AID, PUBLIC SPENDING AND HUMAN WELFARE:
Evidence from Quantile Regressions

by

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Abstract

Does aid contribute to human development other than by increasing growth? In doing so, is aid more or less effective in poorer countries (those with low levels of aggregate welfare)? This paper addresses these issues, assessing if there is cross-country aggregate evidence for an effect of aid on welfare levels. We posit that aid can enhance human development by financing public expenditures that increase welfare indicators. Using quantile regressions, we report evidence that aid is associated with higher human development (the Human Development Index) and lower infant mortality (both indicators of aggregate welfare). Where there are differences across quantiles, aid is more effective in countries below the median of the welfare distribution, i.e. with lower levels of human development. Insofar as aggregate welfare is (inversely) correlated with poverty, we find evidence that aid can make a positive contribution to *alleviating* poverty, and that the effect appears to be greater in countries with lower levels of human development indicators.

JEL: F35, I30, O40

Keywords: Aid Effectiveness, Human Welfare (HDI and infant mortality), Quantile Regressions.

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1 Introduction

Following the recent proliferation of cross-country studies of the impact of aid on growth, attention has turned to how aid can most effectively be allocated so as to reduce poverty. One answer is premised on the view that aid cannot be targeted to the poor. Consequently, aid should be allocated to those countries with good policies, thereby achieving growth, which in turn reduces poverty (Collier and Dollar, 2002). Given the absence of a long series of cross-country data on poverty, it is difficult to test empirically for any direct impact of aid on poverty. We can try to address the link indirectly, but doing so necessarily requires making some assumptions. The approach adopted here is to assess the impact of aid on aggregate (country) indicators of human welfare. The underlying premise is that countries with low levels of human welfare will, *ceteris paribus*, have higher levels of poverty. While there will obviously be exceptions, our cross-country approach only requires this to hold on average.

Some studies have tested for any impact of aid on aggregate welfare. In one of the best known studies, Boone (1996) found no evidence that aid was associated with lower levels of infant mortality. Previous studies have not identified an effect of aid on increasing welfare indicators. We contend that such studies have been based on inappropriately specified regressions. Aid will not have a direct impact on welfare. However, if aid affects the amount of public expenditure directed at areas that enhance welfare (health, education, water and sanitation), then aid can indirectly contribute to levels of welfare. This is the hypothesis we test here.

To signal the potential link to poverty, we describe such welfare-enhancing spending as pro-poor public expenditure (PPE). It is doubtless true that increased spending on health, for example, does not necessarily benefit the poor. Whether the poor benefit from particular expenditures depends, *inter alia*, on the incidence of expenditure and effective targeting of specific programmes. Nevertheless, it is not unreasonable to assume that across countries on average, higher expenditure on social sectors increases the potential of the poor to benefit. If adequate cross-country data on expenditure incidence were available, this assumption could be tested. We emphasise that the focus here is on poverty *alleviation* (improving aggregate or average human welfare should, *ceteris paribus*, improve the welfare of the poor) rather than on poverty reduction.

Improvements in aggregate welfare may not be associated with any reduction in (income) poverty. We explore the proposition that aid can alleviate poverty by financing public expenditures that are more likely to benefit the poor.

Irrespective of whether growth is welfare-enhancing and of whether aid contributes to such growth, there are other ways in which aid can contribute to welfare. Most aid finances public expenditure. Some expenditure, such as that on health and education, is more likely to enhance welfare than other types, and thus more likely to benefit the poor. To capture this, we construct an index of pro-poor expenditures (PPE), and account for the fact that some portion of aid will finance these expenditures. We then test for the effect of aid and PPE on indicators of the welfare of the poor, in a sample of 38 countries over 1980-98. We use two indicators of welfare, the Human Development Index (HDI) and the infant mortality rate (IM). Using quantile regressions, we report evidence that aid is associated with higher human development and lower infant mortality, and that aid tends to have a greater effect on indicators in those countries with lower welfare (lower values of HDI or higher values of infant mortality).

The organisation of the paper is as follows. Section 2 outlines how the PPE index is constructed and describes the econometric specification used. Section 3 describes the technique of quantile regressions and presents the results for the effect aid on HDI and infant mortality, before presenting the results. Section 4 is the conclusion, where we discuss the implications for poverty-alleviating aid allocations.

2 Aid, Government Spending and Welfare

In recent years, the objective of reducing poverty has moved to the forefront of the donor agenda. If aid contributes to growth, and growth contributes to poverty reduction, then aid can contribute to poverty reduction or, more generally, to improving the welfare of the poor. Indeed, some consider the effect via growth as the only way that aid can reduce poverty. As 'donors cannot target their money on particular households, [t]hey can only affect poverty by raising aggregate income' (Collier and Dollar, 2002: 1483). This is not obviously true. Most aid finances government spending, and if some such expenditure enhances average welfare (even if it cannot be accurately targeted on poor households), then aid potentially benefits the poor via public expenditure (rather than via growth).

Constructing a PPE Index

There is no clear definition of which categories of public spending should be included in a pro-poor expenditure index, and any choice is to some extent constrained by data availability. Even if the incidence of spending is regressive, spending on social sectors is more likely to benefit the poor than are other types of expenditure, while health and education services are most likely to contribute to welfare indicators. 'Greater public spending on primary and secondary education has a positive impact on widely used measures of education attainment, and increased health care spending reduces child and infant mortality rates' (Gupta *et al*, 2002: 732). Public expenditures on 'social services' (sanitation, education and health) are the most likely to provide benefits to the poor (see Verschoor, 2002, for a detailed discussion).

A simple pro-poor expenditure index (PPE) can be constructed as $PPE = P_S + P_E + P_H$, where P_S is public expenditure on sanitation and housing services, P_E is public expenditure on education, and P_H is public expenditure on health services (all measured as a share of GDP). The most readily available PPE measure is expenditure on social sectors as a share of GDP (*SS/GDP*, from *World Development Indicators*). However, this data does not distinguish the three components separately. It is unlikely that the effect on welfare is uniform across the three public expenditure components. For example, health spending may be expected to have a greater impact on infant mortality than education spending. One way of accounting for this is to assign weights to each component of the index based on their relative importance in reducing poverty, using beta coefficients, which are unit-free, as weights. These weights are recovered from a regression of each welfare indicator on each type of expenditure to obtain two beta-weighted PPEs, PPE_{bh} and PPE_{bm}, where HDI and infant mortality are the respective dependent variables:[1]

$$PPE_{bh} = 0.1276\ P_s + 0.1084\ P_e + 0.2177\ P_h$$

$$PPE_{bm} = 0.1036\ P_s + 0.1569\ P_e + 0.2290\ P_h$$

[1] The beta coefficient of expenditure category *X* is obtained by multiplying the regression coefficient on *X* by the standard deviation of *X* and then dividing this product by the standard deviation of the dependent variable.

Note that health spending has the highest weight in both indices, although on average health spending has the lowest value of the three components. Spending on education is, on average, greater than on health or education, but this does not mean that it has the highest weight. Consequently, it is possible that the unweighted PPE (*SS/GDP*) may yield different results to these weighted PPEs. Unfortunately data on all three categories is not available for all countries in all periods. We have 81 observations (countries and periods) for all three elements of the PPE, and this comprises the restricted sample for the two beta-weighted PPE indices (see Gomanee *et al*, 2003, for details on constructing the index and tests for which categories of spending to include). The full sample using *SS/GDP* is somewhat larger, with about 113 observations. We present results using the full sample and also compare the unweighted and weighted indices for the restricted sample.

Econometric Specification

We want to test the hypothesis that aid contributes to higher levels of PPE and thereby contributes to welfare. Although we are ultimately interested in the effect on poverty, comparative cross-country data on poverty over time is scarce, and such data as exist are based on income measures of poverty, and therefore only capture one dimension of the welfare of the poor (albeit an important one). A household that is income poor but has access to health care may be no worse off, in welfare terms, than a household that is (marginally) income non-poor but has no access to health care. Non-monetary indicators of welfare, such as health status indicators, may be as good as income poverty measures to capture the material hardship aspect of being poor (Reddy and Pogge, 2002). Aid can finance expenditures that improve the welfare of the poor, such as universal access to primary education and health care. In this way aid can benefit the poor without necessarily having any impact on measured income poverty.

Two indicators of human welfare (assumed to be indicators of the welfare of the poor) are used. The infant mortality rate (IM) is likely to be correlated with poverty, and as such is a reasonable indicator of the welfare of the poor (Reddy and Pogge, 2002). The correlation between infant mortality and the '$1 a day' measure of income poverty is quite high (0.78 for countries in our sample for which both measures are available), suggesting an overlap in informational value. An alternative broad-based measure of welfare is the human development index (HDI), an index (between 0 and 1) of different dimensions of quality of life (health status, education and income). The benefit of both measures is that they are available for many countries over a relatively long time period, so that we can begin by constructing a panel of 38 countries in four four-year and one three-year period over 1980-98. The availability of data to construct the PPE indices limits the size of the sample.

We posit a basic relationship (subscripts designating country *i* in period *t*):

$$W_{it} = \beta_0 + \beta_1 Y_{it} + \beta_2 G_{p_{it}} + \beta_3 A_{it} + \varepsilon_{it} \qquad (1)$$

where W is a measure of welfare.
Y is a measure of income.
G_p is an indicator of pro-poor public expenditures (PPE).
A is a measure of aid.

To the extent that aid allows the level of PPE to be higher than would otherwise be the case, it is inappropriate to include both aid and PPE in (1), as some double-counting is implied.[2] An appropriate econometric technique is to use a constructed regressor ($\widetilde{G}_p$) rather than G_p, to represent PPE that are *not* financed by aid, and estimate:

$$W_{it} = \beta_0 + \beta_1 Y_{it} + \beta_2 \widetilde{G}_{p_{it}} + \beta_3 A_{it} + \varepsilon_{it} \qquad (2)$$

Two steps are required in constructing $\widetilde{G}_p$. First, it is necessary to establish that PPE (i.e. the share of public expenditures allocated to social sectors) is indeed influenced by aid, among other explanatory variables. Second, having established this, one regresses PPE on Aid and the residual of this bi-variate regression (*PPEres*) is the measure of $\widetilde{G}_p$ – the proportion of PPE that is not financed by aid. One can then proceed to estimate (2). Gomanee *et al* (2003) show that PPE does tend to be higher in countries receiving more aid, controlling for other variables, and derive the *PPEres* measures used below.

[2] We abstract from concerns of fungibility and fiscal response (see McGillivray and Morrissey, 2000, 2001). For our purposes, it is immaterial whether aid finances PPE directly or releases other revenues to finance PPE.

3 Quantile Regression Analysis

It can be reasonably assumed that the effectiveness of aid in improving welfare will depend on whether this effect is being observed at the lowest or highest level of welfare. It is possible that aid is less effective in cases where aggregate welfare is very low (typically, in such cases poverty is severe), perhaps because low welfare is associated with weak social infrastructure (and public spending fails to target the poor), or even with poor policies. If the economy has an effective social infrastructure, aid (by financing public expenditure on social sectors) may prove to be more effective in improving welfare (including of the poor). On the other hand, aid may be more effective in increasing welfare in poorer countries if the marginal effectiveness of aid in improving welfare is greatest where welfare is lowest. To examine the effect of aid and social expenditures at different points of the welfare distribution, we use the semi-parametric technique of quantile regression analysis introduced by Koenker and Bassett (1978, 1982).

Standard OLS techniques concentrate on estimating the mean of the dependent variable subject to the values of the independent variables. Usually, variables are included as uncentred regressors. Quantile regression allows us to center the regressor around different quantiles (for example, regressors are centred around the median at the 0.5 quantile). This adds value to estimation results, especially that distribution of welfare over countries is likely to be skewed. Given a set of explanatory variables, quantile regression estimates the dependent variable conditional on the selected quantile. For example, it allows us to evaluate how far aid flows have been successful when we examine observations centred around the 5th percentile of welfare distribution. The resulting coefficients give an estimate of the impact on countries with relatively low values of the dependent variable (low welfare indicators in the case of HDI, but high welfare in the case of IM).

By estimating the model at different quantiles, one can trace the entire conditional distribution of welfare rates given a set of regressors. A further advantage of employing this estimation method is that the regression coefficient vector is not sensitive to outlying values of the dependent variable, as the quantile regression objective function is a weighted sum of absolute deviations. Provided error terms are homoscedastic, the Koenker and Bassett (1982) and Rogers (1992) methods would be adequate to calculate the variance-covariance matrix. Rogers (1992) reports that in the presence of heteroscedastic errors, this method understates the standard errors. Consequently, we report the bootstrapped estimator of standard errors, as he suggests.

With two indicators of the welfare of the poor (HDI and IM) and two PPE indices (unweighted and weighted), we have four tests of the hypothesis that aid contributes to the welfare of the poor through its effect on spending. For most of the 38 countries we have PPE observations for at least two periods, although for a few countries there is only one observation (see Gomanee *et al*, 2003). In all regressions we use aid lagged one period (to account for potential endogeneity) and *PPEres* (to remove spending 'directly' financed by aid) computed for the unweighted index. We also include a measure of spending on the military as a share of GDP (G_M), as the may be expected to be negatively associated with welfare.

Tables 1 and 2 about here

Tables 1 and 2 present the HDI and infant mortality regression estimates respectively, for the full sample, at five different quantiles, namely, 5th, 25th, 50th (median), 75th and 95th percentile of the welfare distribution. We can see from both tables that income per capita, social expenditures and aid inflows are associated with higher welfare at all quantiles (positive coefficients for HDI, negative for IM), albeit not always significantly so. There is no evidence that military spending has an adverse effect on welfare. Aid and PPE have a greater positive impact on HDI at the lower end of its distribution, although aid is only significant in the 0.25 quantile. The coefficient on *PPEres* increases as we move down the distribution. On average, each extra percent of PPE improves HDI by about 0.24% in the 0.05 quantile, declining (monotonically) to an 0.09% increase in HDI for the 0.75 quantile. HDI is consistently lower in SSA countries, controlling for the other factors, and there is some evidence that this is because PPE is lower (see note to Table 1).

Where there are differences across the quantiles, aid and PPE are more effective in enhancing welfare in countries with lower values of welfare, especially for IM. Indeed, aid is only effective in increasing welfare in that part of the distribution where infant mortality is above the median (welfare is lower). Additional support is obtained by the F-test statistics; the null hypothesis of equality of aid coefficients across quantiles is rejected for higher as aginst lower quantiles, implying increasing aid effectiveness moving down the welfare distribution. There is evidence that PPE and aid separately contribute to reducing infant mortality, the more so in countries where IM is higher.

Tables 3 and 4 about here

Tables 3 and 4 present the HDI and infant mortality regression estimates comparing the weighted and unweighted PPE indices. We can see from both tables that income per capita, social expenditures and aid inflows are associated with higher welfare at all quantiles, albeit not always significantly so. There is no evidence that military spending has an adverse effect on welfare. Where there are differences across the quantiles, aid is more effective in enhancing welfare in countries with lower values of welfare. Pro-poor public expenditure and aid have a greater positive impact on HDI at the lower end of its distribution, whichever PPE index is used (the results are stronger for the weighted PPE). On average, each extra percent of weighted PPE improves HDI by about 0.3% in the 0.05 quantile, declining (monotonically) to an 0.05% increase in HDI for the 0.95 quantile. In regressions with the weighted PPE, each extra percent of aid adds about 0.3% to HDI in the 0.05 quantile, declining to 0.1% addition to HDI in the median quantile, and has no effect on HDI in higher quantiles. Additional support is obtained by the F-test statistics; the null hypothesis of equality of aid coefficients across quantiles is rejected in most cases comparing the distribution above the median with that below. As the HDI is highly correlated with per capita income, and aid tends to decline as income rises, this is consistent with increasing returns to aid (in terms of the contribution to human development).

When unweighted PPE is used, we again find evidence that PPE and aid are only effective in increasing welfare in that part of the distribution where infant mortality is above the median (welfare is lower). The results are more uniform for infant mortality when the weighted PPE is used. On average, each extra percent of weighted PPE improves IM by about 0.6% for all quantiles, and each extra percent of aid adds about 0.5% to IM in all quantiles. Additional support is obtained by the F-test statistics; the null hypothesis of equality of aid coefficients across quantiles is accepted in most cases, implying uniform aid effectiveness across the welfare distribution. As the weighted index is statistically preferred, this is evidence that pro-poor spending and aid each (separately) contribute to increasing welfare.[3]

4 Conclusions and Discussion

Collier and Dollar (2002) have argued that the most effective way to allocate aid so as to reduce poverty is by allocating to those countries with good policies, which are most likely to use the aid effectively, thereby achieving growth that benefits the poor. Our results provide grounds on which to suggest refinement of their aid allocation rule. We find that aid can affect welfare via public expenditure, and this effect tends to be greater in countries with lower welfare. Irrespective of whether growth is pro-poor and of whether aid contributes to such growth, there are other ways in which aid can contribute to welfare. In particular, most aid finances public expenditure, some of which (what we define as PPE) can increase the provision of public 'social' services that increase welfare, including potentially that of the poor. Even if PPE cannot be targeted on poor households, or if the incidence of public spending is regressive, the access of the poor to welfare-enhancing social services is likely to be positively correlated with spending on the provision of such services.

We report evidence that aid is associated with higher human development and lower infant mortality. In general, where there are differences, aid is more effective in enhancing welfare in countries with lower values of welfare. One might anticipate that welfare indicators are lowest in the poorest countries, and such countries tend to receive more aid(on average). In this sense, our results are consistent with concluding that aid is most effective in improving welfare in the poorest countries. It would therefore seem that the lower the human development in the recipient economy, the more effective aid and social expenditure may be in promoting welfare. One possible explanation would be that the lower the welfare, the more room for improvement to be brought by aid and pro-poor spending hence the larger their impact. The estimates support our hypothesis

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[3] This result is in marked contrast to Boone (1996), who finds no evidence that aid is associated with lower levels of infant mortality. However, he used relatively simple cross-section econometric techniques. The results here are consistent with the panel estimates in Gomanee *et al* (2003).

that effectiveness of aid does vary across economies depending on where they are located in the welfare distribution.

Although no macroeconomic policy controls are included in the quantile regressions, PPE and G_M can be interpreted as representing policy towards public expenditure (allocation). In this sense, our results for the positive contribution of aid to welfare indicators are independent of policy. It seems probable that there are economic policies that enhance growth prospects, and even that some policies enhance aid effectiveness, but we find no evidence that economic policies are *necessary* to ensure aid effectiveness either in contributing to welfare.

It may be a reasonable conjecture that economic performance is weaker and poverty is more severe in countries with 'bad' policies. If this is true, welfare indicators should have lower values in countries with inappropriate policies. Our results, however, suggest that aid is more effective in countries with lower welfare. This does *not* imply that aid works better in countries with bad policies. It is quite probable that non-policy factors are important determinants of poor growth and welfare performance, such as susceptibility to shocks or uncertainty (Guillaumont and Chauvet, 2001; Lensink and Morrissey, 2000). Rather than policy enhancing aid effectiveness, we posit that aid can enhance the effectiveness of policies (expenditure allocation) for improving welfare and that the leverage of aid may be greater in more disadvantaged countries.

Low levels of welfare indicators may well signal the desirability of increasing aid, rather than interpreting low values as indicating bad policies and so reducing entitlement to add. Furthermore, if increasing human welfare and reducing poverty are the principle objectives, the leverage of aid on public spending may be as relevant than any effect on growth. Aid to the poorest countries is increasingly in the form of budget support, much of which is targeted on addressing poverty or welfare (e.g. Poverty Action Funds under the HIPC initiative). Such aid can be effective.

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Table 1: Quantile Regressions for HDI (Full Sample)

	5%	**25%**	**50%**	**75%**	**95%**
		Using SS/GDP as PPE			
GDP_{t-1}	0.000	0.000	0.000	0.000	0.000
	(1.75)*	(3.10)***	(1.32)	(1.03)	(1.93)*
PPEres	0.242	0.201	0.126	0.064	0.028
	(2.31)**	(3.57)***	(2.30)**	(1.71)*	(1.00)
A_{t-1}	0.089	0.095	0.037	0.030	0.004
	(1.16)	(2.79)***	(1.04)	(1.57)	(0.29)
G_M	-0.077	-0.054	0.005	-0.003	-0.043
	(0.80)	(0.98)	(0.12)	(0.10)	(1.05)
SSA	-0.388	-0.246	-0.387	-0.355	-0.257
	(1.43)	(1.95)*	(3.61)***	(3.51)***	(2.20)**
Asia	-0.528	0.045	0.038	-0.006	-0.000
	(1.68)*	(0.36)	(0.44)	(0.14)	(0.01)
LAC	-0.005	0.041	0.022	0.072	0.004
	(0.05)	(0.75)	(0.31)	(1.55)	(0.08)
Constant	-0.769	-0.572	-0.306	-0.299	-0.562
	(2.44)**	(2.60)**	(1.46)	(1.44)	(2.60)**
Observations	113	113	113	113	113
Psuedo R^2	0.46	0.48	0.45	0.39	0.30
Testing equality of aid coefficients: F-Stat (Prob>F)					
	5%	25%	50%	75%	95%
5% (1, 105)		0.01(0.939)	0.42(0.519)	0.57(0.453)	1.25(0.266)
25%			2.86(0.094)	3.69(0.057)	7.06(0.009)
50%				0.07(0.785)	0.96(0.330)
75%					2.37(0.127)

Notes: All variables except initial GDP (GDP_{t-1}) in logs. Absolute values of bootstrapped *t*-ratios in parentheses. Significance levels indicated as *, **, *** for 10%, 5% and 1% respectively. The F-stat tests the null of equal coefficients (probability of rejecting the null in parenthesis).

Including an interactive dummy, *PPEres*SSA*, only GDP_{t-1} and *PPEres*SSA* are significant. When the interactive term A_{t-1}*SSA is included, GDP_{t-1} and in some cases *PPEres* are significant

Table 2: Quantile Regressions for IM (Full Sample)

	5%	25%	50%	75%	95%
			Using SS/GDP for PPE		
GDP_{t-1}	-0.0002	-0.0002	-0.0002	-0.0003	-0.0002
	(1.32)	(2.06)**	(1.99)**	(3.04)***	(4.65)***
PPEres	-0.127	-0.440	-0.470	-0.306	-0.104
	(0.70)	(2.35)**	(3.18)***	(1.91)*	(0.94)
A_{t-1}	-0.053	-0.156	-0.168	-0.224	-0.129
	(0.64)	(1.51)	(1.94)*	(2.47)**	(1.74)*
G_M	-0.107	0.029	0.022	0.075	0.070
	(0.77)	(0.28)	(0.30)	(1.00)	(1.28)
SSA	1.154	0.412	0.297	0.218	0.373
	(2.34)**	(1.84)*	(1.50)	(1.36)	(3.27)***
Asia	0.283	-0.162	-0.102	-0.158	0.289
	(0.58)	(0.69)	(0.66)	(0.85)	(1.66)*
LAC	0.308	0.100	0.205	0.237	0.189
	(0.83)	(0.46)	(1.03)	(1.63)	(1.10)
Constant	2.506	3.132	3.296	3.883	4.385
	(2.58)**	(4.28)***	(5.78)***	(7.18)***	(12.26)***
Observations	112	112	112	112	112
Psuedo R^2	0.48	0.47	0.45	0.44	0.46
Testing equality of aid coefficients: F-Stat (Prob>F)					
	5%	25%	50%	75%	95%
5% (1, 104)		094(0.334)	1.15(0.287)	2.59(0.111)	0.48(0.489)
25%			0.02(0.893)	0.54(0.462)	0.05(0.817)
50%				0.53(0.466)	0.15(0.701)
75%					0.99(0.322)

Notes: As for Table 1. Including an interactive dummy, *PPEres*SSA*, GDP_{t-1} and A_{t-1} are significant at the 5th quantile; for all other quantiles, only GDP_{t-1} is significant. When A_{t-1}*SSA is included, GDP_{t-1} and in some cases *PPEres* are significant

Table 3: Quantile Regressions for HDI (restricted sample)

	Using unweighted PPE				
	5%	**25%**	**50%**	**75%**	**95%**
GDP_{t-1}	0.0001	0.0001	0.00003	0.00004	0.0001
	(2.99)**	(2.74)**	(1.71)*	(1.79)*	(2.33)**
PPEres	0.178	0.151	0.106	0.033	0.027
	(1.82)*	(2.18)**	(2.77)*	(0.98)	(1.09)
A_{t-1}	0.088	0.061	0.016	-0.006	0.009
	(1.78)*	(1.94)*	(0.47)	(0.26)	(0.43)
G_M	-0.100	-0.045	-0.020	0.029	-0.060
	(0.86)	(0.64)	(0.32)	(0.54)	(0.96)
Observations	81	81	81	81	81
Psuedo R^2	0.46	0.45	0.42	0.36	0.29

Testing equality of aid coefficients: F-Stat (Prob>F)

	5%	25%	50%	75%	95%
5% (1,73)		0.20(0.658)	1.34(0.251)	3.11(0.082)	2.14(0.148)
25%			2.04(0.158)	1.18(0.280)	0.84(0.363)
50%				0.78(0.380)	0.06(0.813)
75%					0.69(0.408)

	Using beta-weighted PPE				
	5%	**25%**	**50%**	**75%**	**95%**
GDP_{t-1}	0.0001	0.0001	0.00002	0.00003	0.00005
	(1.74)*	(2.42)**	(0.96)	(2.82)***	(2.09)**
PPEres	0.342	0.234	0.159	0.064	0.052
	(2.88)***	(2.80)***	(3.05)***	(2.00)**	(1.94)*
A_{t-1}	0.288	0.194	0.111	0.035	0.040
	(2.92)***	(2.44)**	(2.17)**	(1.08)	(1.55)
G_M	-0.041	-0.035	-0.030	0.032	-0.011
	(0.36)	(0.64)	(0.58)	(0.84)	(0.14)
Observations	81	81	81	81	81
Psuedo R^2	0.49	0.49	0.45	0.38	0.30

Testing equality of aid coefficients: F-Stat (Prob>F)

	5%	25%	50%	75%	95%
5% (1,128)		0.74(0.393)	3.30(0.073)	5.78(0.019)	5.91(0.018)
25%			1.37(0.245)	4.08(0.047)	3.14(0.080)
50%				2.75(0.101)	1.42(0.238)
75%					0.01(0.909)

Notes: As for Table 1. All regressions include a constant term and regional dummies.

Table 4: Quantile Regressions for IM (restricted sample)

	Using unweighted PPE				
	5%	**25%**	**50%**	**75%**	**95%**
GDP_{t-1}	-0.0001	-0.0002	-0.0002	-0.0003	-0.0003
	(0.74)	(1.84)*	(1.97)*	(4.01)***	(3.34)***
PPEres	-0.153	-0.292	-0.462	-0.225	-0.314
	(1.52)	(1.25)	(2.18)**	(1.08)	(2.14)**
A_{t-1}	-0.085	-0.108	-0.100	-0.159	-0.263
	(1.08)	(0.72)	(0.61)	(1.88)*	(2.04)**
G_M	0.016	-0.040	-0.016	0.050	-0.056
	(0.12)	(0.32)	(0.16)	(0.50)	(0.56)
Observations	80	80	80	80	80
Psuedo R^2	0.49	0.46	0.46	0.44	0.47
Testing equality of aid coefficients: F-Stat (Prob>F)					
	5%	25%	50%	75%	95%
5% (1,72)		0.03(0.860)	0.01(0.917)	0.31(0.582)	2.05(0.157)
25%			0.00(0.957)	0.13(0.721)	1.06(0.306)
50%				0.37(0.547)	1.16(0.286)
75%					0.86(0.356)
	Using beta coefficient weighted PPE				
	5%	**25%**	**50%**	**75%**	**95%**
GDP_{t-1}	-0.0001	-0.0001	-0.0001	-0.0002	-0.0003
	(0.88)	(2.43)**	(1.74)*	(1.65)	(2.32)**
lnPPEres	-0.690	-0.781	-0.678	-0.583	-0.553
	(2.74)***	(4.89)***	(2.90)***	(1.71)*	(1.97)*
LnA_{t-1}	-0.544	-0.603	-0.464	-0.518	-0.574
	(4.24)***	(4.29)***	(2.10)**	(1.94)*	(2.78)***
lnG_M	0.021	0.030	0.049	-0.034	-0.007
	(0.18)	(0.19)	(0.51)	(0.34)	(0.07)
Observations	80	80	80	80	80
Psuedo R^2	0.59	0.57	0.52	0.46	0.50
Testing equality of aid coefficients: F-Stat (Prob>F)					
	5%	25%	50%	75%	95%
5% (1,71)		0.18(0.669)	0.16(0.688)	0.01(0.915)	0.02(0.894)
25%			0.85(0.359)	0.11(0.736)	0.02(0.897)
50%				0.05(0.823)	0.19(0.664)
75%					0.07(0.796)

Notes: As for Table 3.