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An analysis of the basic relations

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Abstract:

Aid flows are included into the standard cross-country catch-up relation. Robustness of the result is tested by changing time periods and by adding extra variables. The main results are: Absolute convergence and absolute aid effectiveness are both rejected. While conditional convergence is accepted, conditional aid effectiveness is found to be weak. The two relations are largely independent. However, aid has a clear activity effect in the short run. Finally, we try to divide the countries into an A-group where aid is effective and a B-group where it harms. Several criteria of division were explored, but none were very successful – the most satisfactory is the one that divides countries according to their level of development.

Jel.: C14, C23, F35, O4

Keywords: *Convergence, growth, development aid effectiveness*

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1. Introducing the aid-growth puzzle

Poverty in the less developed countries (LDCs) causes huge losses of welfare in the world. Thus, enormous welfare gains would be associated with increasing the income level of the poorest of the poor. Until recently most people believed that development aid was the cure. Since aid programs started in the mid 1960s, the LDC world has received about 2½% of its aggregate GDP in aid per year.[1] Over 40 years this roughly corresponds to one year of GDP for all LDCs combined. Some have received less, and some much more. The average African country has thus received about 4 years of GDP in aid over the period. However, gradually many have come to doubt that aid works, and aid fatigue has spread in the donor countries. This paper took off from the idea that things might have gone much worse without aid, hence the question in the headline.

We started our quest from the idea that an answer could be found by merging two bodies of economic literature, the growth literature, or more precisely, the convergence literature (CL) and the aid effectiveness literature (AEL). Both employ large data sets on cross-sections of countries, and usually start from the puzzling observation that *the raw data show no correlation between economic growth and development aid*:

CL *Convergence Literature:* It considers the (g, y)-set of data, where y is the income level, and g is real economic growth. Convergence occurs if growth rates decrease with income levels, i.e., $\beta = \partial g/\partial y < 0$. It is rejected by the data, i.e., $\beta \approx 0$, so poor countries do not catch up with the rich countries: *Absolute* convergence is rejected.

AEL *Aid Effectiveness Literature:* It considers the (g, h)-set of data, where h is the development aid ratio, and g is growth as before. Aid is effective if growth increases with aid: $\mu = \partial g/\partial h > 0$. It is rejected by the data, i.e., $\mu \approx 0$, so aid is ineffective: *Absolute* aid effectiveness is rejected, by the criteria given.

Researchers in both fields have demonstrated that by imposing structures on the seemingly unrelated data it is possible to make them tell a different – *conditional* – story. The key structure imposed is the *model* used; but also the data may be reduced to a *subset*. Numerous structures are possible, and they often produce different results. Consequently we have chosen to be parsimonious as to structures permitted.

1. The unweighted average of the aid shares in the data is 7.4%. However, aid is heavily biased toward small countries, and about 30% of the data are missing. Countries with no data probably receive below average, so aid to the aggregate LDC-world is about 2½%.

The models used are always presented as being derived from economic theory, but they may also be a result of researchers mining the data. This is not so problematic in the growth literature, where the basic model has a clear link to neoclassical growth theory. It has been analyzed by numerous researchers, with many different priors. However, the aid effectiveness literature (of about 100 papers) is much smaller, the theory is less established, and the research may have a major prior, as will be discussed.

We proceed as follows: Section 2 surveys the theoretical framework used in the two bodies of literature. Section 3 presents the data and descriptive statistics. Section 4 analyzes the cross-country relations, studying the robustness to changes in the estimation periods, while section 5 presents panel data estimates, and tests the robustness by inclusion of extra variables. Section 6 divides the countries into an A-group where aid helps and a B-group where aid harms. Section 7 discusses the results, and finally section 8 summarizes the results.

2. The CL and the AEL: Two bodies of literature

Recent surveys, e.g., Barro and Sala-i-Martin (2004) and Doucouliagos and Paldam (2005), exist of both literatures, so we will be brief. For easy reference table 1 lists the models and variables discussed throughout the paper. The numbering indicates correspondence of models.

Table 1. The equations analyzed in the paper

Unmerged equations	CL: Growth equation		AEL: Aid effectiveness equation	
Basic version	$g_{it} = \alpha+\beta y_{it}+u_{it}$	(1a)	$g_{it} = \alpha+\mu h_{it}+u_{it}$	(1b)
Extended with controls	$g_{it} = \alpha+\beta y_{it}+\boldsymbol{\gamma}_j \boldsymbol{x}_{jit}+u_{it}$	(2a)*	$g_{it} = \alpha+\mu h_{it}+\boldsymbol{\gamma}_j \boldsymbol{x}_{jit}+u_{it}$	(2b)*
Extended with fixed effects	$g_{it} = \boldsymbol{\alpha}+\beta y_{it}+u_{it}$	(3a)	$g_{it} = \boldsymbol{\alpha}+\mu h_{it}+u_{it}$	(3b)
Level adjusted version	$g_{it} = \boldsymbol{\alpha}+\beta y_{it}+\delta g_{it-1}+u_{it}$	(4a)	$g_{it} = \boldsymbol{\alpha}+\mu h_{it}+\delta g_{it-1}+u_{it}$	(4b)
	Merged equation			
Basic	$g_{it} = \alpha+\beta y_{it}+\mu h_{it}+u_{it}$	(1c)		
Extended with fixed effects	$g_{it} = \boldsymbol{\alpha}+\beta y_{it}+\mu h_{it}+u_{it}$	(3c)		
Extended with one control	$g_{it} = \boldsymbol{\alpha}+\beta y_{it}+\mu h_{it}+\gamma x_{it}+u_{it}$	(3d)		
Level adjusted version	$g_{it} = \boldsymbol{\alpha}+\beta y_{it}+\mu h_{it}+\delta g_{it-1}+u_{it}$	(4c)		

Variables, coefficients, indices

g_{it}	real per capita growth for T = 5, 10, 15 years	α, $\boldsymbol{\alpha}$	Constant, fixed effects for countries $\boldsymbol{\alpha}_i$ and time $\boldsymbol{\alpha}_t$
y_{it}	log to initial real GDP per capita, PPP prices	β	Estimated coefficient of convergence,
h_{it}	aid, ODA, in % of GNP	μ	Estimated effect of aid
$\boldsymbol{x}_{jit}$	vector of j controls, one control is not bolded	δ, $\boldsymbol{\gamma}_j$	coefficients to be estimated
u_{it}	Residuals	i,t,j	Indices for countries, time and controls

Note: The models with * are not estimated in the present paper. Equation (3d) is used in section 5. Versions of (3) and (4) are estimated with the aid share lagged, they are termed (3dL), (4cL) etc.

2.1 The mining observation

The *Aid Effectiveness* (AEL) is the smaller literature of the two. The relevant macro data from the mid 1960s, where aid started, till the end of 2004, amount to about 4,050 annual observations. The models are estimated on data averaged to periods of 4 to 10 years. This reduces the data to between 400 and 800 observations. The study of the AEL cited shows that on subsets of these data 1,025 regressions have been published, but many more have surely been run. Consequently these data have been thoroughly mined. However, data mining in the convergence literature is much larger.

Test limits in econometrics are, by convention, the ones of *one* analysis run on virgin data. Mining reduces the risk of Type I errors (rejection of true model) and increases the risk of Type II errors (acceptance of false models). Three conclusions follow: (C1) Results that are not clearly visible in the raw data – or follow from basic models – should only be believed after repeated replication by independent authors on new data. (C2) Results hinging upon controls that are not strongly justified should be treated with suspicion. (C3) Moral hazard may be a problem – i.e., source critique is important in the field.

2.2 Absolute convergence rejected. Extended models agree on conditional convergence

One of the key theories of economics is the neo-classical growth model. Under rather general assumptions it shows that economies accumulate capital so as to reach the same steady state income per capita. A robust prediction from the model is that eventually all countries will converge to the same level of income.[2] The starting point for the growth literature is the question: Do the data show convergence? It is analyzed by the cross-country relation between income levels, y, and growth rates, g: $\beta = \partial g/\partial y$. Convergence implies that $\beta < 0$.

Data for y and g cover many countries and three to five decades, and thus include components of both time series and country heterogeneity. This calls for the question if convergence is *absolute*, so that it occurs irrespective of country heterogeneity, or if it is *conditional*, so that it only occurs if country heterogeneity is controlled for. This point was made in the classical study of cross-country growth patterns by Barro (1991) as extended in Barro and Sala-i-Martin (1995, 2004).[3] Consequently, it uses two steps of models:

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2. Two mechanisms secure the catch-up: (1) the logic of the model itself, i.e., diminishing returns to the two inputs (labour and capital), (2) technological catch-up.
3. Several alternative methods are used to study cross-country growth patterns. One is to study the pattern of growth paths for countries, see e.g., Quah (1993). It appears that a (small) A-group of LDCs does manage to get on a high growth path, where they catch up, while others stay in a B-group with a low growth path, where they lag increasingly more behind. Countries rarely cross over between the A- and the B-groups.

The first step analyzes absolute convergence by equation (1a) $g_{it} = \alpha + \beta y_{it} + u_{it}$. When model (1a) is estimated for rich countries only (see Baumol, 1986) convergence does occur, but for large data sets including the LDCs there is no absolute convergence, i.e., $\beta \approx 0$. The second step uses the two extended models (2a) or (3a) to control for country heterogeneity either by a set of concrete control variables $\boldsymbol{x}_{jit}$ or by fixed effects for countries $\boldsymbol{\alpha}_i$. Conditional convergence means that $\beta < 0$ in the extended model.

Version (2a) $g_{it} = \alpha + \beta y_{it} + \boldsymbol{\gamma}_j \boldsymbol{x}_{jit} + u_{it}$. The *j controls* are country levels of, e.g., education, health, investment, governance, resources, etc. A fairly broad range of the most credible $\boldsymbol{x}$-sets turn β negative. It appears optimistic that 5-10 controls can account for all country differences, but it is appealing that the controls are concrete. However, each variable of the $\boldsymbol{x}$-set normally misses some observations, so with a large $\boldsymbol{x}$-set only a subset of the (g, y)-data can be used in analysis. Also, the choice of $\boldsymbol{x}$-set gives the researcher considerable control over the resulting value of β, causing a problem of moral hazard.

Version (3a) $g_{it} = \boldsymbol{\alpha}_{it} + \beta y_{it} + u_{it}$. The constant is decomposed into a set of *fixed effects* for *countries*, $\boldsymbol{\alpha}_i$.[4] This cannot be done in pure cross-country regressions, so panel-regression techniques have to be used. Fixed effects for countries "only" assume that the country heterogeneity is approximately constant for the period analyzed. Fixed effects normally turns β negative, and the results are thus the same as the most credible results by (2a).

In choosing between version (2a) and (3a), we prefer the latter as it has six advantages: (a1) Policy questions are normally time series questions, so the data should be converted into time series as much as possible; (a2) it is simple; (a3) it is void of moral hazard. (a4) dummies are always available, so the full (g_{it}, y_{it})-set can be analyzed; (a5) such dummies are truly exogenous; and finally (a6) it leaves the variables from the standard $\boldsymbol{x}$-set for robustness tests, as we do in section 5.

2.3 Absolute aid effectiveness rejected. Extended models do not agree

The AEL empirically analyzes whether the macro data[5] for aid shares has an impact on growth rates, using models that are almost mirror images of those of the CL models as shown in Table 1. The discussions of aid effectiveness was started by theoretical papers by Friedman (1958) and Bauer (1971), who argued from an (explicit) libertarian position that aid goes to governments, and thus encourages countries to pursue unsound socialist policies.

4. Also, a set of fixed effects for time periods $\boldsymbol{\alpha}_t$ is often included to delete international economic fluctuations.
5. The corresponding micro literature analyzes the success rate of development projects, see e.g., Cassen (1994), the annual IBRD-OED reports. The main finding is that aid projects have a success rate of about 50%. Only very few projects do harm. By aggregation total aid thus have a positive impact on the recipient economy.

The AEL was started by an empirical critique of aid by Griffin (1970) and Weisskopf (1972),[6] who demonstrated that aid did not cause increased capital accumulation. Since then aid data have multiplied and a stream of papers have been published. At the start of 2005 the AEL has reached 97 studies. Doucouliagos and Paldam (2005) is a meta-analysis of these studies. It shows that average aid effectiveness coefficient, μ, is small, but positive. However, the AEL has not demonstrated that it is significant. As data have accumulated, the estimate of μ has steadily fallen, but it is (still) positive. The meta-analysis also shows that the usual priors affect the results.[7]

As under the convergence literature we can speak of two levels of models, which are formally parallel in both fields of research. Step 1 considers *absolute aid effectiveness* by the basic model (1b) $g_{it} = \alpha+\mu h_{it}+u_{it}$, which has no controls for country heterogeneity. Aid works if $\mu > 0$. Here $\mu \approx 0$ if all available data are considered – see tables 5 and 6 – absolute aid effectiveness is thus rejected. This seems an uncontroversial result.

Step 2 considers the two extended models (2b) and (3b) that control for country heterogeneity. Here no agreement has been reached. Researchers have managed to prove that $\mu > 0$ (38%), $\mu = 0$ (56%), and $\mu < 0$ (6%) by using version (3b) of the step 2 models.[8]

Version (2b) $g_{it} = \alpha+\mu h_{it}+\boldsymbol{\gamma}_j \boldsymbol{x}_{jit}+u_{it}$. The *j controls* of the $\boldsymbol{x}$-set are meant to catch irrelevant country differences, hereby letting the substantial coefficient, μ, of the model stand out clearly. However, the choice may also bias the estimate of μ. Even for the researcher it is probably often difficult to know if he has found the true model or confirmed his priors when somehow a model and the resulting estimates seem eminently believable.

Version (3b) $g_{it} = \boldsymbol{\alpha}+\mu h_{it}+u_{it}$, with fixed effects is our preferred extended version of the aid effectiveness relation. The arguments for preferring (3b) to (2b) are the same as the ones given above for preferring (3a) to (2a). Note that item (a1), *policy relevance* is strong. What we want to know is: What happens to the typical country if aid is either increased or decreased? We use this model to test for conditional aid effectiveness.

Many aggregate time series contain occasional cyclical components. When the series are aggregated to 5 years, the cyclical component may appear as a residual autocorrelation. Therefore it is possible that the results are sensitive to the inclusion of growth lagged. The

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6. Griffin and Weisskopf argued from an (explicit) left-wing position that aid is part of the world imperialist system causing the poverty of the poor countries.
7. The most problematic prior is that about 35% of the researchers in the field work in or for the *aid industry.* The annual aid budget is currently about \$60 billion. Many donors reserve a small fraction of the budgets for research, and about 35% of the AEL research is financed by such funds, see Doucouliagos and Paldam (2005c). The effect of *aid business affiliation* is small, but it is often significant, and in the direction expected.
8. The percentage numbers in the brackets are from Doucouliagos and Paldam (2005b).

two-level adjusted models: (4a) $g_{it} = \boldsymbol{\alpha}+\beta y_{it}+\delta g_{it-1}+u_{it}$, and (4a) $g_{it} = \boldsymbol{\alpha}+\mu h_{it}+\delta g_{it-1}+u_{it}$, have a δg_{it-1}-term to control for cyclical effects. As we shall see, it is a highly significant term when we consider 5-year averages in section 5.

2.4 *Merging the models – what may happen?*

When the two equations (1a) and (1b) are merged, they become: (1c) $g_{it} = \alpha+\beta y_{it} +\mu h_{it}+u_{it}$, as shown in table 1 The same happens to equations (2a) and (2b), etc. In each set of equations (#a) and (#b) are *unmerged* while equation (#c) is the *merged* version. We thus get an unmerged estimate of β and μ and a merged set of estimates of the same two variables.

A main point of our study is to systematically examine what happens to the two coefficients, β and μ, when the merged equation is estimated. Table 2 lists the five possibilities. One possible result is that aid and convergence is basically independent, while the others possibilities show that aid and convergence are interdependent. Note in particular the possible result 1, which shows that aid is effective, but the effect is "hidden" by the convergence mechanism, so everything becomes clearer once the two relations are merged.

Table 2. The five possible effects of merging the two basic equations

Possible result 1	Merger causes $\beta\downarrow$ and $\mu\uparrow$
Interpretation	Aid works. Less convergence with no aid
Possible result 2	Merger causes $\beta\uparrow$ and $\mu\uparrow$
Interpretation	Aid works. More convergence with no aid. Inconsistent
Possible result 3	Merger causes $\beta\uparrow$ and $\mu\downarrow$
Interpretation	Aid harms. More convergence with no aid
Possible result 4	Merger causes $\beta\downarrow$ and $\mu\downarrow$
Interpretation	Aid harms. More divergence with no aid. Inconsistent
Possible result 5	Merger has no effect on β and μ
Interpretation	Convergence is independent of aid. Consistent if $\mu \approx 0$

Note: Two inconsistent possibilities are shaded in gray.

2.5 *Third generation aid effectiveness studies: Dividing counties into A- and B-groups*

Another way to consider the absolute aid ineffectiveness result is that it shows that aid helps in about half of the cases and harms in the other half. This also happens if you toss a coin: In half the cases you get *heads* and in the other half you get *tails*. So a credible *condition*, z, is needed to divide the cases into the two groups, several such conditions have been proposed, and generated models (5a) and (5b), where $z = h$ is aid itself.

$$g_{it} = \alpha + \sigma z_{it} + \mu h_{it} + \omega z_{it} h_{it} + u_{it} \quad (5a)$$

$$g_{it} = \alpha + \mu h_{it} + \omega h_{it}^2 + u_{it} \quad (5b)$$

Both models can be extended with controls or fixed effects. As of the start of 2005 no less than 31 papers have proposed 10 conditioning variables.[9] The pace of publications during the last five years predicts that many more studies in this family may appear during the next five years. For reasons given above, the key criterion for the credibility of an effect is that it has been independently verified by other researchers on new data.[10] This has only been done for two of the models (discussed in the next two paragraphs), where replication failed so none of the proposed conditioning factors have, as of now, been established.

By far the most influential conditional model is the *Good Policy Model* of Burnside and Dollar (2000),[11] where z is an index of good policy, that is scaled to divide the countries in two groups: The A-group with good policies, where $z > 0$, and the B-group of countries with bad policies, where $z < 0$. The original estimate was $\sigma \approx 1$, $\mu \approx 0$ and $\omega > 0$. The good policy index is almost an index of outcomes, so it is trivial that $\sigma > 0$, and $\mu \approx 0$ is not surprising either. However, it is important that $\omega > 1$, as it means that aid increases growth in the A-group of countries, while it decreases growth in the B-group of countries. This result has appeared credible to many development practitioners, and it was popularized in World Bank (1998), *The Economist*, etc.[12] By now 22 papers have appeared with estimates of the model, of which 17 are independent attempts to replicate the model on expanded data, for different controls, etc. The replication attempts have rejected the model decisively.

The second most studied conditionality model is *the Medicine Model* (5b), where aid is interacted with itself. It has been proposed by several authors – most vigorously by Hansen and Tarp (2000). Their findings are that $\mu > 0$ and $\omega < 0$, so that while some aid increases growth, too much aid is harmful, just like medicine. Thus, the model predicts that an optimal dose of aid, h^*, exists. It has been estimated in 15 papers, but only nine are independent replications. The two coefficients μ and ω are both dubious for this model. Below in tables 7a and 7b we include aid squared, with no effect.

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9. Doucouliagos and Paldam (2005c) is a meta-study of the 31 papers.

10. The last eight conditioning variables are proposed in one or two papers. They await independent replication.

11. Burnside and Dollar use the EDA aid data, from Chang, Fernandez-Arias and Serven (1998), where each aid loan/gift is cleaned for non-grant elements. The results are seemingly invariant to this refinement, as the standard ODA and the new EDA data have a coefficient of correlation of 0.83.

12. It was also advocated in Paldam (1997a) and in several popular articles till the author attempted to replicate the model, see Jensen and Paldam (2005).

Our conclusions from the literature review are: (R1) Absolute aid effectiveness is rejected. (R2) A weak and non-conclusive conditional relation from aid to growth has been found. (R3) Aid may work differently in different countries. That is, we may be able to identify an A-group of countries, where aid works, and a B-group, where it rather harms.

2.6 Three types of possible biases in the AEL

In estimates of cross-country relations between macro variables it is very difficult to single out a relation where the explanatory variables are fully independent and exogenous. It is thus always possible to point to possible biases – this is also the case at present. We shall treat the possible biases under three headings:

(B1) ***Reverse causality*** bias: Many studies adjust the estimates for reverse causality (by TSLS or GMM estimates), but it appears to have no effect on the results (see Doucouliagos and Paldam 2005b). The main reason is that growth is a minor explanatory variable in explaining aid; see e.g. Alesina and Dollar (2000). To deal with this bias we lag the aid variable relative to the *g* and the *y* variable in section 5.

(B2) Distinguishing between ***activity and capacity effects***: Aid does lead to (public) spending, in order to generate development (i.e., growth).[13] There is some lag involved, but standard macro theory predicts that aid must lead to economic activity in the short run. Activity has multiplier effects, so one can count on aid causing an increase in *y* the same year, and for perhaps two more years – this will appear as a short-run positive correlation between aid and growth as shown in section 3. This peak is not a growth effect. It would appear even in the proverbial case where the aid is used to finance the digging of holes and filling them up again. It is our impression that some of the findings in the literature of a positive aid-to-growth effect reported in the literature are activity effects.

(B3) ***Omitted variable biases***: Two of these are: (B3.1) The big country bias: Large LDCs tend to grow faster than small ones and to receive less aid. (B3.2) The scaring-away bias: Particularly bad rulers tend to scare away both aid and investment, see Levy (1988). We have decided to disregard these biases, assuming that they cancel each other out. However, we control for the Gastil index for political freedom in section 5.

13. A large literature deals with the expressed (and other) purposes of aid. We note that aid is given to poor countries, and when countries cease to be poor, aid flows stop, so the sine qua non of aid is poverty.

3. Data and some descriptive statistics

This section describes the data and takes a first look at some descriptive statistics, showing the structure of correlations.

3.1 Data: Three main time series and six control variables

Growth rate, g = $(\ln(GDP_t) - \ln(GDP_{t-T}))/T$, where T = 10, 15 in the cross-section regressions and 5 in the panel regression: WDI data on GDP per capita. Growth rates in domestic prices reflect the trade-offs agents actually face.

Initial GDP, y = logarithm of RGDPCH (real GDP per capita in 1985 international prices, chain index) from the Penn World Tables.[14]

Aid share, h = ODA/GDP, both in current US $. ODA (Official development assistance) is net disbursements of loans and grants made by official agencies of the members of DAC and some Arab countries, to promote economic development and welfare in recipient economies listed as developing by DAC. Only loans with a grant element of more than 25% are included. ODA also includes technical cooperation and assistance.[15]

Investment share: This is an average of real gross domestic investment, private and public, in proportion to GDP (source PWT).

Inflation: Defined as infl/(1+infl) where infl is the average of the log difference of the GDP deflator. This transformation reflects the magnitude of the inflation distortion in production (see Herbertsson, 1999) and, equivalently, the implicit inflation tax rate. It attempts to capture the nonlinear relationship between growth and inflation: Growth is thus less sensitive to an increase in inflation from 500 to 600% per year than, say, an increase from 2 to 100% per year. The deflator is derived by dividing current price estimates of GDP at purchaser values (market prices) by constant price estimates (source WDI).

External debt: The average of foreign debt divided by GDP at market prices. Foreign debt consists of the outstanding stock or recognized direct liabilities of the government to the rest of the world, generated in the past and scheduled to be extinguished by government operations in the future or to continue as perpetual debt (source WDI).

Openness: The average of the sum of exports and imports of goods and services divided by GDP. Exports (imports) of goods and services represent the value of merchandise exports

14. See Nuxoll (1994) on use of WDI-data in local prices and Penn World Tables in PPP prices.

15. Official aid refers to aid flows from official donors to the transition economies of Eastern Europe and the former Soviet Union and to certain advanced developing countries and territories as determined by DAC. Official aid is provided under terms and conditions similar to those for ODA.

(imports) plus amounts receivable from (payable to) nonresidents for the provision of non-factor services to residents. Nonfactor services include transportation travel, insurance, and other nonfactor services such as government transactions and various fees (source PWT).

Economic Freedom: The logarithm of economic freedom from Fraser Institute.

Political Freedom: The Gastil index of political freedom from Freedom House.

Table 3. Averages in 1971-2000 based on 72 aid recipients where full data set exists

Sorted according to growth			Sorted according to aid		
Three fractiles	Growth	Aid share	Three fractiles	Aid share	Growth
Slowest growth	-1.7%	9.9%	Highest aid	14.3%	-0.4%
Middle group	0.8%	5.9%	Middle group	4.7%	1.1%
Fastest growth	3.5%	3.9%	Lowest aid	0.7%	1.8%

Note: The averages are unweighted. Guinea-Bissau and Sao Tome and Principe are excluded. They have had moderate growth, but an average aid inflows of no less than 48% and 62% respectively.

3.2 *Some correlations*

Table 3 shows a negative connection between aid and growth. This can be interpreted in the two ways the data are sorted: (i) The countries with the slowest growth receive most aid; or (ii) the more aid countries receive the slower they grow. If argument (ii) is true, then aid is rather harmful. The top line in the table considers (72/3 =) 24 countries with average aid shares of 14.3% and an average growth of -0.4%, while the bottom line show that the 24 countries that receive 0.7% in aid grow by 1.8%, no less than 2.2% faster per year.

Table 4. The cross-country correlations between aid and growth

5-year averages			10-year averages			15-year averages			30-year averages		
Period	LDCs	All	Period	LDCs	All	Period	LDCs	All	Period	LDCs	All
1971 - 75	-0.03	0.05	1971 - 80	0.02	0.00	1971 - 85	0.03	-0.01	1971 - 00	**-0.25**	**-0.39**
1976 - 80	-0.07	**-0.23**	1981 - 90	-0.02	-0.04	1986 - 00	-0.16	-0.19			
1981 - 85	0.13	0.12	1991 - 00	0.04	-0.01						
1986 - 90	-0.08	-0.12									
1991 - 95	-0.03	-0.04									
1996 - 00	0.10	-0.03									

Note: The sample has 170 countries, of which 140 are LDCs. Some series have missing observations, so the number of observations varies depending on data availability. The 5% significance point for the two-sided coefficient of correlation is about ± 0.2 for 100 observations.

The strong negative connection between the average values of the two series shows up in the last column to the right in table 4. The average correlation is no less than -0.39 or -0.25 if only LDCs are considered. However, the rest of table 4 shows that the picture is more complex. Most of the 24 correlations are negative, including all three significant ones. However, 21 correlations are insignificant, and eight are positive.

3.3 Correlograms: A first look at the dynamics

Figures 1 and 2 show average correlograms done for the annual data for the same 72 countries analyzed in table 3. For the data of country i we have calculated the correlogram c_{ij} = corr(h_{it+j}, g_{it}), where j = -14, -9, ..., +14. This generated 72 correlograms, but we only present (2 x 3) averages, corresponding to the (2 x 3) data sets of table 3. Each point is calculated from between 1,152 and 2,160 observations, with less at the two ends and most at the center. The correlations move by 0.2 to 0.3 around the zero axis, so even when most of the averages are in the range from -0.1 to +0.1, there are nevertheless substantial movements in the curves.

Figure 1. Aid-growth correlograms for the 72 countries of table 3, sorted by aid share

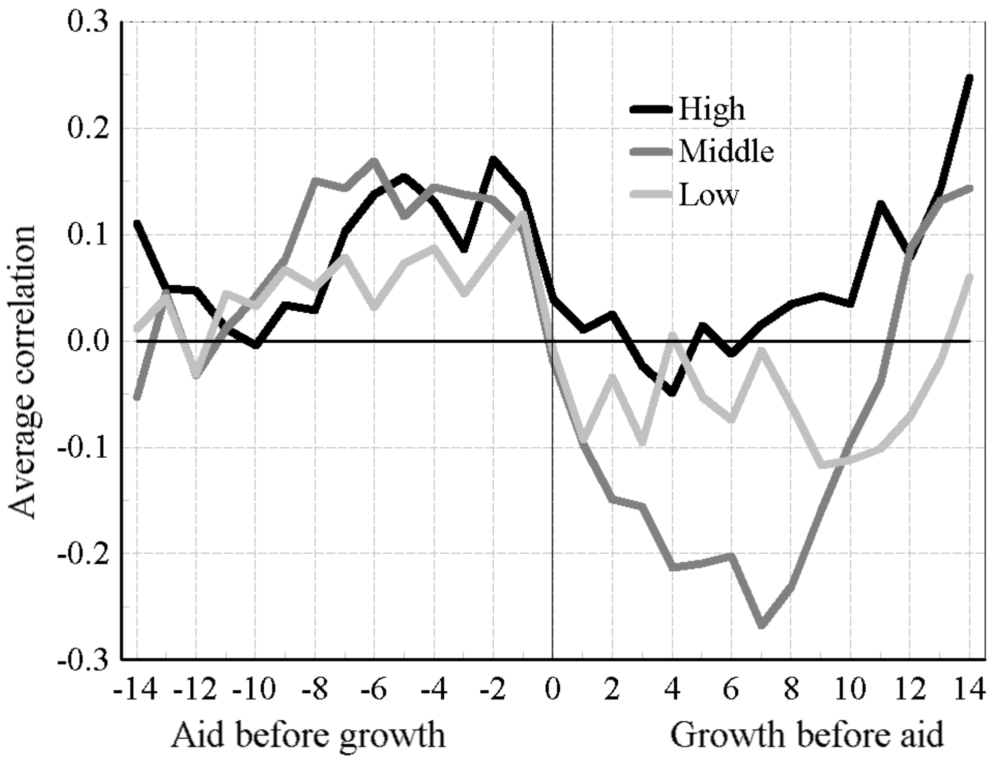
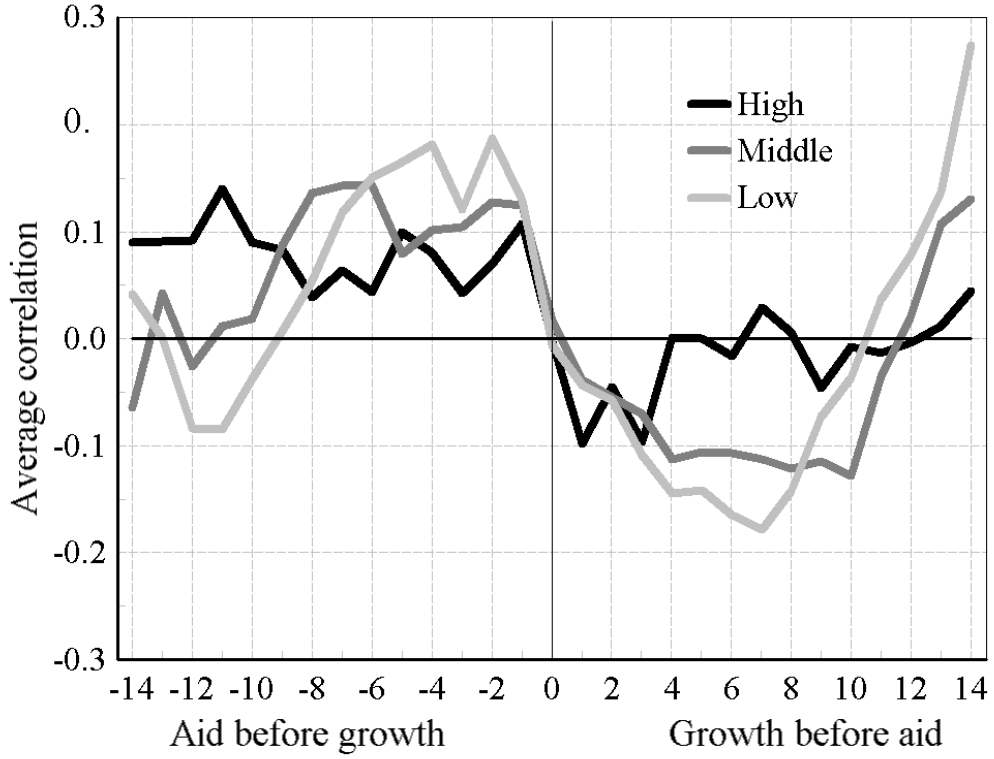


Figure 2. Aid-growth correlograms for the 72 countries of table 3, sorted by growth



Figures 1 and 2 provide no information about the catch-up of poor countries. The figures illustrate the dynamics, and hence the causality, between aid and growth within the average country of each group. It is hence a starting point when we sort out two biases: (B1) the reverse causality bias and (B2) the activity effect that should be separated from the growth effect.

The ***aid before growth*** part of the graphs is the left hand part, which analyzes the causal link from aid to growth. For j = -14 to -10 we see how aid in year t is correlated with growth 14 to 10 years later. With such a long lag there should be very little to see, as is indeed the case. However, for j = -8 to -1 we see the effect of aid in the form of a *positive hump* on curves. For j = 0 we look at the simultaneous relation between the two variables – it should be small as is the case. Note the positive humps are in the order of 0.05 to 0.15, so the growth hump due to aid is small. Also, figure 1 shows that the hump is largest for countries receiving the least aid, and smallest for the countries receiving most aid. On figure 2 the hump is lowest for the countries with the lowest growth. Obviously countries that already receive high aid and have low growth benefit little from additional aid.

The ***growth before aid*** part of the graphs is the right hand part, which analyzes the causal link from growth to aid. Here the picture is less clear, but we do see – on most curves – a *negative hump* for j = 1 to 3-8. So an economic crisis does give more aid, and after 3-9 years there is an upswing. Whether this upswing is due to the aid or would have happened anyhow is not clear. Note that the negative bumps are smallest in high aid and in the high growth countries. However, there are two problems with this interpretation. Firstly, the largest positive growth effect (hump) is found in the countries receiving less than 1% in aid. This appears unreasonable. Secondly, it is well known that correlograms are sensitive to cyclical movements in the series. That is, some of the systematic movements may be cyclical movements in the growth rate and the level of aid. In other words the positive humps at the right hand side of the two figures may be an upturn automatically following the downturn shown at left hand side – not due to the aid.

The possibility of cyclicality explains why we include the term δg_{it-1} in the equations (4) of tables 1 and in the estimates below. With lags of five years between growth and past growth, cyclicality should cause a negative coefficient to past growth. We expect some multicollinearity between the effect of aid and the effect of past growth if past growth produces negative coefficients as expected.

4. Cross-country estimates: Robustness to period changes

In this section we look for the contribution of aid to catch-up in a standard cross-country convergence equation; we here consider averages over 10 and 15 years.

4.1 The basic cross-country regressions

Tables 5a and 5b show the basic cross-country regressions for as many countries as we have been able to include and for LDCs alone. No control variables are included, and no countries have been deleted for any other reason than missing data. Each section contains two 15-years averages and three 10-years averages separated by a dotted line.

In both table 5a and 5b all estimates are very small with R^2 are below 0.1, and only few coefficients are significant. Also we see from the 20 estimates of β by relation (1a) that absolute convergence is rejected (the simple average[16] is 0.003, with the standard error of 0.004), and from the 20 estimates of μ by relation (1b) that absolute aid effectiveness is rejected too (the simple average is 0.005, with the standard error of 0.044). This is all as expected. There is neither absolute convergence nor absolute aid effectiveness.

16. The simple average is, of course, a very crude measure as the statistics are calculated on samples of the same data, but other averages give almost the same result, as the reader can easily verify.

Table 5a. Basic cross-country regressions for all countries. Three versions of model (1)

Models see Table 1	g Period	α Constant	y Init	B Catch-up	μ Aid effect	R^2	N
(1a)	71-85	-0.011 (0.56)	71	0.003 (1.37)		0.02	103
$g_{it} = \alpha$	86-00	**-0.033 (2.00)**	86	**0.006 (2.83)**		0.06	135
$+\mu y_{it}+u_{it}$	71-80	-0.012 (0.54)	85	0.004 (1.51)		0.02	103
	91-00	**-0.045 (2.30)**	90	**0.007 (2.86)**		0.07	119
	91-00	-0.030 (1.54)	95	0.005 (2.27)		0.03	149
(1b)	71-85	**0.010 (2.51)**			-0.003 (0.07)	0.00	96
$g_{it} = \alpha$	86-00	**0.013 (4.51)**			**-0.042 (2.23)**	0.04	138
$+\mu h_{it}+u_{it}$	71-80	**0.019 (3.91)**			0.001 (0.03)	0.00	97
	81-90	0.007 (1.68)			-0.015 (0.50)	0.00	114
	91-00	**0.011 (3.07)**			-0.004 (0.17)	0.00	154
(1a)	71-85	-0.022 (0.57)	75	0.004 (0.89)	0.038 (0.66)	0.01	77
$g_{it} = \alpha+\mu y_{it}$	86-00	-0.022 (0.76)	86	0.004 (1.27)	-0.016 (0.60)	0.04	111
$+\mu y_{it}+u_{it}$	71-80	**-0.085 (1.94)**	85	**0.013 (2.36)**	**0.131 (1.88)**	0.08	77
	81-90	-0.029 (0.81)	90	0.005 (1.11)	-0.017 (0.44)	0.03	92
	91-00	-0.022 (0.70)	95	0.004 (1.15)	-0.008 (0.27)	0.02	125

Notes: Estimates in brackets are (t-tests). Significant coefficients, where $t \geq 1.7$, are bolded.
Init means initial value is from the said year.

Table 5b. Same cross-country regressions as table 5a for LDCs only

Models see Table 1	g Period	α Constant	y Init	B Catch-up	μ Aid effect	R^2	N
(1a)	71-85	0.040 (1.32)	71	-0.004 (0.95)		0.01	74
$g_{it} = \alpha$	86-00	-0.020 (0.82)	86	0.004 (1.21)		0.02	97
$+\mu y_{it}+u_{it}$	71-80	0.002 (0.06)	85	0.002 (0.44)		0.00	74
	91-00	0.023 (0.78)	90	-0.003 (0.70)		0.01	83
	91-00	-0.021 (0.70)	95	0.004 (1.01)		0.01	108
(1b)	71-85	**0.008 (2.13)**			0.012 (0.29)	0.00	80
$g_{it} = \alpha$	86-00	**0.011 (3.26)**			**-0.042 (1.90)**	0.03	111
$+\mu h_{it}+u_{it}$	71-80	**0.017 (3.72)**			0.009 (0.16)	0.00	80
	81-90	0.001 (1.15)			-0.006 (0.18)	0.00	91
	91-00	**0.008 (1.97)**			0.013 (0.45)	0.00	124
(1a)	71-85	0.030 (0.74)	75	-0.003 (0.52)	0.010 (0.17)	0.01	71
$g_{it} = \alpha+\mu y_{it}$	86-00	-0.005 (0.15)	86	0.002 (0.54)	-0.023 (0.87)	0.03	96
$+\mu y_{it}+u_{it}$	71-80	-0.045 (0.93)	85	0.008 (1.24)	0.112 (1.50)	0.04	70
	81-90	0.045 (1.22)	90	-0.005 (1.12)	-0.044 (1.18)	0.02	79
	91-00	-0.013 (0.35)	95	0.003 (0.64)	-0.009 (0.29)	0.01	107

Notes: See table 5a.

When all 30 regressions of tables 5 are considered, they give 10 (dependent) estimates of the change in the catch-up coefficient $\Delta\beta \approx 0.001$, and the change in aid effectiveness $\Delta\mu \approx 0.025$, so instead of a small negative aid effectiveness of -0.008 a small positive one of 0.017 appears. However, the two coefficients remain insignificant.

5. Panel estimates: Robustness to extra variables

Tables 6a and 6b repeat table 5a and 5b for the panel-version of the model. Section 5.2 contains a set of robustness tests. The R^2-score rises dramatically, when we control for fixed effects, and convergence, $\beta < 0$, becomes stable and significant for all 12 regressions shown. All estimates of β are in the small range from -0.038 to -0.051, with t-ratios between six and eight. They hardly react to the merger between the two models, nor to the inclusion of a cyclical component, which is growth lagged. In fact, when we try the six controls in 5.2, the estimate to β is still unchanged. Conditional convergence is thus confirmed as expected.

5.1 The mixed effect of aid in the panel estimates

The first observation is that μ has a systematic change of sign. When aid is unlagged it is always negative and insignificant, but when lagged it is positive and significant in all four lagged regressions (3aL) and (4aL). On a first glance we thus find that aid works. However, as soon as we merge the relations – that is, control for development level – all four estimates of μ fall (by an average of 0.147) and become insignificant (though still positive). It is remarkable that the fall of the coefficient is significant in all four cases. As there are no contrary movements in the estimates of β, we cannot conclude that aid has prevented convergence, but only that if the relation is not controlled for GDP level, it is misspecified.

The coefficient to past growth is negative – as it should be if there is a cyclical component in growth. When it is included, it reduces the negativity of aid to insignificance. If we accept this interpretation, we have to go back to figures 1 and 2 and interpret the growth effect we thought we found at lags j = +5 to +9 as a cyclical effect. However, this interpretation is dubious. So, our basic result is that aid has no clear effect on growth. As the numbers of observations are from 422 to 766, even small effects should show up significant. The results are much like the cross-country results, as regards aid. Nothing is believable and significant, in spite of the fact that the other two variables produce statistically significant results, and a very stable catch-up effect is found.

Table 6a. Panel estimates for all countries – note the versions with aid lagged (L)

Models (3) and (4) with fixed effects	g Starts	y Init	β Catch-up	μ Aid effect	δ Cyclical	R^2	N	NC
(3a) $g_{it} = \boldsymbol{\alpha}+\beta y_{it}+u_{it}$	71-75	71	**-0.038 (6.77)**			0.42	766	166
(3b) $g_{it} = \boldsymbol{\alpha}+\mu h_{it}+u_{it}$	71-75			-0.033 (0.97)		0.32	744	162
(3bL) $g_{it} = \boldsymbol{\alpha}+\mu h_{it-1}+u_{it}$	76-80			**0.185 (6.39)**		0.43	592	160
(3c) $g_{it} = \boldsymbol{\alpha}+\beta y_{it}+\mu h_{it}+u_{it}$	71-80	71	**-0.047 (6.89)**	-0.050 (1.56)		0.43	610	141
(3cL) $g_{it} = \boldsymbol{\alpha}+\beta y_{it}+\mu h_{it-1}+u_{it}$	76-80	76	**-0.046 (6.07)**	0.037 (1.43)		0.54	499	141
(4a) $g_{it} = \boldsymbol{\alpha}+\beta y_{it}+\delta g_{it-1}+u_{it}$	76-80	76	**-0.039 (5.81)**		**-0.225 (5.49)**	0.54	632	165
(4b) $g_{it} = \boldsymbol{\alpha}+\mu h_{it}+\delta g_{it-1}+u_{it}$	76-80			-0.042 (1.08)	**-0.357 (7.56)**	0.44	604	158
(4bL) $g_{it} = \boldsymbol{\alpha} +\mu h_{it-1}+\delta g_{it-1}+u_{it}$	76-80			**0.204 (6.57)**	**-0.186 (4.11)**	0.47	581	158
(4c) $g_{it} = \boldsymbol{\alpha} +\beta y_{it}+ \mu h_{it}+\delta g_{it-1}+u_{it}$	76-80	76	**-0.049 (6.03)**	**-0.065 (1.76)**	**-0.210 (4.59)**	0.55	507	140
(4cL) $g_{it} = \boldsymbol{\alpha}+\beta y_{it}+\mu h_{it-1}+ \delta g_{it-1}+u_{it}$	76-80	76	**-0.044 (5.69)**	0.032 (1.08)	**-0.112 (2.46)**	0.56	492	140

Note: $\boldsymbol{\alpha} = \boldsymbol{\alpha_i}+\boldsymbol{\alpha_t}$ are fixed effects. *Init*, means the initial year corresponding to the first period.

Table 6b. Panel estimates for LDCs only – note the versions with aid lagged (L)

Models (3) and (4) with fixed effects	g Starts	y Init	β Catch-up	μ Aid effect	δ Cyclical	R^2	N	NC
(3a) $g_{it} = \boldsymbol{\alpha}+\beta y_{it}+u_{it}$	71-75	71	**-0.048 (6.35)**			0.40	543	120
(3b) $g_{it} = \boldsymbol{\alpha}+\mu h_{it}+u_{it}$	71-75			-0.020 (0.54)		0.32	596	129
(3bL) $g_{it} = \boldsymbol{\alpha}+\mu h_{it-1}+u_{it}$	76-80			**0.162 (5.04)**		0.41	475	129
(3c) $g_{it} = \boldsymbol{\alpha}+\beta y_{it}+\mu h_{it}+u_{it}$	71-80	71	**-0.051 (6.50)**	-0.040 (1.23)		0.41	526	119
(3cL) $g_{it} = \boldsymbol{\alpha}+\beta y_{it}+\mu h_{it-1}+u_{it}$	76-80	76	**-0.050 (5.54)**	0.040 (1.49)		0.53	427	119
(4a) $g_{it} = \boldsymbol{\alpha}+\beta y_{it}+\delta g_{it-1}+u_{it}$	76-80	76	**-0.047 (5.00)**		**-0.194 (3.85)**	0.52	446	119
(4b) $g_{it} = \boldsymbol{\alpha}+\mu h_{it}+\delta g_{it-1}+u_{it}$	76-80			-0.071 (1.54)	**-0.382 (6.72)**	0.42	488	127
(4bL) $g_{it} = \boldsymbol{\alpha} +\mu h_{it-1}+\delta g_{it-1}+u_{it}$	76-80			**0.184 (5.18)**	**-0.153 (2.70)**	0.43	467	127
(4c) $g_{it} = \boldsymbol{\alpha} +\beta y_{it}+ \mu h_{it}+\delta g_{it-1}+u_{it}$	76-80	76	**-0.049 (5.06)**	-0.055 (1.39)	**-0.195 (3.80)**	0.53	437	118
(4cL) $g_{it} = \boldsymbol{\alpha}+\beta y_{it}+\mu h_{it-1}+ \delta g_{it-1}+u_{it}$	76-80	76	**-0.046 (4.97)**	0.036 (1.16)	**-0.080 (1.56)**	0.54	422	118

Note: See table 6a.

The two changes when the model is merged can be calculated for eight (dependent) pairs. All but one values of $\Delta\beta$ are negative, but small, as the average $\Delta\beta \approx -0.005$. $\Delta\mu$ is negative too in all cases but one, with an average value of $\Delta\mu \approx -0.079$. This is substantial relative to the size of the coefficients, and shows that the positive effect of aid lagged in (3bL) is an artifact. Also, note that the sign of the two changes is the reverse for the cross-country and the panel estimates. Note finally that the marginal R^2 generated by the merger of the models is always very small. As in section four we find no clear evidence of aid effectiveness.

5.2 *Extra variables – some robustness tests*

Table 7a tests the basic relation (3c) of table 6 for robustness, by including a set of extra variables. Table 7b does the same for (3cL). We have included only variables with some basis in economic theory, so that each of the new variables included might tell a story.

The first line repeats the regression tested from table 6a, and then six extra variables are included one at the time. The convergence coefficient stays as constant as one could wish. However, also the coefficient to aid remains largely stable. Only one of the extra variables changes the coefficient in size, but two of them destroy the significance, so the robustness of the aid effect is also reasonably good. The economic interpretation is straightforward:

Table 7a. Equation (3c) with one control variable, γx

Aid unlagged Extra variable x =	*B* Catch-up		*μ* Aid effect		*γ* Effect of x		R^2	N	NC
Equation (3c)	**-0.047**	**(6.89)**	-0.050	(1.56)			0.43	610	141
Investment	**-0.044**	**(6.52)**	-0.040	(1.27)	**0.135**	**(3.48)**	0.44	595	129
Inflation	**-0.046**	**(7.15)**	**-0.053**	**(1.74)**	-0.000	(0.04)	0.44	587	128
Debt burden	**-0.060**	**(7.62)**	**-0.082**	**(2.41)**	**-0.001**	**(6.63)**	0.46	547	126
Openness	**-0.055**	**(7.99)**	**-0.065**	**(2.10)**	**0.050**	**(4.86)**	0.46	595	129
Economic	**-0.054**	**(7.86)**	**-0.075**	**(1.71)**	**0.067**	**(7.66)**	0.53	448	98
Gastil index	**-0.049**	**(6.48)**	-0.046	(1.38)	0.001	(0.08)	0.42	562	130
Aid squared	**-0.048**	**(6.96)**	**-0.085**	**(1.76)**	0.057	(0.97)	0.43	610	141

Note: This is done for the full data set. Once more we have done everything for the LDCs alone and found the same pattern at a marginally lower level of significance.

Table 7b. Equation (3cL) – for aid lagged – with one control variable, γx

Aid lagged Extra variable x =	*β* Catch-up		*μ* Aid effect		*γ* Effect of x		R^2	N	NC
Equation (3cL)	**-0.046**	**(6.07)**	0.037	(1.43)			0.54	499	141
Investment	**-0.042**	**(5.60)**	0.036	(1.41)	**0.121**	**(2.77)**	0.55	484	128
Inflation	**-0.046**	**(6.03)**	0.043	(1.69)	**0.020**	**(2.01)**	0.55	481	128
Debt burden	**-0.047**	**(5.29)**	0.043	(1.63)	0.001	(1.28)	0.53	450	126
Openness	**-0.050**	**(6.75)**	0.013	(0.51)	**0.050**	**(4.84)**	0.57	484	128
Economic	**-0.058**	**(7.10)**	-0.066	(1.54)	**0.059**	**(6.06)**	0.56	391	98
Gastil index	**-0.048**	**(5.55)**	0.041	(1.51)	0.001	(0.10)	0.54	456	130
Aid squared	**-0.046**	**(6.04)**	0.038	(1.44)	-0.008	(0.54)	0.54	499	141

Note: See note to table 7a.

Investment is known to be the most robust variable in growth regressions since Levine and Renelt (1992), and investment does get a large and significant coefficient in the estimate. However, it leaves the two other coefficients unchanged. The aid flows and domestic investments give rise to no multicollinearity. The next four variables are meant to catch aspects of domestic policies.

High inflation and high debt are strong signs of unsuccessful policies. However, while the inflation tax is an alternative to borrowing money, aid is not all gifts, so aid adds to debt. These connections are quite visible in our regressions – there is an uncannily strong (and unreasonable) negative effect of aid when the debt burden is added. However, when the aid variable is lagged the effect disappears.

The effect of adding the economic freedom index is confusing. It has no effect on the size of the effect of aid, but it takes away the significance. This is likely to be an effect of multicollinearity, but we note that the economic freedom index has a rather strong effect on growth. Our experience is that it works better in log form, indicating that while it helps to go from a very highly restricted economy to a more liberal one, the additional effect of going all the way to the laissez faire is not so large. Also, we have tried the Gastil index of democracy with little success. Finally we controlled for aid squared to test the Medicine Model from section 2.4. It fails in both regressions.

6. Can we identify an A- and a B-group of LDCs?

The above discussion of the literature and some of our findings suggest that the aid recipients may fall in two groups: The A-group where aid increases growth, and the B-group where it harms growth. Below we use three criteria for sorting the countries in the two groups.

We start the analysis by sorting the countries by the grouping criterion, and estimate the aid equation on all data. Then one country is deleted at a time, from the most *extreme* end, and the relation is then re-estimated, to see how the coefficient reacts. As we want to identify structural breaks, we have to use a consistent sample, so from now we look at the 72 LDCs where we have a full data set only.

6.1 Three possible division criteria for the groups

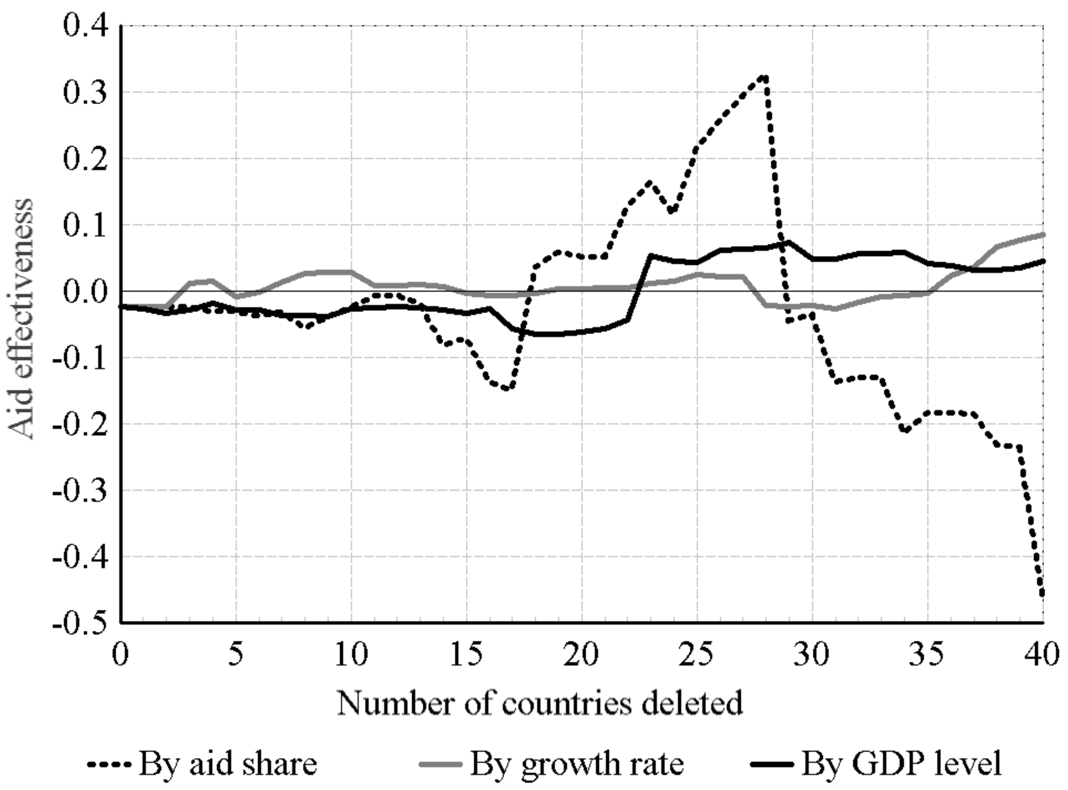
We have encountered two theories about the nature of the groups in the literature, and have added a third model that we term the *Low Trap Model*.

The *Good Policy Model* characterizes the groups according to policies: The A-group consists of countries with good policies, the B-group consist of countries with bad policies. While the A-countries use aid successfully, it harms the B-countries. Some of the results quoted in section 5.2 seem to support this view. Here the countries sorted by average growth. The extreme end is the country with the lowest growth, indicating that it has the worst policy. The theory here predicts *one shift* from a negative to a positive coefficient.

The *Medicine Model* distinguishes between an A-group that receives little to moderate aid, while the B-group is a (small) group suffering from aid dependence. Some of the results in section 3 seemed to support this view, but it failed in the direct tests reported in the last lines of tables 7a and b. Here the countries are sorted by aid share and the extreme end is the country with the highest aid share. The theory predicts negative coefficients for all countries, and then that the curve turns positive, and finally falls to zero.

The *Low Trap Model* essentially says that the B-group is the poorest countries, who are trapped in some low level equilibrium, where the development process cannot be started in spite of aid. The countries are here sorted by GDP level, with the poorest country as the most extreme. We predict a negative curve that switches over to positive.

Figure 3. Looking for breaks establishing the A- and the B-group



The three experiments are all made on simplified versions of the models, so that the results are no full test of the models, they only give an indication of the support for the model.

6.2 Three division experiments

The estimates give the three curves of figure 3. They all start at the same point:

(3c) $g_{it} = \boldsymbol{\alpha} - 0.083(7.9)\, y_{it} - 0.023(0.4)\, h_{it} + u_{it},$

where $R^2 = 0.61$, N = 198, NC = 72. This is almost the same relation as (3b) in table 7b, though estimated for consistent series, and thus only for 72 countries. That is the estimate above 0 on the horizontal axis. Then the most extreme observation is deleted in the three ways described, and then the second most, and the third most, and now the three curves start to deviate a little.

The least interesting curve is the one where deletion is done by growth rate. It never deviates much from zero, so we find no support for the *Good Policy Model*. The most volatile curve is the one for the *Medicine Model*. It does behave mostly as it should according to the model, but there are too many swings suggesting that something more is going on. However, also the *Low Trap Model* has one shift as it should. When the 22 poorest countries are included, aid has a negative effect on growth, and when they are all deleted the effect is positive. The main problem is the small size of the shift.

When everything is put together we have to conclude that the evidence that the data contains an A-group where aid works and a B-group where aid rather harms is dubious.

7. How "bad" are our bad results?

The above analysis tried to answer the following question: Does development aid help poor countries catch up? The question is analyzed by standard cross country and panel regression techniques. With some qualifications the answer is: The present aid flows have no clear effect on the catch-up. The result we have reached in the above empirical analysis is thus negative. This raises three questions: (Q1) How robust are the results? Would other approaches produce a different answer? The other two questions assume that the result is robust: (Q2) How can it be explained? (Q3) Can the aid be reformed so as to generate catch-up? The next three sections address these questions.

7.1 *Are the results robust to the choice of analytical technique?*

The results of our study confirm the results found in the recent meta-studies cited. So readers who know the literature should not be surprised. However, we know that our results are controversial – see, e.g., the more optimistic conclusions in the set of papers introduced by Hudson (2004).

There are alternatives to the models and technique we employ – notably it appears that many authors prefer more structured models, where the relation is controlled for half a dozen possible biases. However, it also appears that only few of the leading researchers are prepared to say that there exists clear macro evidence demonstrating that the present aid flows are an effective tool to close the gap between poor and rich countries. Furthermore, even if we accept the argument that the aid flows have no impact on the growth rate, we are still left with the micro-macro paradox and the negative growth externality of aid.

The main argument against the cross-country approach is surely that it takes dynamics into consideration to a far too modest extent. The panel data estimates are made to answer that critique, and they are actually different from the cross-country estimates, but unfortunately they are not better.

7.2 *What is the negative growth externality of aid?*

The micro-macro paradox implies that even successful micro projects have a negative externality on the real growth rate. Hence there must be an invisible villain in the aid game. Three actors appear to be able to play that role. All three fulfill the essential requirement of being invisible at the project level.

(i) The Dutch Disease effect of aid.[17] In a quasistatic analysis it is obvious that any transfer from abroad must appreciate the real exchange rate. The dynamic mechanism whereby this is brought about depends upon the exchange rate regime, domestic policies, etc. The appreciation will inevitably harm the domestic tradables sector. If the projects generate little growth, and the tradables sector is the one that should generate the growth, a lopsided development might result. This mechanism can be dramatically observed in a few small countries receiving very much (resource rent or) aid, see Paldam (1997b) on Greenland and Hall and Herbertsson (2003) on Uganda.

(ii) The hidden cost syndrome. Studies of development often conclude that many LDCs suffer from a lack of executive capacity, i.e., both public and private sectors have too

17. The *disease* is the effect from a *booming aid sector* on the rest of the economy. The problem used to be termed the *transfer problem*. See Gylfason, Herbertson and Zoega (1999).

little competent personnel. Also, it is well known that aid projects use relatively much of this scarce resource. Hence, such projects may deprive other LDC activities of competent personnel, and thus make them fail. Aid projects may thus cause unrelated projects to fail.

Table 8. The status quo bias of aid

1	A country is in disequilibrium, needing an adjustment
2	The adjustment has short-run political costs
3	The country receives an external donation, and does not need to adjust
4	The disequilibrium grows, and so does the adjustment costs.
5	Go to 1

The country is hooked once the disequilibrium is so large that the cost of adjustment exceeds the limit the government can bear and stay in office

(iii) The status quo bias of aid. Table 8 describes a likely mechanism. Many detailed studies of policymaking in countries receiving aid support that there is a mechanism as described (see e.g., White, 1998).[18] Both authors have a strong impression that they have experienced this type of behavior from politicians in a different aid-dependent economy. However, aid is also sometimes used as a device for supporting reform, so maybe the status quo bias has not been so strong in the recent past as it used to be.

7.3 Can aid become more effective and the vicious circle be reversed?

In our opinion aid is suffering from *a vicious circle.* It is caused by *the growing gulf* between promises and accomplishment in development aid. The gulf causes aid fatigue. In its turn aid fatigue gradually undermines the will to donate in the DCs. Because aid is slowly declining, the need for bigger promises to everybody is increasing. In particular it increases the number of goals of each development project. Hereby projects become less easily to monitor and evaluate, and consequently less efficient. This widens the gulf both ways.

Development aid is now supposed to bring about several types of sustainability, reduce discrimination against women and minorities of all kinds, abolish world poverty, build social capital, stop corruption and increase good governance, curb terrorism, increase the export of donor countries, make peace between warring states and tribes, reward friends, secure employment for aid workers, reconstruct countries after wars and natural disasters, etc.

18. The core of the book is four studies of countries that followed dirigist policies that failed and were reversed: Guinea-Bissau, Nicaragua, Tanzania and Zambia, which were for long supported by donors for political/ideological reasons. It is demonstrated that the support delayed adjustment. However, Burnside and Dollar (2000) claim that they could not find a connection between aid flows and economic policy changes.

In addition, numerous NGOs are involved with still more diverse goals. There is hardly a problem in the world aid is not supposed to cure or at least reduce.

All this is to be accomplished for about 0.3% of the GDP of the aggregate GDP of the rich countries or about 2.5% of the aggregate GDP in the LDCs.

We thus propose that aid could be made more effective, simply by reducing the number of goals and by making them (much) more coordinated, concrete and realistic. We thus propose to go for simple, easily monitored, quantitative goals. The simple devise of trying to do what can be done, i.e., of harvesting the low-hanging fruit first, may increase the efficiency of aid. If it could be shown to work, surely the willingness to give would increase. Maybe one could even hope that the vicious circle could be turned into a good one.

8. Conclusions

The purpose of this study is to explore the catch-up and the aid effectiveness together, and to do so by fully transparent models. Everything is done as simple as possible; all observations are included, etc. The results are clear:

(1) We found no absolute convergence, but a remarkably robust and significant conditional convergence, very much as expected from the literature.

(2) We found no absolute aid effectiveness, but *neither* did we find conditional aid effectiveness. Also this is very much as expected from the literature.

(3) Finally, we found practically no interaction between the two models: Aid hardly has any effect on catch-up, as follows from (2).

The results (2) for aid effectiveness are controversial – not for reasons of economic research – they do confirm the results of almost 40 years of research, but they have remained controversial simply because all of us want them to be different.

Perhaps we should simply note that the results are in accordance with the teaching of economics: Trade is better than aid.

References:

Alesina, A., Dollar, D., 2000. Who gives foreign aid to whom and why? *Journal of Economic Growth* 5, 33-63

Barro, R.S., 1991. Economic growth in a cross section of countries. *Quarterly Journal of Economics* 106, 407-33

Barro, R.S., Sala-i-Martin, X., 1995, 2004. *Economic growth*. MIT Press, Cambridge, MA

Bauer, P.T., 1971. *Dissent on development: Studies and debates in development economics*. Weidenfeld and Nicolson, London

Baumol, W.J., 1986. Productivity growth, convergence, and welfare. *American Economic Review* 76, 1072-85

Burnside, C., Dollar, D., 2000. Aid, policies and growth. *American Economic Review* 90, 847-68

Cassen, R., *et al.*, 1986, 1994. *Does aid work?* Clarendon, Oxford

Chang, C. C., Fernandez-Arias, E., Serven, L., 1998. *Measuring aid flows: A new approach*. World Bank. URL: <http://www.worldbank.org/research/growth/ddaid.htm>

Doucouliagos, H., Paldam, M., 2005a. Aid effectiveness on accumulation. A meta study[19]

Doucouliagos, H., Paldam, M., 2005b. Aid effectiveness on growth. A meta study[19]

Doucouliagos, H., Paldam, M., 2005c. Conditional aid effectiveness. A meta study[19]

Doucouliagos, H., Paldam, M., 2005d. Aid effectiveness: The sad result of 35 years of research[19]

Fraser Institute. Home of the Economic Freedom Index. URL: http://www.fraserinstitute.ca/

Freedom House. Home of the Gastil Index. URL: http://www.freedomhouse.org/

Friedman, M., 1958. Foreign economic aid: Means and objectives. *Yale Review* 47, 500-16

Griffin, K., 1970. Foreign capital, domestic savings and economic development. *Oxford Bulletin of Economics and Statistics* 32, 99-112

Gylfason, T., Herbertson, T.T., Zoega, G., 1999. A mixed blessing: Natural resources. *Macroeconomic Dynamics* 3, 204-25

Hall, A., Herbertsson, T.T., 2003. *Monetary transmissions and monitoring of the real economy in Uganda*. Report to the Governor of the Bank of Uganda.

Hansen, H., Tarp, F., 2000. Aid effectiveness disputed. *Journal of International Development* 12, 375-98

Herbertsson, T.T., 1999. *Sources of economic growth*. University of Iceland Press, Reykjavík

Hudson, J., 2004. Introduction: Aid and development. *Economic Journal* 114, 185-190. See also the three articles pp 191-271 in the same issue of the journal by P. Collier, C.J. Dalgaard, D. Dollar, H. Hansen, J. Hudson, P. Mosley, F. Tarp and P. Verschoor

IBRD-OED. *Evaluation results*. (Annual) World Bank Operations Evaluation Department, Washington DC

Jensen, P.S., Paldam, M., 2005. Can the two new aid-growth models be replicated? *Public Choice*, forthcoming[19]

Levine, R., Renelt, D.D., 1992. A sensitivity analysis of cross-country growth regressions. *American Economic Review* 82, 942-63

Levy, V., 1988. Aid and growth in Sub-Saharan Africa: The recent experience. *European Economic Review* 32, 1777-95

Nuxoll, D.A., 1994. Differences in relative prices and international differences in growth rates. *American Economic Review* 84, 1423-36

19. Available from the working paper series of the Department of Economics at Aarhus University or from http://www.martin.paldam.dk.

Paldam, M., 1997a. *Dansk u-landshjælp. Altruismens politiske økonomi*. Aarhus Universitetsforlag, Aarhus

Paldam, M., 1997b. Rent seeking and Dutch disease. An essay on Greenland. *European Journal of Political Economy* 13, 591-614

Penn World Tables, URL: http://nber.harvard.edu/pwt56.html. See also Summers, R., Heston, A., 1991. The Penn World Table (Mark 5). An Expanded Set of International Comparisons, 1950-1988. *Quarterly Journal of Economics* 105, 327-68.

Quah, D., 1993. Empirical cross-section dynamics in economic growth. *European Economic Review* 37, 426-34

WDI, World Development Indicators, annual CD-Rom. World Bank, Washington CD

Weisskopf, T.E., 1972. The impact of foreign capital inflow on domestic savings in underdeveloped countries. *Journal of International Economics* 2, 25-38

White, H., ed., 1998. *Aid and macroeconomic performance: Theory, empirical evidence and four country cases.* (International Finance and Development Series) Palgrave Macmillan, London

World Bank, 1998. *Assessing aid: What works, what doesn't, and why*. A Policy Research Report. Oxford UP, New York

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