Especially, when the time lag with which program participation is included in the regressions is increased, less exclusion restrictions satisfy the requirement of being significant in the selection equation but insignificant in the outcome equation. Estimating the effect of two years lagged program participation on the income distribution measured before redistribution, none of the exclusion restriction is valid for any of the model specifications.

effect of IMF programs disappears. Averaging over OLS fixed effects estimations reveals a statistically insignificant effect of IMF programs on income inequality. Our results support the findings of Vreeland (2002) who finds a deterioration of income equality due to a decline in the labor share of income resulting from the adoption of IMF programs.[44]

Concerning the effect of other variables we find evidence for an equalizing effect of higher levels of democracy and a bigger amount of years a country has spent under IMF program, while countries with higher *per capita* GDP and countries that vote in line with the G7 are connected to a higher degree of inequality. According to these results a higher average income leads to both, a reduction in poverty, and a deterioration in income inequality. Hence, an increase in GDP *per capita* does not translate into a proportional rise in the income of the poor, as opposed to what is sometimes assumed in the literature (Collier & Dollar 2002). We find that inequality before taxes and redistribution is rising in program years, while both indicators are worsening after program participation. There is some limited evidence that before program participation inequality has been decreasing. For our sample we can confirm Kuznets' (1955) hypothesis that inequality is increasing with income, but as a certain income *per capita* is attained the income distribution becomes more egalitarian. Furthermore, the data reveal strong evidence that higher levels of investment and domestic credit to the private sector as well as higher life expectancy are correlated with higher inequality. As those indicators, among others, can be seen as reflecting the development status of a country, the income gap is found to widen as countries become more developed. Thus, in the context of Kuznets's (1955) hypothesis, the countries in our sample did not yet reach the state of development beyond which the income distribution becomes more equal. Notwithstanding, *ceteris paribus*, the general development in our sample is a decrease in inequality over time. Apart from that, we find that higher openness to trade is associated with a greater degree of inequality,[45] in contrast to currency depreciation and deflation, which are connected to a more equal income distribution.[46] Finally, there is some limited evidence that higher rates of population growth and government consumption are connected to higher inequality (Ghura *et al.* 2002, Kuznets 1955), while a bigger value added in the agricultural sector, higher growth of GDP *per capita*, and a higher average level of education lead to a decline in inequality.[47]

(d) Have things changed after 2000?

One can argue that with the introduction of the PRGF in 1999 and the adoption of poverty alleviation in the IMF's agenda bigger focus has been paid to the reduction of poverty and inequality. Therefore, we estimate the same equations for the 2000-2009 period. Table 8 summarizes the results for this subsample.[48]

Insert Table 8 here.

[44] Running separate regressions for three income-group subsamples we fail to detect significant results in most cases. A surprising finding is the statistically significant gross inequality decreasing effect of IMF programs in lower-middle income countries. The result is, however, based on one single model specification only.

[45] In comparison to Meschi & Vivarelli (2009) we lack data to control for the origin of imports and the destination of exports to take into account the development status of the trading partner. Meschi & Vivarelli (2009) find that trade with industrialized countries worsens the income distribution of middle income countries, while trade with other developing countries leads to an improvement.

[46] Meschi & Vivarelli (2009) find a deterioration in income equality due to high levels of inflation.

[47] These results are in line with Kuznets (1955), Nissanke & Thorbecke (2006), and Ravallion & Chen (1997).

[48] For space reasons Table 8 only reports the results of treatment effect regressions relying on at least one fulfilled exclusion restriction and OLS regressions.

The effects of IMF programs from year 2000 onwards are found to be different from the results of the unrestricted sample, providing evidence for the IMF's success in taking into account poverty issues. The contemporaneous effect of program participation is now a decrease in poverty rates. However, this effect seems to disappear as the time lag with which program participation enters the estimation increases. For some poverty indicators program participation even leads to higher poverty rates when the program dummy is entered with one or two years time lag. Fixed effects regressions result in statistically insignificant impacts of IMF programs on poverty. Concerning inequality, the results indicate that in the 2000-2009 period program participation leads to a decrease in (gross and net) income inequality, independent of the time lag with which program participation enters the estimations.[49]

But is it really the introduction of the PRGF that drives the results? Figure 1 shows the frequency of participation in different IMF programs for different time periods. It can be seen that after the beginning of the year 2000 the importance of SBA, and programs under the EFF and SAF decreased, while the amount of programs under the ESAF and the PRGF increased after 2000. Although it is possible that the results for the post-2000 period are driven by the increased amount of ESAF/PRGF programs, a clear confirmation therefore is not provided by this analysis.

Insert Figure 1 here.

In order to shed light on the question if the poverty decreasing effect is due to the higher frequency of lending programs under the ESAF/PRGF, we disaggregate the program dummy to concessional and non-concessional lending agreements.[50] The results can be found in Table 9.

Insert Table 9 here.

As Table 9 shows, the poverty decreasing effect of IMF programs after the year 2000 does not seem to be due to the higher number of ESAF/PRGF participations. Concessional lending agreements turn out to be generally connected to rising poverty rates.[51] In contrast, the same programs are found to lead to an improvement in the income distribution, both before and after taxes and transfers, although the effect turns insignificant

[49] The results of the averaging over OLS fixed effects regressions for 2 year lagged program participation contradict the results of the treatment effect regressions when looking at the net income inequality indicator. Controlling for selection bias can lead to different results than not taking this source of bias into account, even if selection bias is not detected statistically. I thank two anonymous referees for suggesting to include the analysis of the post-2000 sub period in the paper.

[50] According to the cluster analysis results we cannot detect different clusters based on SAF and ESAF/PRGF participation but find that those programs are similarly distributed across clusters. The same applies to SBAs and EFF programs. Therefore, program participation is not disaggregated even further to the individual program level. When estimating the effects of each individual program type separately—in a two-stage treatment effects framework due to the lower variability in the program dummies—all program types are found to be connected to a rise in poverty rates. SBAs and SAF programs are found to lead to rising income inequality, while ESAF/PRGF and EFF programs seem to be connected to lower inequality. The findings concerning EFF and SAF programs rely on a relatively small number of program observations and a relatively small number of models that enter in the model averaging. I thank one anonymous referee for suggesting to include this explorative analysis in the paper.

[51] The only exception is the fall in headcount ratios at the 2$ line when the concessional program dummy is included with one year time lag. This outcome relies, however, on only two model specifications that enter in the averaging.

when program participation is included with two years time lag.[52]

Although confirmed for a large group of developing countries in our sample, we would like to remind the reader that our results should not be interpreted as being universally applicable. A more detailed causal analysis that does not merely rely on cross-country comparisons would be needed, especially if predictions are the sphere of interest. This kind of analysis has, however, been impeded so far due to data limitations and it remains to hope it will be made possible in the future.

5 CONCLUSION

We investigated how IMF lending programs affect six indicators measuring three dimensions of poverty—the number of people living in poverty (measured at poverty lines of 1.25$ and 2$ per day), the shortfall of poor people from these poverty lines, and income inequality before and after redistribution. With an (unbalanced) panel dataset covering 86 low- and middle income countries during the time period 1982-2009, we confront the issue of sample selection and explicitly control for model uncertainty. Our findings are based on treatment effect regressions, which account for endogenous selection of countries into IMF programs. As this modeling approach allows to test for the existence of selection bias, we compare the results to the outcome of OLS regressions with country fixed effects for model specifications in which selection bias is not detected. In total, we estimate 90 different treatment effect models for each poverty indicator and, in order to make use of all the information obtained, average over the resulting parameters with model weights that are proportional to the BIC. This allows to obtain results—concerning the consequences of program participation on poverty and inequality that are common to a large group of countries—that are not conditional on a single selected model but are robust to different model specifications.

Although the findings of this study should be interpreted with the appropriate caution we can be confident in stating that in our 1982-2009 sample the relatively bigger part of the costs connected to the adjustment process inherent to IMF agreements is borne out by lower income classes, leading to a worsening of income equality and a rise in poverty. Participation in IMF programs is found to go hand in hand with an increase in poverty, measured by the number of people living below poverty income, as well as by the income shortfall of those people from the poverty line. The effect on poverty is strongest in the year the program is implemented and declines as program participation is included in the estimations with a one year time lag. The significant influence of an IMF agreement on poverty vanishes when it enters the equations two years lagged.[53] Concerning the distribution of income, inequality, both, measured before and after redistribution rises due to the implementation of IMF programs.[54] Two years lagged program participation

[52] Performing the same estimations for income-group subsamples in a two-stage treatment effects framework with equal model weights confirms the poverty increasing effect of concessional programs for low-income countries, while we fail to detect significant results for lower-middle income countries. While we find a statistically significant decrease in net inequality in lower-middle income countries, the results for low-income countries are insignificant. Upper-middle income countries are not eligible for concessional lending programs. The insignificance of the program effects might stem from the inefficiency of the two-stage approach as compared to maximum likelihood estimates and a smaller sample size.

[53] The only exception to this is the program effect on the development of the income shortfall from the poverty line of 2$ per day, which increases with the time lag with which program participation is included.

[54] Martin & Segura-Ubiergo (2004) find that social expenditure on public health and education does

ceases to significantly affect the income distribution.

Conducting the same analysis for the 2000-2009 sub period in order to see if the Fund's adoption of poverty alleviation in its agenda has been successful a different pattern is observed. Program participation contemporaneously leads to a decrease in most poverty indicators. The significant effect disappears as the program dummy is included with one or two years time lag or even changes direction, leading to a increase in some of the 2$ line poverty indicators. Post-2000 IMF programs are found to have a (gross and net) income inequality decreasing effect. This result is stable to the time lag with which program participation enters the estimation. Although the introduction of the PRGF might be a cause of this change in program effects, the analysis presented in this paper does not provide a clear confirmation. Estimations of the effects of concessional programs only reveal poverty increasing but inequality lowering impacts of this program type.

The IMF alludes that although there might exist negative impacts of adjustment policies on poverty due to a temporary contraction of economic activity in the short-run, greater benefits to the poor are expected as a result of the restoration of macroeconomic stability in the long-run (Ames *et al.* 2001). Our results provide a first indication that detrimental consequences of IMF programs for poverty might die out moving away from the short-run. The insight that income is distributed more equally in countries that spent more years under IMF agreements in their past also points in that direction. On the other hand, though, also beneficial implications of IMF programs for poverty seem to disappear when the time horizon under consideration increases. The suggestion of vanishing effects of IMF programs on poverty and inequality should, however, not be taken as a definite declaration as, due to data constraints, we do not tackle longer-run effects of IMF programs explicitly in this article. This study provides evidence that the inclusion of poverty alleviation in the IMF's agenda has led to the desired effects. What is left to be answered in future investigation is the role that each of the economic reforms that are connected to IMF agreements plays in driving the effect on poverty and inequality, what would certainly further enrich this field of research. While in this study we could shed some light on the short-run effects of IMF programs on poverty and income equality, many questions remain to be answered in the future.

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not decrease due to IMF programs.

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TABLES AND FIGURES

Table 1: Selection equations

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Reserves_{t-1}	+	+	+	+	+
Ln(GDP pc)_{t-1}	+	+	+	+	+
Ln(GDP pc)_{t-1}, squared	+	+	+	+	+
Trade_{t-1}	+	+	+	+	+
$\text{Debt Service}_{t-1}$	+	+	+	+	+
$\text{Vote in line with G7}_{t-1}$	+	+	+	+	+
$\text{Countries under program}_{t}$	+	+	+	+	+
$\text{Past program years}_{t}$	+	+	+	+	+
Ln(GDP)_{t-1}		+			+
Ln(GDP)_{t-1}, squared		+			+
$\text{Change in GDP growth}_{t-1}$			+		+
GDP growth_{t-1}			+		+
$\text{Current account balance}_{t-1}$				+	+

NOTE: + indicates that the variable is included in the specification.

Table 2: Outcome equations

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**	**(17)**	**(18)**
Ln(GDP pc)$_{t-1}$	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
Democracy index$_{t-1}$	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
Gini net$_{t-1}$ $^{(a)}$	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
Country dummies	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
Years before program$_t$, trend	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
Program years$_t$, trend	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
Years after program$_t$, trend	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
Countries under program$_t$	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
Past program years$_t$	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
Vote in line with G7$_{t-1}$	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
Ln(GDP pc)$_{t-1}$, squared		+																+
GDP pc growth$_{t-1}$			+														+	+
Population growth$_{t-1}$				+														+
Ln(Investment)$_{t-1}$					+												+	+
Ln(Trade)$_{t-1}$						+											+	+
Ln(Trade)$_{t-1}$, LIC						+											+	+
Ln(Trade)$_{t-1}$, MIC						+											+	+
Exchange rate growth$_{t-1}$							+										+	+
$>$ 200% depreciation dummy$_{t-1}$ $^{(b)}$							+										+	+
Ln(Credit)$_{t-1}$								+									+	+
Government consumption$_{t-1}$									+								+	+
Ln(Inflation)$_{t-1}$										+								+
Deflation dummy$_{t-1}$ $^{(c)}$										+							+	+
Hyperinflation dummy$_{t-1}$ $^{(c)}$										+							+	+
Natural resource rents$_{t-1}$											+						+	+
Value added of agriculture$_{t-1}$												+						+
Urban population$_{t-1}$													+					+
Years of schooling$_{t-1}$														+				+
Life expectancy$_{t-1}$															+			+
Time trend$_t$																+		+

NOTE: + indicates that the variable is included in the specification.

$^{(a)}$ The variable is only included in models with poverty gaps or headcount ratios as dependent variable.

$^{(b)}$ We add a dummy for countries with devaluations of more than 200% to control for outliers.

$^{(c)}$ We add dummies for deflation and hyperinflation.

Table 3: Poverty gaps and headcount ratios by program participation status

Poverty gap 1.25$	Obs.	Mean	Median	Std. Dev.	Min.	Max.
never	13	9.16	0.66	14.32	0.50	47.74
before	18	9.96	6.61	9.13	0.50	31.27
program	198	7.12	3.66	9.29	0.50	53.09
between	64	7.03	2.94	10.77	0.50	47.28
after	63	3.12	0.94	4.40	0.50	20.72
Total	356	6.62	3.00	9.27	0.50	53.09

Poverty gap 2$	Obs.	Mean	Median	Std. Dev.	Min.	Max.
never	13	15.78	3.23	19.22	1.29	61.65
before	18	18.83	11.87	15.97	0.50	52.42
program	198	14.68	9.74	14.50	0.50	67.22
between	64	13.87	8.53	15.73	0.08	64.07
after	63	7.98	3.50	9.87	0.50	40.84
Total	356	13.60	8.28	14.50	0.08	67.22

Headcount ratio 1.25$	Obs.	Mean	Median	Std. Dev.	Min.	Max.
never	13	20.89	3.22	25.62	2.00	78.59
before	18	26.09	15.22	23.79	2.00	78.10
program	196	19.67	12.62	20.49	2.00	88.52
between	63	18.41	11.03	21.71	2.00	86.43
after	63	10.72	3.53	13.94	2.00	60.18
Total	353	18.22	10.79	20.35	2.00	88.52

Headcount ratio 2$	Obs.	Mean	Median	Std. Dev.	Min.	Max.
never	13	33.03	12.31	28.86	6.84	89.31
before	18	39.92	27.04	29.84	2.00	93.37
program	198	34.82	26.80	26.47	2.00	96.57
between	64	31.77	22.59	27.70	2.00	95.41
after	63	22.23	15.13	22.62	2.00	84.62
Total	356	32.24	23.29	26.64	2.00	96.57

Table 4: Gini indexes by program participation status

Gini gross	Obs.	Mean	Median	Std. Dev.	Min.	Max.
never	76	53.72	54.23	6.78	40.32	68.51
before	102	44.95	44.14	9.48	29.10	70.10
program	658	45.68	45.56	8.20	27.52	72.33
between	237	47.25	47.50	8.09	30.62	70.19
after	200	43.99	43.75	6.03	33.13	57.14
Total	1273	46.13	46.08	8.19	27.52	72.33

Gini net	Obs.	Mean	Median	Std. Dev.	Min.	Max.
never	76	49.23	49.68	8.09	35.55	68.27
before	102	41.83	41.16	8.53	26.57	58.94
program	658	42.66	42.34	8.42	24.53	67.62
between	237	44.63	45.08	7.85	27.00	62.69
after	200	40.64	40.79	6.22	28.56	53.31
Total	1273	43.03	42.74	8.22	24.53	68.27

Table 5: Selection equations - Estimation

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Reserves_{t-1}	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ln(GDP pc)_{t-1}	1.709***	1.699***	1.690***	1.716***	1.654***
	(0.329)	(0.347)	(0.337)	(0.329)	(0.350)
Ln(GDP pc)_{t-1}, squared	-0.124***	-0.120***	-0.122***	-0.124***	-0.117***
	(0.021)	(0.022)	(0.022)	(0.021)	(0.022)
Trade_{t-1}	-0.000	-0.001*	-0.000	-0.000	-0.001
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
$\text{Debt Service}_{t-1}$	0.008*	0.009**	0.007	0.008*	0.008*
	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)
$\text{Vote in line with G7}_{t-1}$	0.270*	0.255	0.257	0.277*	0.245
	(0.159)	(0.163)	(0.160)	(0.160)	(0.163)
$\text{Countries under program}_{t}$	0.004**	0.004***	0.003*	0.004**	0.003**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\text{Past program years}_{t}$	0.017***	0.017***	0.020***	0.017***	0.020***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Ln(GDP)_{t-1}		0.159			0.208
		(0.260)			(0.258)
Ln(GDP)_{t-1}, squared		-0.004			-0.005
		(0.005)			(0.005)
GDP growth_{t-1}			-0.015***		-0.014***
			(0.004)		(0.005)
$\text{Change in GDP growth}_{t-1}$			0.009**		0.009**
			(0.004)		(0.004)
$\text{Current account balance}_{t-1}$				0.002	0.001
				(0.003)	(0.003)
Europe & Central Asia [(a)]	0.494***	0.461***	0.479***	0.497***	0.451***
	(0.051)	(0.058)	(0.054)	(0.051)	(0.061)
Latin America & Carribean [(a)]	0.380***	0.313***	0.350***	0.384***	0.292***
	(0.064)	(0.074)	(0.067)	(0.064)	(0.077)
Middle East & North Africa [(a)]	0.139*	0.093	0.127	0.139*	0.084
	(0.076)	(0.080)	(0.077)	(0.076)	(0.081)
Sub Saharan Africa [(a)]	0.228***	0.168**	0.194***	0.232***	0.145**
	(0.059)	(0.066)	(0.060)	(0.059)	(0.067)
Asia Pacific [(a)]	0.014	0.030	0.014	0.012	0.026
	(0.070)	(0.070)	(0.070)	(0.070)	(0.071)
N	1273	1273	1273	1273	1273
BIC	1519.941	1526.237	1520.731	1526.694	1535.132

NOTE: Probit estimations. Dependent variable: Program participation dummy.
Marginal effects; Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
[(a)] for discrete change of dummy variable from 0 to 1.

Table 6: Model averaging results - poverty indicators

	Valid exculsion restrictions	Poverty Gap 1.25$	Poverty Gap 2$	Headcount Ratio 1.25$	Headcount Ratio 2$
$\tau = 0$	Min one	0.7015 ***	0.3343 ***	0.5208 ***	0.3099 ***
		(0.1940)	(0.1248)	(0.1373)	(0.1065)
		86 (96%)	90 (100%)	88 (98%)	87 (97%)
	Min two	0.7419 ***	0.3643 ***	0.5225 ***	0.3276 ***
		(0.1932)	(0.1114)	(0.1335)	(0.0964)
		10 (11%)	21 (23%)	32 (36%)	13 (14%)
	Vote in line with G7	0.7419 ***	0.3643 ***	0.5225 ***	0.3276 ***
		(0.1932)	(0.1114)	(0.1335)	(0.0964)
		12 (13%)	21 (23%)	34 (38%)	22 (24%)
	Past program years	0.7015 ***	0.3343 ***	0.5208 ***	0.3099 ***
		(0.194)	(0.1248)	(0.1373)	(0.1065)
		84 (93%)	90 (100%)	86 (96%)	78 (87%)
$\tau = 1$	Min one	0.6190 ***	0.4875 ***	0.4309 ***	0.2571 ***
		(0.2262)	(0.1369)	(0.1133)	(0.094)
		85 (94%)	90 (100%)	81 (90%)	85 (94%)
	Past program years	0.6190 ***	0.4875 ***	0.4309 ***	0.2571 ***
		(0.2262)	(0.1369)	(0.1133)	(0.094)
		85 (94%)	90 (100%)	81 (90%)	85 (94%)
	OLS fixed effects	-0.1256		-0.1313 *	
		(0.0844)		(0.0705)	
		3 (3%)		3 (3%)	
$\tau = 2$	Min one	-0.1872	0.5051 ***	0.2116	0.1883
		(0.3372)	(0.1792)	(0.4205)	(0.1319)
		83 (92%)	88 (98%)	85 (94%)	87 (97%)
	Min two	-0.3270		-0.5026	
		(0.3474)		(0.5609)	
		42 (47%)		4 (4%)	
	Past program years	-0.1861	0.5051 ***	0.2116	0.1883
		(0.3372)	(0.1792)	(0.4205)	(0.1319)
		79 (88%)	88 (98%)	85 (94%)	85 (94%)
	Countries under program	-0.3266		-0.5026	0.1964 **
		(0.3432)		(0.5609)	(0.0848)
		46 (51%)		4 (4%)	2 (2%)
	OLS fixed effects	-0.0201		0.0050	0.0787
		(0.0793)		(0.0614)	(0.0497)
		74 (82%)		51 (57%)	38 (42%)

NOTE: Averaged coefficient estimates of program participation, based on BIC.
*** p<0.01, ** p<0.05, * p<0.1. Averaged standard errors in parentheses.
Number of averaged model specifications below, percentage of total in parentheses.

Table 7: Model averaging results - income inequality indicators

	Valid exculsion restriction	**Gini gross**	**Gini net**
$\tau = 0$	Min one	2.5150 ***	3.0500 ***
		(0.8124)	(0.9058)
		39 (43%)	69 (77%)
	Min two		2.9835 **
			(1.3104)
			5 (6%)
	Vote in line with G7	2.5150 ***	
		(0.8124)	
		34 (38%)	
	Past program years		2.9834 **
			(1.310247)
			15 (17%)
	Countries under program	2.4599 ***	3.0500 ***
		(0.9024)	(0.9058)
		5 (6%)	59 (66%)
	OLS fixed effects	-0.7919	-0.1728
		(0.6351)	(0.6553)
		3 (3%)	7 (8%)
$\tau = 1$	Min one	3.4348 ***	2.8888 ***
		(0.8027)	(0.9880)
		5 (6%)	55 (61%)
	Min two		2.7580 **
			(1.2503)
			3 (3%)
	Past program years		2.8618 ***
			(1.098)
			10 (11%)
	Countries under program	3.4348 ***	2.8888 ***
		(0.8027)	(0.9880)
		5 (6%)	48 (53%)
$\tau = 2$	Min one		2.2063
			(1.6704)
			8 (9%)
	Past program years		2.2063
			(1.6704)
			8 (9%)
	OLS fixed effects		0.2092
			(0.2499)
			7 (8%)

NOTE: Averaged coefficient estimates of program participation, based on BIC.
*** p<0.01, ** p<0.05, * p<0.1. Averaged standard errors in parentheses.
Number of averaged model specifications below, percentage of total in parentheses.

Table 8: Model averaging results - programs after 2000

		Poverty Gap 1.25$	**Poverty Gap 2$**	**Headcount Ratio 1.25$**	**Headcount Ratio 2$**	**Gini gross**	**Gini net**
$\tau = 0$	*Treatment effects*	-0.0912	-0.7869 ***	-0.4480 **	-0.6128 ***	-3.4115 ***	-2.7923 ***
		(0.4192)	(0.2109)	(0.1984)	(0.1492)	(0.5992)	(0.5022)
		1 (1%)	66 (73%)	63 (70%)	24 (27%)	90 (100%)	90 (100%)
	OLS fixed effects	0.2575	-0.2894	0.0765	-0.2081		
		(0.1939)	(0.2554)	(0.1368)	(0.1293)		
		52 (58%)	19 (21%)	16 (18%)	14 (16%)		
$\tau = 1$	*Treatment effects*		0.3968 *		0.3872	-3.1039 ***	-1.8541 ***
			(0.2376)		(0.3609)	(0.5411)	(0.4474)
			7 (8%)		54 (60%)	90 (100%)	90 (100%)
	OLS fixed effects	-0.0827	-0.1794	-0.0164	-0.0340		
		(0.1078)	(0.1690)	(0.0870)	(0.0933)		
		59 (66%)	38 (42%)	8 (9%)	62 (69%)		
$\tau = 2$	*Treatment effects*	-0.2739	0.3444	0.0751	0.2964 *	-3.0066 ***	-2.1680 ***
		(0.4071)	(0.2599)	(0.3231)	(0.1735)	(0.6216)	(0.3355)
		15 (17%)	70 (78%)	16 (18%)	85 (94%)	52 (58%)	55 (61%)
	OLS fixed effects	-0.1351	-0.0523	-0.0490	0.0474	0.5131	0.6797 ***
		(0.1151)	(0.1204)	(0.0871)	(0.0988)	(0.3302)	(0.2384)
		72 (80%)	64 (71%)	34 (38%)	50 (56%)	36 (40%)	20 (22%)

Note: Averaged coefficient estimates of program participation, based on BIC. *** p<0.01, ** p<0.05, * p<0.1. Averaged standard errors in parentheses. Number of averaged model specifications below, percentage of total in parentheses. Averaged effect of programs since 2000 if entered with τ=0,1,2 years time lag. *Treatment effects* report the results of the averaging over treatment effects model specifications in which at least one exclusion restriction is fulfilled.

Table 9: Model averaging results - concessional programs

		Poverty Gap 1.25$	Poverty Gap 2$	Headcount Ratio 1.25$	Headcount Ratio 2$	Gini gross	Gini net
$\tau = 0$	*Treatment effects*	0.4602 *	0.5356 ***	0.4578 ***	0.3864 ***	-3.3896 ***	-1.7922 ***
		(0.2524)	(0.1367)	(0.1475)	(0.11)	(0.6295)	(0.5672)
		90 (100%)	88 (98%)	89 (99%)	1 (1%)	57 (63%)	71 (79%)
	OLS fixed effects	0.0626	-0.0226	0.0359	-0.0797		-1.0176 *
		(0.1693)	(0.1096)	(0.1331)	(0.0867)		(0.5855)
		63 (70%)	60 (67%)	34 (38%)	14 (16%)		29 (32%)
$\tau = 1$	*Treatment effects*	0.4194	0.4848	0.4961 *	-0.3219 ***	-2.5637 ***	-0.9234 *
		(0.4516)	(0.6121)	(0.2761)	(0.1068)	(0.5717)	(0.4758)
		90 (100%)	17 (19%)	44 (49%)	2 (2%)	63 (70%)	16 (18%)
	OLS fixed effects	-0.0044	0.0001	-0.0428	0.0116	-0.8591 *	-0.7167 *
		(0.1415)	(0.0854)	(0.1147)	(0.0572)	(0.5029)	(0.4308)
		81 (90%)	48 (53%)	59 (66%)	24 (27%)	1 (1%)	30 (33%)
$\tau = 2$	*Treatment effects*	-0.1979	0.4919 ***	0.2343	0.1192		1.2600
		(0.4479)	(0.1691)	(0.4038)	(0.1573)		(1.634)
		83 (92%)	88 (98%)	85 (94%)	85 (94%)		10 (11%)
	OLS fixed effects	-0.0266		0.0162	0.0042	-0.7037	-0.7199
		(0.1356)		(0.0904)	(0.0575)	(0.614)	(0.518)
		75 (83%)		48 (53%)	38 (42%)	3 (3%)	16 (18%)

Note: Averaged coefficient estimates of concessional program participation, based on BIC. *** p<0.01, ** p<0.05, * p<0.1. Averaged standard errors in parentheses. Number of averaged model specifications below, percentage of total in parentheses. Averaged effect of concessional programs (SAF, ESAF, PRGF) if entered with τ=0,1,2 years time lag, controlling for non-concessional programs.

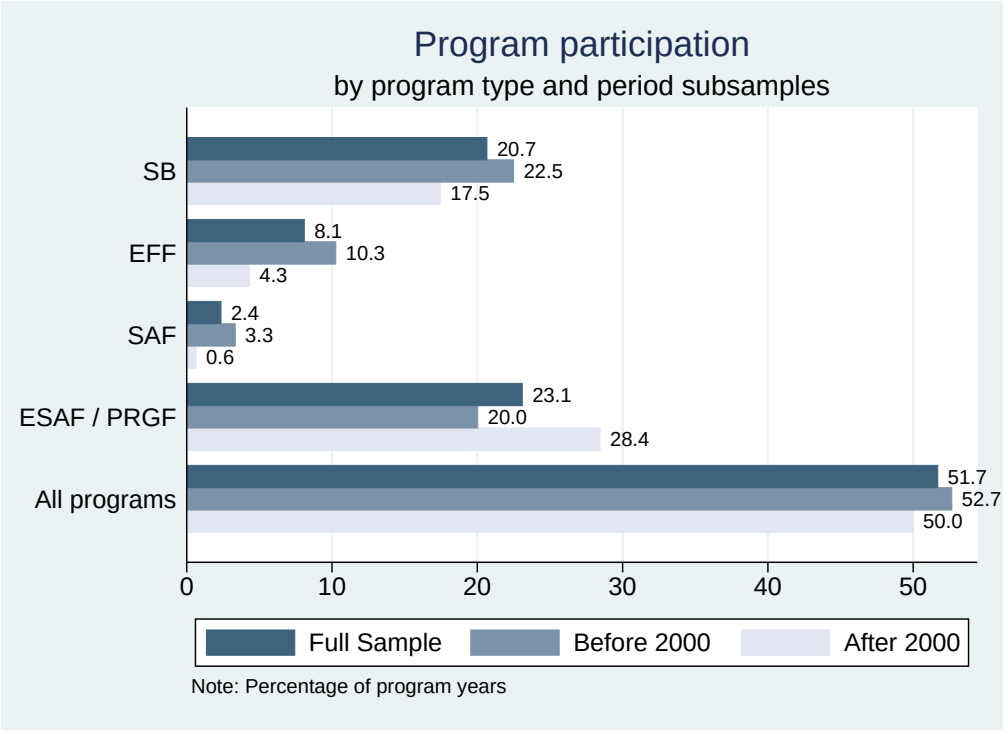

Figure 1: IMF program participation

A DATA

Information on participation in IMF programs was obtained from the IMF Member's Financial Data (IMF 2011j), which reports the participation in adjustment programs beginning in 1982, thus limiting the scope of this analysis to start in that year. Data on poverty as well as on economic variables were taken from the World Development Indicators (WDI) of the World Bank (2010). The poverty indicators used in this study are poverty gaps and headcount ratios (both at poverty lines of $1.25 per day and $2 per day). All financial and economic variables are reported in constant purchasing power parity adjusted international dollars, or shares of GDP. The Standardized World Income Inequality Database (SWIID) provides comparable Gini indexes of gross and net (of redistribution) income inequality (Solt 2009). It overcomes the problem of comparability that arise because of different definitions of income, recipient units, and population coverage of the United Nations University's World Income Inequality Database (WIID, UNU-WIDER 2008). The SWIID incorporates data from different sources and uses a missing-data algorithm to standardize the WIID. Dreher & Sturm (2012) and Dreher & Walter (2010) provide data on UN General Assembly Voting and data on non-compliance with IMF conditionality, while other political indicators are obtained from the Polity IV dataset (Marshall *et al.* 2010). Education data are obtained from Barro & Lee (2010). A detailed explanation of the variables can be found below.

A.1 List of variables

Variable	Explanation	Source
Poverty indicators:		
Poverty gap $1.25:	Poverty gap at $1.25 a day, purchasing power parity (PPP) (%).	World Bank (2010).
Poverty gap $2:	Poverty gap at $2 a day (PPP) (%).	World Bank (2010).
Headcount ratio $1.25:	Poverty headcount ratio at $1.25 a day (PPP) (% of population).	World Bank (2010).
Headcount ratio$ 2:	Poverty headcount ratio at $2 a day (PPP) (% of population).	World Bank (2010).
Gini gross:	Estimate of Gini index of inequality in equivalized (square root scale) household gross (pre-tax, pre-transfer) income, using Luxembourg Income Study data as the standard.	Solt (2009).
Gini net:	Estimate of Gini index of inequality in equivalized (square root scale) household disposable income, using Luxembourg Income Study data as the standard.	Solt (2009).
Explanatory variables:		
$>$ 200% depreciation dummy:	Dummy variable equal to one if the annual depreciation exceeds 200%, one year lagged.	World Bank (2010), own calculations.
Change in GDP growth:	Annual change in GDP growth.	World Bank (2010), own calculations.
Countries under program:	Number of other countries participating in an IMF program.	IMF (2011j), own calculations.
Credit, in logarithm:	Domestic credit to private sector (% of GDP), natural logarithm, one year lagged.	World Bank (2010).
Current account balance:	Current account balance (% of GDP), one year lagged.	World Bank (2010).
Debt service:	Total debt service (% of GNI).	World Bank (2010).
Deflation dummy:	Dummy variable equal to one for deflation in country i in year t, one year lagged.	World Bank (2010), own calculations.

Democracy index:	Polity2 index, ranging from -10 (strongly autocratic) to +10 (strongly democratic)	Marshall *et al.* (2010).
Exchange rate growth:	Annual growth rate in the official exchange rate (local currency unit (LCU) per US$, period average), one year lagged.	World Bank (2010), own calculations.
GDP, in logarithm:	GDP, PPP (constant 2005 international $), one year lagged.	World Bank (2010).
GDP growth:	GDP growth (annual %), one year lagged.	World Bank (2010).
GDP *per capita*, in logarithm:	GDP *per capita*, PPP (constant 2005 international $), natural logarithm, one year lagged.	World Bank (2010).
GDP *per capita* growth:	GDP *per capita* growth (annual %), one year lagged.	World Bank (2010).
Government consumption:	General government final consumption expenditure (% of GDP), one year lagged.	World Bank (2010).
Hyperinflation dummy:	Dummy equal to one for hyperinflation in country i in year t, one year lagged. Hyperinflation is defined as inflation exceeding 50% in one year.	World Bank (2010), own calculations.
Inflation, in logarithm:	Inflation, GDP deflator (annual %), natural logarithm, one year lagged.	World Bank (2010).
Investment, in logarithm:	Gross fixed capital formation (% of GDP), one year lagged.	World Bank (2010).
Life expectancy:	Life expectancy at birth, total (years), one year lagged.	World Bank (2010).
Natural resource rents:	Total natural resources rents (% of GDP), one year lagged.	World Bank (2010).
Past program years:	Cumulative number of years that a country has been under IMF agreement.	IMF (2011j), own calculations.
Population growth:	Population growth (annual %), one year lagged.	World Bank (2010).
Program dummy:	Dummy variable coded 1 for participation in an IMF program (SBA, EFF, SAF, ESAF, PRGF) of at least 4 months of year i and 0 otherwise.	IMF (2011j).
Program years, trend:	Time trend counting consecutive program years of a country.	IMF (2011j), own calculations.
Reserves:	Total reserves (% of total external debt), one year lagged.	World Bank (2010).
Trade:	Trade (% of GDP), one year lagged.	World Bank (2010).
Trade LIC, natural logarithm:	Interaction of Trade (% of GDP) in natural logarithm and a dummy variable equal to one for low income countries (LIC), one year lagged.	World Bank (2010).
Trade LMIC, natural logarithm:	Interaction of Trade (% of GDP) in natural logarithm and a dummy variable equal to one for lower middle income countries (LMIC), one year lagged.	World Bank (2010).
Trend:	Time trend starting in 1982.	Own calculations.
Urban population:	Urban population (% of total), one year lagged.	World Bank (2010).
Value added of agriculture:	Agriculture, value added (% of GDP), one year lagged.	World Bank (2010).
Vote in line with G7:	Voting in line with G7, definition according to Barro & Lee (2005), one year lagged.	Dreher & Sturm (2012).
Years after program, trend:	Time trend counting the years that passed since the completion of the last IMF program until time t.	IMF (2011j), own calculations.
Years before program, trend:	Time trend counting in how many years from time t on a program starts.	IMF (2011j), own calculations.
Years of schooling:	Average years of schooling, whole population, from 15 to 99, one year lagged.	Barro & Lee (2010).

A.2 List of countries

Table A.2: Countries included in the study

1	Albania (g,p)	29	Guatemala (g,p)	58	Pakistan (g,p)
2	Algeria (g,p)	30	Guyana (g,p)	59	Panama (g,p)
3	Argentina (g,p)	31	Honduras (g,p)	60	Papua New Guinea (g,p)
4	Armenia (g,p)	32	India (g,p)	61	Paraguay (g,p)
5	Bangladesh (g,p)	33	Indonesia (g,p)	62	Peru (g,p)
6	Belize (g,p)	34	**Iran, Islamic Rep.** (g)	63	Philippines (g,p)
7	Benin (g,p)	35	Jamaica (g,p)	64	Poland (g,p)
8	Bolivia (g,p)	36	Jordan (g,p)	65	Romania (g,p)
9	**Botswana** (g,p)	37	Kazakhstan (g,p)	66	Russian Federation (g,p)
10	Brazil (g,p)	38	Kenya (g,p)	67	Rwanda (g,p)
11	Bulgaria (g,p)	39	Kyrgyz Republic (g,p)	68	Senegal (g,p)
12	Burundi (g,p)	40	Lao PDR (g,p)	69	Sierra Leone (g,p)
13	Cambodia (g,p)	41	Latvia (g,p)	70	**South Africa** (g,p)
14	Cameroon (g,p)	42	Lesotho (g,p)	71	Sri Lanka (g,p)
15	Central African	43	**Liberia** (g)	72	**Swaziland** (g,p)
	Republic (g,p)	44	Lithuania (g,p)	73	Tajikistan (g,p)
16	Chile (g,p)	45	Malawi (g,p)	74	Tanzania (g,p)
17	China (g,p)	46	**Malaysia** (g,p)	75	Thailand (g,p)
18	Colombia (g,p)	47	Mali (g,p)	76	Togo (g,p)
19	Congo, Rep. (g,p)	48	Mauritania (g,p)	77	Tunisia (g,p)
20	Costa Rica (g,p)	49	Mauritius (g)	78	Turkey (g,p)
21	Cote d'Ivoire (g,p)	50	Mexico (g,p)	79	Uganda (g,p)
22	Dominican Republic (g,p)	51	Moldova (g,p)	80	Ukraine (g,p)
23	Egypt, Arab Rep. (g,p)	52	Mongolia (g,p)	81	Uruguay (g,p)
24	El Salvador (g,p)	53	Morocco (g,p)	82	Venezuela, RB (g,p)
25	**Fiji** (g)	54	Mozambique (g,p)	83	Vietnam (g,p)
26	Gabon (g,p)	55	Nepal (g,p)	84	Yemen, Rep. (g,p)
27	Gambia, The (g,p)	56	Nicaragua (g,p)	85	Zambia (g,p)
28	Ghana (g,p)	57	Niger (g,p)	86	Zimbabwe (g)

NOTE: Countries without any IMF program in the period 1982 to 2009 in bold.
(g) refers to countries with Gini observations.
(p) refers to countries with poverty observations.

A.3 Descriptive statistics

Table A.3: Descriptive statistics (1982-2009)

	Poverty dataset					Income inequality dataset				
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Obs.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Poverty gap 1.25$	356	6.617	9.269	0.500	53.090					
Poverty gap 2$	356	13.599	14.496	0.080	67.220					
Headcount ratio 1.15$	353	18.221	20.355	2.000	88.520					
Headcount ratio2$	356	32.236	26.642	2.000	96.570					
Gini gross						1273	46.129	8.188	27.518	72.326
Gini net						1273	43.034	8.220	24.526	68.271
> 200% depreciation dummy	356	0.028	0.165	0.000	1.000	1273	0.020	0.139	0.000	1.000
Change in GDP growth	356	0.443	4.387	-12.472	26.042	1273	0.206	4.969	-21.740	27.136
Countries under program	356	53.756	9.839	16.000	66.000	1273	52.840	10.861	16.000	66.000
Credit	356	33.275	29.002	0.000	165.719	1273	29.966	27.021	0.000	165.719
Current account balance	356	-2.889	6.160	-37.620	18.035	1273	-3.355	6.563	-37.620	31.982
Debt service	356	6.393	4.438	0.504	36.171	1273	6.253	4.262	0.098	36.171
Deflation dummy	356	0.045	0.207	0.000	1.000	1273	0.046	0.210	0.000	1.000
Democracy index	356	4.326	5.790	-9.000	10.000	1273	2.582	6.387	-10.000	10.000
Exchange rate growth	356	0.345	1.655	-1.000	19.695	1273	0.333	2.476	-1.000	69.470
GDP	356	2.80E+11	5.31E+11	1.24E+09	4.82E+12	1273	2.01E+11	4.32E+11	1.09E+09	4.38E+12
GDP growth	356	4.287	4.487	-12.200	27.462	1273	2.142	4.601	-22.551	22.618
GDP *per capita*	356	5170.299	3345.010	340.183	14715.700	1273	4251.344	3369.684	238.597	17009.880
GDP *per capita* growth	356	2.770	4.607	-13.566	22.618	1273	3.966	4.511	-22.934	27.462
Government consumption	356	13.416	4.808	3.219	28.671	1273	13.658	5.080	3.219	35.138
Hyperinflation dummy	356	0.096	0.294	0.000	1.000	1273	0.079	0.270	0.000	1.000
Inflation	356	43.992	216.579	-8.638	2927.843	1273	38.039	271.196	-11.366	6836.880
Investment	356	20.628	6.988	5.298	70.815	1273	20.750	7.454	-23.763	70.815
Life expectancy	356	66.871	7.630	40.613	78.667	1273	63.583	8.971	38.172	78.918
Natural resource rents	356	5.298	7.536	0.036	45.302	1273	5.621	7.291	0.005	45.302
Past program years	356	6.961	4.681	0.000	21.000	1273	6.025	4.699	0.000	21.000
Population growth	356	1.478	1.282	-2.069	11.181	1273	1.775	1.210	-2.397	11.181
Program dummy	356	0.556	0.498	0.000	1.000	1273	0.517	0.500	0.000	1.000
Program years, trend	356	2.927	3.972	0.000	20.000	1273	2.565	3.732	0.000	20.000
Reserves	356	31.627	43.311	0.117	617.085	1273	38.615	108.614	0.089	1474.781
Trade	356	71.440	39.200	12.726	280.361	1273	71.399	39.003	11.545	280.361
Trade LIC	356	9.141	25.249	0.000	142.899	1273	14.736	28.864	0.000	142.899
Trade LMIC	356	30.799	46.306	0.000	280.361	1273	29.816	45.107	0.000	280.361
Trend	356	17.110	6.094	2.000	27.000	1273	15.409	6.511	2.000	28.000
Urban population	356	54.010	20.704	7.140	92.300	1273	46.450	21.285	6.620	92.300
Value added of agriculture	356	16.804	11.076	0.931	60.993	1273	20.189	12.727	0.801	61.969
Vote in line with G7	356	0.502	0.165	0.000	0.912	1273	0.457	0.158	0.000	0.912
Years after program, trend	356	1.514	2.957	0.000	18.000	1273	1.496	2.986	0.000	20.000
Years before program, trend	356	0.885	2.146	0.000	12.000	1273	1.004	2.351	0.000	17.000
Years of schooling	356	6.846	2.284	0.950	11.338	1273	6.043	2.465	0.901	11.429

Table A.4: Descriptive statistics (2000-2009)

	Poverty dataset					Income inequality dataset				
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Poverty gap 1.25$	164	5.129	7.705	0.500	46.840					
Poverty gap 2$	164	11.075	12.827	0.080	64.380					
Headcount ratio 1.25$	163	14.837	18.006	2.000	88.520					
Headcount ratio 2$	164	27.599	24.962	2.000	96.570					
Gini gross						464	44.748	7.000	27.518	68.507
Gini net						464	42.050	7.538	24.526	68.271
> 200% depreciation dummy	164	0.000	0.000	0.000	0.000	464	0.002	0.046	0.000	1.000
Change in GDP growth	164	0.627	4.450	-12.472	26.042	464	0.391	4.136	-18.174	26.042
Countries under program	164	52.134	8.654	35.000	64.000	464	53.856	8.124	34.000	64.000
Credit	164	32.537	27.330	2.888	134.442	464	31.471	28.058	2.072	149.153
Current account balance	164	-2.337	6.470	-22.682	18.035	464	-2.532	6.832	-28.918	18.035
Debt service	164	6.662	4.277	0.875	29.229	464	6.164	4.240	0.522	29.229
Deflation dummy	164	0.061	0.240	0.000	1.000	464	0.063	0.242	0.000	1.000
Democracy index	164	5.537	5.098	-9.000	10.000	464	4.705	5.283	-9.000	10.000
Exchange rate growth	164	0.050	0.145	-0.278	0.960	464	0.065	0.194	-0.282	2.065
GDP	164	3.13E+11	6.29E+11	2.29E+09	4.82E+12	464	2.54E+11	5.49E+11	1.69E+09	4.38E+12
GDP growth	164	5.187	4.367	-11.032	27.462	464	4.721	3.826	-11.032	27.462
GDP *per capita*	164	5861.306	3608.153	340.183	14715.700	464	5128.514	3941.984	340.183	17009.880
GDP *per capita* growth	164	4.041	4.518	-11.036	22.618	464	3.324	4.087	-11.742	22.618
Government consumption	164	13.365	4.453	4.589	28.671	464	13.764	4.699	4.506	35.138
Hyperinflation dummy	164	0.006	0.078	0.000	1.000	464	0.006	0.080	0.000	1.000
Inflation	164	9.013	9.742	-4.084	52.851	464	8.952	9.942	-5.101	72.387
Investment	164	20.268	5.388	6.296	40.730	464	20.471	5.515	3.480	43.423
Life expectancy	164	68.474	7.798	41.625	78.667	464	65.324	9.689	40.811	78.918
Natural resource rents	164	5.851	9.266	0.052	45.302	464	6.001	8.889	0.005	45.302
Past program years	164	9.890	4.313	0.000	21.000	464	9.323	4.645	0.000	21.000
Population growth	164	1.108	1.064	-1.820	4.579	464	1.358	1.162	-1.879	6.577
Program dummy	164	0.543	0.500	0.000	1.000	464	0.500	0.501	0.000	1.000
Program years, trend	164	3.567	4.815	0.000	20.000	464	3.280	4.743	0.000	20.000
Reserves	164	34.213	28.473	2.135	251.514	464	49.439	139.065	0.124	1474.781
Trade	164	77.127	35.002	21.720	194.195	464	79.187	37.864	20.227	220.407
Trade LIC	164	11.600	30.571	0.000	142.899	464	16.596	32.277	0.000	142.899
Trade LMIC	164	31.476	47.060	0.000	178.961	464	32.542	48.760	0.000	209.410
Trend	164	22.457	2.266	19.000	27.000	464	22.153	2.285	19.000	28.000
Urban population	164	57.614	20.035	9.500	92.300	464	50.807	21.965	8.080	92.300
Value added of agriculture	164	14.257	9.543	0.931	47.805	464	17.273	12.179	0.801	61.969
Vote in line with G7	164	0.580	0.142	0.000	0.912	464	0.543	0.161	0.000	0.912
Years after program, trend	164	2.207	3.683	0.000	18.000	464	2.429	3.978	0.000	20.000
Years before program, trend	164	0.543	1.641	0.000	9.000	464	0.429	1.322	0.000	9.000
Years of schooling	164	7.641	2.143	1.126	11.338	464	6.974	2.520	1.025	11.429

Table A.5: Poverty and inequality by program participation status (2000-2009)

Poverty gap 1.25$	Obs.	Mean	Median	Std. Dev.	Min.	Max.
never	3	12.69	8.18	14.96	0.50	29.38
before	1	7.80	7.80	.	7.80	7.80
program	89	6.42	2.83	8.92	0.50	46.84
between	22	5.23	2.04	7.46	0.50	27.13
after	49	2.23	0.89	2.61	0.50	10.83
Total	164	5.13	1.94	7.70	0.50	46.84

Poverty gap 2$	Obs.	Mean	Median	Std. Dev.	Min.	Max.
never	3	21.84	18.31	22.44	1.37	45.84
before	1	13.42	13.42	.	13.42	13.42
program	89	13.43	8.06	14.15	0.50	64.38
between	22	10.76	6.28	13.59	0.08	45.80
after	49	6.24	3.45	6.96	0.50	30.41
Total	164	11.08	6.28	12.83	0.08	64.38

Headcount ratio 1.25$	Obs.	Mean	Median	Std. Dev.	Min.	Max.
never	3	30.35	26.20	30.64	2.00	62.85
before	1	17.23	17.23	.	17.23	17.23
program	88	18.01	10.80	20.01	2.00	88.52
between	22	14.76	6.88	19.34	2.00	64.60
after	49	8.17	3.39	9.32	2.00	41.64
Total	163	14.84	7.76	18.01	2.00	88.52

Headcount ratio 2$	Obs.	Mean	Median	Std. Dev.	Min.	Max.
never	3	43.91	42.90	36.62	7.81	81.02
before	1	28.10	28.10	.	28.10	28.10
program	89	32.44	22.28	26.28	2.00	96.57
between	22	25.43	16.42	27.29	2.00	85.42
after	49	18.77	13.97	18.05	2.00	75.60
Total	164	27.60	19.57	24.96	2.00	96.57

Gini gross	Obs.	Mean	Median	Std. Dev.	Min.	Max.
never	24	53.41	52.34	9.36	40.32	68.51
before	4	53.86	53.82	0.34	53.53	54.26
program	232	43.78	43.31	6.91	27.52	58.29
between	65	45.63	46.75	6.37	32.67	59.25
after	139	44.19	44.53	5.77	33.13	56.30
Total	464	44.75	44.90	7.00	27.52	68.51

Gini net	Obs.	Mean	Median	Std. Dev.	Min.	Max.
never	24	51.29	50.45	10.64	35.55	68.27
before	4	52.33	52.27	0.19	52.17	52.60
program	232	41.39	42.17	7.61	24.53	55.54
between	65	42.53	44.91	6.16	30.36	56.56
after	139	41.04	41.17	6.12	28.56	53.31
Total	464	42.05	42.34	7.54	24.53	68.27

B MODEL SPECIFICATIONS

The inclusion of the variables that form part of the selection and the outcome equations in this study is motivated by previous research that deals with the determinants of participation in IMF agreements on the one hand and on the driving factors of poverty and income inequality on the other hand. This section provides a short overview of the studies we refer to in this paper.

Tables B.1. to B.3. are build up in a similar way. Table B.2. and B.3. summarize empirical work and provide for each study information concerning the sample of countries and the time period included, as well the specification of the dependent variable and the estimation technique that is applied by the authors. The tables also summarize the authors' findings concerning the effects of the variables that also form part of this study on the dependent variable together with their significance level, in order to facilitate a comparison with the here presented work. Table B.3. on the determinants of program participation additionally indicates which IMF programs have been taken into consideration in the study. In contrast, Table B.1. summarizes theoretical studies and surveys on the drivers of poverty and inequality and therefore leaves out the empirical background but provides orientation concerning the expected theoretical effects.

Table B.1: Determinants of poverty and inequality - Theoretical studies and surveys

	Gunter et al (2005)	Kanbur (1987)	Kuznets (1955)
Dependent variable	poverty	poverty	inequality
Ln(GDP *pc*)			+
Gini index		+	
Ln(GDP *pc*), squared			-
GDP *pc* growth		-	-
Population growth			+
Ln(Investment)			+
Ln(Trade)	+/-		+
Exchange rate growth	-	-	
Ln(Inflation)	-		
Value added of agriculture			-
Urban population			+
	Morduch (1994)	Nissanke & Thorbecke (2006)	
Dependent variable	poverty	poverty	
Gini index		+	
GDP *pc* growth		-	
Ln(Investment)		+	
Ln(Trade)		+/-	
Ln(Credit)	-		
Ln(Inflation)		+	
Natural resource rents		+	
Value added of agriculture	-	-	
Urban population		+	
Years of schooling		-	

Note: Only variables that are included in this study are mentioned in the table.
- indicates a negative effect on the dependent variable, + indicates a positive effect, +/- indicates that the effect is ambiguous.

Table B.2: Determinants of poverty and inequality - Empirical studies

	Adams (2004)	Adams (2004)	Collier & Dollar (2002)	Deininger & Squire (1998)	Dollar & Kraay (2002)
Sample	60 developing countries; 1980-1999	60 developing countries; 1980-1999	59 developing countries; 1974-1997 (4-year averages)	49 countries; 1960-1992	92 countries; 1960-2000 (decades)
Dependent variable	Ln(Poverty headcount ratio at 1$ line); ln(Poverty gap); ln(squared poverty gap)	Ln(Gini index)	GNP *per capita* growth	Gini index	Ln(Bottom quintile income *per capita*)
Estimation technique	OLS	OLS	OLS	OLS	OLS, 2SLS, GMM
Ln(GDP *pc*)		-** (1)	+ (a1)	-	+***
Gini index	+ (***)				
Ln(GDP *pc*), squared		+** (1)			
GDP *pc* growth	- (***)				
Ln(Trade)			-		+/-
Government consumption			-		+/-***
Ln(Inflation)			+/-		-***
Value added of agriculture					+* (e1)
Years of schooling					+* (f1)
Time trend	n.a.				

	Dollar & Kraay (2004)	Easterly & Fischer (2001)	Easterly & Fischer (2001)	Fanta & Upadhyay (2008)	Ghura et al (2002)
Sample	92 countries, n.a.	55 countries; 1970s - 1990s (decades)	42 countries; 1981-1993	16 African countries; n.a.	85 countries; 1960-1999
Dependent variable	Ln(Bottom quintile income *per capita*)	Δ Bottom quintile income share	Δ Relative poverty headcount ratios	Δ Poverty headcount ratio at 1$ line	Bottom quintile income share
Estimation technique	OLS, 2SLS, GMM	OLS	OLS	GLS	GMM, BACE
Ln(GDP *pc*)	+***				
Democracy index					+
Gini index				+**	-***
GDP *pc* growth		n.a.	-***	-***	
Population growth					+
Ln(Investment)					+ (b)
Ln(Trade)	+/-			-	+/-
Government consumption	+/-*				- (*)
Ln(Inflation)	-	-*** (c)	+** (c)		-**
Natural resource rents					+ (d)
Value added of agriculture					+/- (e2)
Years of schooling				-	+/- (f2)
Life expectancy					+***

	Meschi & Vivarelli (2009)	Mosley *et al.* (2004)	Ravallion & Chen (1997)	Ravallion & Chen (1997)	Wood & Ridao-Cano (1999)
Sample	65 developing countries; 1980-1999	34 countries; 1980-2000	67 developing countries; 1981-1994	67 developing countries; 1981-1994	90 countries; 1960-1990
Dependent variable	Gini index	Ln(Poverty headcount ratio at 1$ line)	Gini index; Wolfson polarization index	Δ Poverty headcount ratio at 1$ line; Δ Poverty gap index; Δ relative poverty headcount ratios	School enrollment rates (as proxy for income inequality)
Estimation technique	least squares dummy variable corrected estimator	3SLS	OLS	OLS	OLS, GLS, MAD (minimum absolute deviations), ML
Ln(GDP *pc*)	-	-*** (a2)			+
Gini index	+***	+***			
Ln(GDP *pc*), squared	+				
GDP *pc* growth			-	-	
Ln(Trade)	+				
Ln(Trade), LIC	-				
Ln(Trade), MIC	-***				
Ln(Inflation)	+***				
Years of schooling	+/-				
Time trend		-	+	+/- (g)	

Note: Only variables that are included in this study are mentioned in the table. - indicates a negative coefficient, + indicates a positive coefficient, +/- indicates that the sign of the coefficient depends on the model specification. N.a. if the variable is included in the estimation but the authors do not mention the sign of the coefficient. A coefficient is labeled as significant, *** p<0.01, ** p<0.05, * p<0.1, if it is significant in at least one model specification.

(1) Coefficient changes sign and gets insignificant when excluding Eastern Europe and Central Asia. (a1) Initial GNP *pc*. (a2) Ln(GNP *pc*). (b) Coefficient for Ln(Overall investment/GDP). Sign of ln(Private investment/GDP) is "-" and of ln(Public investment/GDP) "+*". (c) Inflation tax rate. $\Pi/(1+\Pi)$ of the % inflation rate Π. (d) Natural resource exports (% of GNP). (e1) Relative agricultural productivity. (e2) Relative agricultural labor productivity. (f1) Years of secondary schooling. Years of primary schooling "+" but insignificant. (f2) Coefficient of secondary schooling is "+", of primary schooling "-". (g) The coefficient is "-" in regressions with the dependent variables poverty gap, poverty headcount ratio at the 1$ line, and the relative headcount ratios when excluding Eastern Europe and Central Asia. It is "+" for the full sample considering relative poverty lines.

Table B.3: Participation in IMF programs

	Andersen *et al.* (2006)	Atoyan & Conway (2006)	Barro & Lee (2005)	Bird & Rowlands (2001)	Broz & Hawes (2006)
Sample	102 countries; 1995-2000	95 countries; 1993-2002	130 countries; 1975-1999 (5 year averages)	95 countries; 1974-1994	1983-2002
IMF programs	SBA, EFF	SBA, EFF, SAF, ESAF/PRGF	SBA, EFF	SBA, EFF, ESAF	SBA, EFF
Dependent variable	Program dummy	Program dummy	Program approval dummy	Program approval dummy	Program dummy
Estimation technique	Logit model	Probit model	Probit model	Probit model	Random effects logit
Reserves	-		-***	-*** $^{(a1)}$	+
Ln(GDP pc)	- $^{(b)}$		+***	-* $^{(b)}$	-*
Ln(GDP pc), squared			-***		
Trade					+**
Debt Service				+***	+/-
Vote in line with G7			+** $^{(d1)}$		+/- $^{(d2)}$
Past program years		+*** $^{(e1)}$		+***	+***
Ln(GDP)			+**	+	
Ln(GDP), squared			-**		
Change in GDP growth		+***			
GDP growth		-***			
Current account balance	-	-***		-*	

	Dreher *et al.* (2009)	Eichengreen *et al.* (2008)	Elekdag (2008)	Garuda (2000)	Harrigan *et al.* (2006)
Sample	197 countries; 1951-2004	24 emerging market countries; 1980-2003	169 countries; 1970-2004	39 developing countries; 1975-1991	11 MENA countries; 1975-2000
IMF programs	SBA, EFF, SAF, ESAF/PRGF		SBA	SBA, EFF, SAF, ESAF	SAF, ESAF, PRGF
Dependent variable	Program dummy	Program approval dummy	Program approval dummy	Program approval dummy	Program dummy
Estimation technique	Logit model	Probit model	Random effects probit	Logit model	Probit model
Reserves	+*	+ $^{(a1)}$	-***	- ***	-* $^{(a2)}$
Ln(GDP pc)	-***				-**
Trade		+***			
Debt Service	+***	+*** $^{(c)}$			+***
Vote in line with G7		-*** $^{(d3)}$			
Past program years	+***				
GDP growth		-**	-***	- ***	+*
Current account balance	+			+/-	+/-

	Przeworksi & Vreeland (2000)	Przeworksi & Vreeland (2000)	Sturm *et al.* (2005)	Vreeland (2002)	Vreeland (2002)
Sample	79 countries; 1970-1990	79 countries; 1970-1990	118 countries; 1971-2000	110 countries; 1961-1993	110 countries; 1961-1993
IMF programs	SBA, EFF, SAF, ESAF	SBA, EFF, SAF, ESAF	SBA, EFF, SAF, ESAF	SBA, EFF, SAF, ESAF	SBA, EFF, SAF, ESAF
Dependent variable	Program dummy (Government decision)	Program dummy (IMF decision)	Program approval dummy	Program approval dummy	Program dummy
Estimation technique	Dynamic bivariate probit model with partial observability	Dynamic bivariate probit model with partial observability	Probit model	Dynamic Heckman	Dynamic Heckman
Reserves	-**		-*** $^{(a1)}$	-**	-
Ln(GDP pc)			-***	- **	-
Debt Service	+***		+** $^{(c)}$	+**	+*
Countries under program	+***	-***	-	+/-	+
Past program years	+* / -		+*** $^{(e2)}$	+ **	+/-
GDP growth			-***		
Current account balance			-**		

Note: Only variables that are included in this study are mentioned in the table. - indicates a negative coefficient, + indicates a positive coefficient, +/- indicates that the sign of the coefficient depends on the model specification. A coefficient is labeled as significant, *** p<0.01, ** p<0.05, * p<0.1, if it is significant in at least one model specification.
$^{(a1)}$ Reserves (% of Imports). $^{(a2)}$ Change in net reserves (% of GDP). $^{(b)}$ GNP *per capita*. $^{(c)}$ Debt service(% of exports). $^{(d1)}$ Vote in line with US or major Europe in UN General Assembly. $^{(d2)}$ Voting affinity score of countries relative to US/UK/France/Japan position in the UN General Assembly. $^{(d3)}$ The authors recognize that the coefficient does not exhibit the expected sign. $^{(e1)}$ Program participation in the last 10 years. $^{(e2)}$ Five-years moving average of the dummy indicating that a country was under agreement.

C MODEL DIAGNOSTICS

This section provides closer information about the models with the biggest influence on the results of this study for the unrestricted sample. Table C.1. reports the distribution of posterior model probabilities (whose calculation is based on the BIC) which are used as model weights in the averaging process. The calculation of posterior model probabilities is based on the results of the treatment effect regressions (see Section 3(b)). The weights for the 15 best models (per poverty indicator and time lag with which the program dummy enters the equations) that fulfill at least one exclusion restriction can be found in the table. There are cases in which less than 15 model specifications fulfill any of the exclusion restrictions. That is why model probabilities for a smaller number of models can be found in the table.

Tables C.2. and C.3. report the treatment effect results for the three "best" models with the highest posterior model probabilities for each poverty and income inequality indicator. The dependent variable is shown in the first row, while in the second row the model specification is reported. Model 3-2, for example, refers to the third specification of the selection equation which is combined with the second specification of the outcome equation. In addition to the regression coefficients, the tables report values for athro and lnsigma, posterior model probabilities, the number the of observations that are included in the regression, and the BIC. Lnsigma is the natural logarithm of σ, the standard deviation of the error term from the outcome equation (see Section 3(a)). Athrho represents Fisher's z transformed correlation of the error terms of the selection and the outcome equation or, put differently, the arc-hyperbolic tangent of ρ. The high statistical significance of athrho indicates the presence of sample selection, which justifies the use of treatment effect estimations as OLS would lead to biased results.

Table C.1: Posterior model probabilities

$\tau = 0$	$\tau = 1$	$\tau = 2$

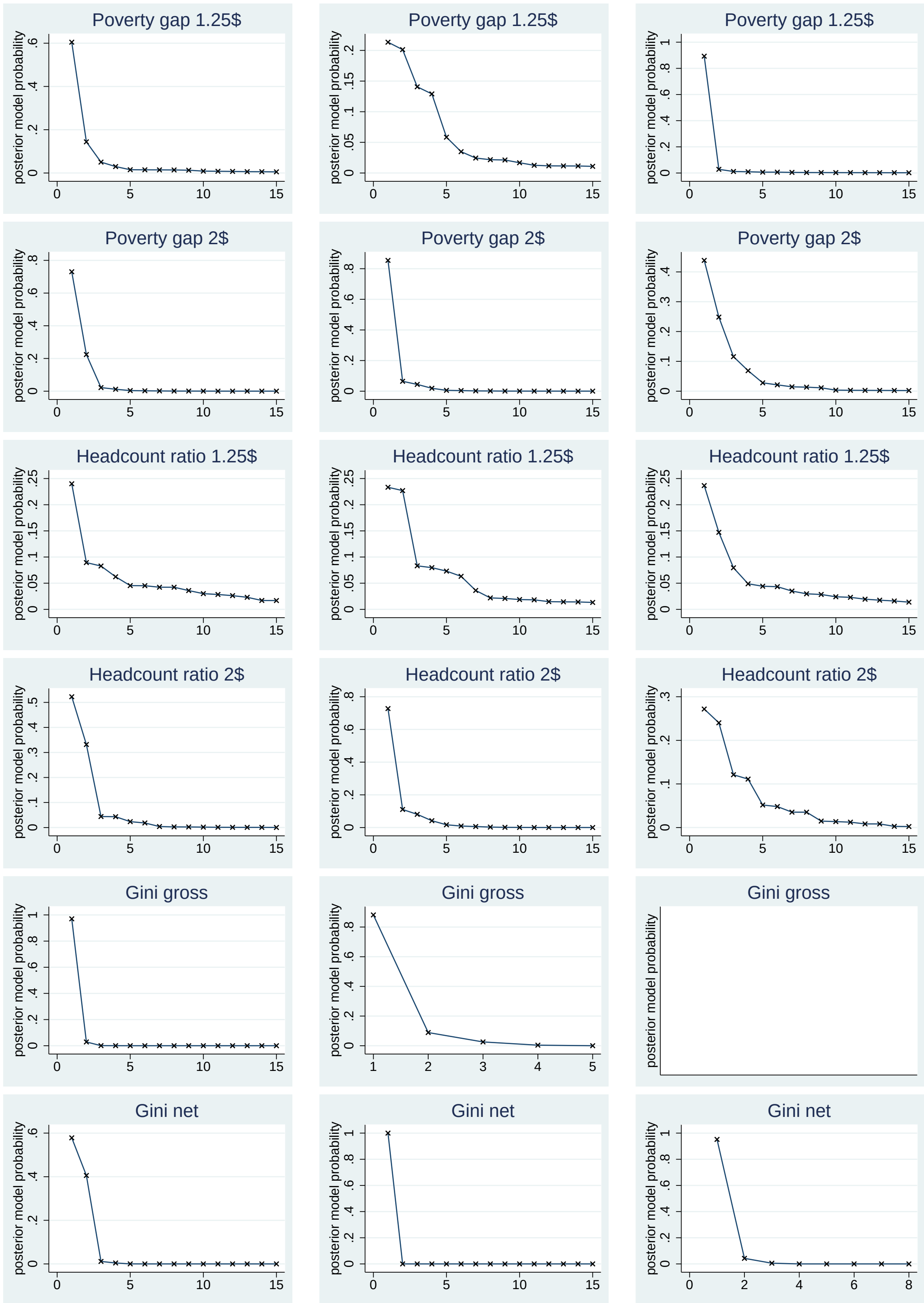

Table C.2: Specifications with highest the posterior model probability - Poverty

		Poverty gap 1.25$			**Poverty gap 2$**			**Headcount ratio 1.25$**			**Headcount ratio 2$**		
		Model 3-2	Model 1-2	Model 3-1	Model 3-8	Model 1-8	Model 2-8	Model 1-1	Model 1-2	Model 1-7	Model 3-8	Model 1-8	Model 3-2
Outcome equation	Gini net$_{t-1}$	0.053***	0.053***	0.048***	0.041***	0.041***	0.041***	0.034***	0.036***	0.032***	0.028***	0.028***	0.020***
		(0.013)	(0.013)	(0.013)	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)	(0.008)	(0.007)	(0.006)	(0.007)
	Years before program$_t$	-0.022	-0.020	-0.024	-0.013	-0.013	-0.013	-0.011	-0.010	-0.008	-0.014*	-0.013*	-0.019**
		(0.016)	(0.016)	(0.016)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)	(0.008)	(0.008)	(0.008)
	Program years$_t$	0.019	0.016	0.017	0.029***	0.028***	0.027**	0.016*	0.017*	0.012	0.020***	0.020***	0.019***
		(0.013)	(0.012)	(0.013)	(0.011)	(0.011)	(0.011)	(0.009)	(0.009)	(0.009)	(0.007)	(0.007)	(0.007)
	Years after program$_t$	0.007	0.011	0.004	-0.008	-0.006	-0.006	-0.001	0.001	0.004	-0.017	-0.015	-0.019*
		(0.018)	(0.018)	(0.018)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.011)	(0.011)	(0.011)
	Vote in line with G7$_{t-1}$	-0.876**	-0.897***	-0.598*	-0.319	-0.331	-0.320	-0.341	-0.461*	-0.359	-0.313	-0.317	-0.200
		(0.345)	(0.346)	(0.355)	(0.263)	(0.262)	(0.262)	(0.264)	(0.263)	(0.269)	(0.196)	(0.196)	(0.204)
	Countries under program$_t$	0.005	0.005	0.003	0.008***	0.008***	0.009***	0.003	0.004	0.003	0.007***	0.007***	0.006***
		(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
	Past program years$_t$	0.009	0.009	0.006	0.007	0.007	0.008	0.001	0.002	-0.003	0.009	0.009	0.006
		(0.013)	(0.013)	(0.014)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.007)	(0.007)	(0.007)
	Ln(GDP pc)$_{t-1}$	-6.027***	-5.637***	-1.084***	-1.125***	-1.146***	-1.162***	-0.960***	-3.203***	-0.951***	-0.855***	-0.883***	2.235**
		(1.410)	(1.407)	(0.247)	(0.164)	(0.164)	(0.165)	(0.204)	(1.136)	(0.207)	(0.147)	(0.149)	(1.052)
	Democracy index$_{t-1}$	-0.017	-0.018*	-0.016	-0.021***	-0.022***	-0.022***	-0.018**	-0.019**	-0.015**	-0.017***	-0.017***	-0.016***
		(0.011)	(0.011)	(0.011)	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.005)	(0.005)	(0.005)
	Ln(GDP pc)$_{t-1}$, squared	0.306***	0.281***						0.138**				-0.199***
		(0.086)	(0.086)						(0.070)				(0.067)
	Ln(Credit)$_{t-1}$				-0.210***	-0.209***	-0.207***				-0.156***	-0.156***	
					(0.063)	(0.063)	(0.063)				(0.041)	(0.041)	
	Exchange rate growth$_{t-1}$									-0.042*			
										(0.025)			
	> 200% depreciation dummy$_{t-1}$									0.132			
										(0.149)			
	Program dummy $_t$	0.692***	0.761***	0.626***	0.324**	0.366***	0.348***	0.503***	0.531***	0.584***	0.303***	0.337***	0.225*
		(0.186)	(0.195)	(0.201)	(0.128)	(0.111)	(0.110)	(0.127)	(0.128)	(0.148)	(0.108)	(0.093)	(0.125)
	Constant	27.406***	25.864***	8.063***	9.435***	9.538***	9.641***	8.653***	17.447***	8.705***	8.715***	8.858***	-3.030
		(5.504)	(5.486)	(1.602)	(1.095)	(1.109)	(1.117)	(1.282)	(4.411)	(1.289)	(0.948)	(0.963)	(3.991)
	Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Selection equation	Reserves$_{t-1}$	-0.009***	-0.010***	-0.009***	-0.011***	-0.012***	-0.014***	-0.010***	-0.009**	-0.010***	-0.011***	-0.012***	-0.011***
		(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
	Ln(GDP pc)$_{t-1}$	6.587***	7.135***	5.406***	6.455***	7.172***	7.563***	6.068***	6.804***	6.118***	6.906***	7.663***	5.858***
		(1.788)	(1.644)	(1.746)	(1.973)	(1.775)	(1.942)	(1.534)	(1.577)	(1.490)	(1.799)	(1.682)	(1.868)
	Ln(GDP pc)$_{t-1}$, squared	-0.461***	-0.492***	-0.388***	-0.456***	-0.497***	-0.500***	-0.426***	-0.472***	-0.428***	-0.484***	-0.528***	-0.420***
		(0.111)	(0.103)	(0.108)	(0.122)	(0.110)	(0.120)	(0.096)	(0.099)	(0.093)	(0.112)	(0.105)	(0.116)
	Trade$_{t-1}$	-0.004**	-0.005**	-0.004**	-0.004*	-0.004**	-0.010***	-0.005***	-0.006***	-0.006***	-0.004*	-0.004**	-0.004*
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
	Debt Service$_{t-1}$	0.037**	0.036**	0.038**	0.037*	0.037*	0.036*	0.051***	0.050***	0.052***	0.040*	0.041*	0.043**
		(0.017)	(0.017)	(0.017)	(0.019)	(0.020)	(0.019)	(0.017)	(0.017)	(0.016)	(0.021)	(0.022)	(0.021)
	Vote in line with G7$_{t-1}$	0.845	1.059*	0.851	0.948	1.204*	1.251*	1.071*	1.085*	1.077*	1.132	1.345**	1.124
		(0.634)	(0.618)	(0.633)	(0.708)	(0.693)	(0.716)	(0.624)	(0.624)	(0.606)	(0.691)	(0.674)	(0.694)
	Countries under program$_t$	0.000	0.003	0.001	0.004	0.008	0.007	0.005	0.005	0.006	0.003	0.007	0.003
		(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)
	Past program years$_t$	0.046**	0.031*	0.046**	0.053***	0.034*	0.038**	0.032*	0.032*	0.028*	0.053***	0.036**	0.054***
		(0.019)	(0.017)	(0.019)	(0.020)	(0.019)	(0.019)	(0.017)	(0.017)	(0.017)	(0.019)	(0.018)	(0.019)
	Ln(GDP)$_{t-1}$						-1.434						
							(1.363)						
	Ln(GDP)$_{t-1}$, squared						0.024						
							(0.026)						
	GDP growth$_{t-1}$	-0.062***		-0.059***	-0.074***						-0.065***		-0.064***
		(0.022)		(0.022)	(0.024)						(0.025)		(0.024)
	Change in GDP growth$_{t-1}$	0.040***		0.037**	0.040**						0.035**		0.036**
		(0.015)		(0.016)	(0.019)						(0.017)		(0.017)
	Constant	-23.249***	-26.013***	-18.543***	-22.694***	-26.299***	-7.698	-21.987***	-24.927***	-22.266***	-24.565***	-28.267***	-20.406***
		(7.167)	(6.526)	(7.015)	(7.977)	(7.138)	(16.821)	(6.096)	(6.270)	(5.902)	(7.251)	(6.748)	(7.576)
	Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	athrho	-1.037***	-1.097***	-0.996***	-0.513***	-0.557***	-0.514***	-1.059***	-1.073***	-1.245***	-0.733***	-0.783***	-0.611**
		(0.245)	(0.254)	(0.272)	(0.182)	(0.135)	(0.133)	(0.219)	(0.217)	(0.271)	(0.231)	(0.168)	(0.277)
	lnsigma	-0.677***	-0.652***	-0.677***	-1.003***	-0.990***	-1.000***	-0.940***	-0.940***	-0.905***	-1.247***	-1.229***	-1.274***
		(0.091)	(0.096)	(0.097)	(0.069)	(0.067)	(0.065)	(0.085)	(0.084)	(0.094)	(0.072)	(0.068)	(0.076)
	Posterior model probability	0.605	0.144	0.050	0.730	0.224	0.022	0.240	0.089	0.083	0.523	0.332	0.044
	N	356	356	356	356	356	356	353	353	353	356	356	356
	BIC	1313.978	1316.848	1318.950	1172.537	1174.900	1179.550	1108.224	1110.199	1110.352	961.198	962.106	966.147

NOTE: Best three models for each poverty indicator reported. Program participation enters contemporaneously ($\tau = 0$).

Table C.3: Specifications with highest the posterior model probability - Inequality

		Gini gross			**Gini net**		
		Model 1-5	Model 4-5	Model 1-8	Model 3-15	Model 1-15	Model 4-15
Outcome equation	Years before program$_t$	0.032	0.032	0.046	0.112**	0.108**	0.108**
		(0.058)	(0.058)	(0.056)	(0.054)	(0.054)	(0.054)
	Program years$_t$	0.160***	0.160***	0.164***	-0.017	-0.020	-0.020
		(0.051)	(0.051)	(0.051)	(0.049)	(0.049)	(0.049)
	Years after program$_t$	0.137***	0.137***	0.101**	0.047	0.059	0.060
		(0.050)	(0.050)	(0.050)	(0.045)	(0.045)	(0.045)
	Vote in line with G7$_{t-1}$	2.233	2.229	1.939	1.999	1.971	1.971
		(1.403)	(1.403)	(1.457)	(1.222)	(1.234)	(1.234)
	Countries under program$_t$	-0.024**	-0.024**	-0.029**	0.008	0.008	0.008
		(0.012)	(0.012)	(0.012)	(0.010)	(0.010)	(0.010)
	Past program years$_t$	-0.405***	-0.406***	-0.427***	-0.207***	-0.209***	-0.209***
		(0.052)	(0.052)	(0.053)	(0.044)	(0.044)	(0.044)
	Ln(GDP pc)$_{t-1}$	3.493***	3.486***	4.021***	3.092***	2.937***	2.937***
		(0.804)	(0.802)	(0.788)	(0.662)	(0.655)	(0.655)
	Democracy index$_{t-1}$	-0.084**	-0.084**	-0.061	-0.066**	-0.066**	-0.066**
		(0.038)	(0.038)	(0.038)	(0.032)	(0.032)	(0.032)
	Ln(Investment)$_{t-1}$	2.686***	2.702***				
		(0.510)	(0.512)				
	Ln(Credit)$_{t-1}$			0.742***			
				(0.179)			
	Life expectancy$_{t-1}$				0.332***	0.331***	0.331***
					(0.043)	(0.043)	(0.043)
	Program dummy $_t$	2.515***	2.502***	2.809***	2.951***	3.187***	3.191***
		(0.812)	(0.819)	(0.752)	(0.889)	(0.910)	(0.916)
	Constant	29.536***	29.520***	32.766***	17.435***	18.159***	18.152***
		(4.213)	(4.223)	(4.326)	(4.419)	(4.371)	(4.365)
	Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Selection equation	Reserves$_{t-1}$	-0.010***	-0.010***	-0.010***	-0.011***	-0.010***	-0.010***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
	Ln(GDP pc)$_{t-1}$	4.580***	4.587***	4.578***	4.247***	4.242***	4.240***
		(0.803)	(0.804)	(0.794)	(0.839)	(0.819)	(0.822)
	Ln(GDP pc)$_{t-1}$, squared	-0.327***	-0.328***	-0.327***	-0.306***	-0.307***	-0.307***
		(0.051)	(0.052)	(0.051)	(0.054)	(0.053)	(0.053)
	Trade$_{t-1}$	-0.001	-0.001	-0.001	0.000	0.000	0.000
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	Debt Service$_{t-1}$	0.021**	0.021**	0.019*	0.011	0.012	0.012
		(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
	Vote in line with G7$_{t-1}$	0.701*	0.707*	0.693*	0.478	0.456	0.454
		(0.413)	(0.414)	(0.412)	(0.446)	(0.454)	(0.456)
	Countries under program$_t$	0.009**	0.009**	0.009**	0.007*	0.009**	0.009**
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
	Past program years$_t$	0.042***	0.042***	0.041***	0.061***	0.055***	0.055***
		(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)
	GDP growth$_{t-1}$				-0.035***		
					(0.010)		
	Change in GDP growth$_{t-1}$				0.020**		
					(0.009)		
	Current account balance$_{t-1}$		0.002				-0.000
			(0.006)				(0.006)
	Constant	-16.872***	-16.880***	-16.882***	-15.261***	-15.406***	-15.403***
		(3.157)	(3.157)	(3.124)	(3.301)	(3.217)	(3.221)
	Region dummies	Yes	Yes	Yes	Yes	Yes	Yes
	athrho	-0.722***	-0.720***	-0.779***	-0.733***	-0.780***	-0.781***
		(0.171)	(0.173)	(0.162)	(0.208)	(0.211)	(0.213)
	lnsigma	1.222***	1.221***	1.243***	1.139***	1.153***	1.153***
		(0.053)	(0.053)	(0.052)	(0.068)	(0.070)	(0.071)
	Posterior model probability	0.970	0.029	0.001	0.578	0.406	0.011
	N	1273	1273	1273	1273	1273	1273
	BIC	8608.036	8615.069	8622.570	8393.817	8394.526	8401.671

NOTE: Best three models for each income inequality indicator reported. Program participation enters contemporaneously ($\tau = 0$).