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The Ineffectiveness of Development Aid on Growth: An update

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Abstract

This note deals with a paradox: A literature growing exponentially even though it keeps finding the same (disappointing) results. We draw upon 1217 estimates of aid effectiveness of which 676 are reported in recent years, to examine three subjects: (S1) Has the literature finally overcome the aid ineffectiveness result? (S2) Increasingly studies try to adjust for simultaneity bias. Has the evidence shown the existence of this bias? To these two questions the answer remains "no". However, (S3) new evidence suggests that some aid components may have a positive effect on growth. This is a promising new result, but it is not yet confirmed by independent replication.

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1. Introduction

Since 2004, the reported findings on development aid effectiveness have more than doubled. The key question asked is: Does development aid cause development? This note is a brief update of our meta study (Doucouliagos and Paldam 2008) that covered the literature until January 2005. We do not try to update all dimensions of our study but focus on three aspects of the key question: (S1) Have the new results changed the central finding of aid ineffectiveness? (S2) Has the new standard practice of adjusting for simultaneity bias actually found such biases? (S3) Has the new attempt to divide aid flows into components shown that disaggregation matters?

The aid ineffectiveness result is well-known but remains controversial. About 30% of the new studies claim to have (finally) shown that aid works.[1] The technique of growth regressions allows authors to generate a range of results, which in the case at hand are distributed, with an average that is very close to zero. We have argued elsewhere that this literature has *a reluctancy bias*, so that the distribution of the reported results (over their precision) is asymmetric. The asymmetry is caused by two priors generating observationally equivalent biases:[2] (i) Idealism, aid ineffectiveness disappoints hopes for a more equal world, and (ii) Interests, the 'aid industry' gives many researchers (extra) income and other benefits.[3] Meta-analysis can be used to correct the average result in a literature for such biases, once enough studies exist and all are included.

Our previous study covered a total of 541 published estimates in 68 papers. We now add 676 *new* estimates from the 32 new studies available as of December 2008.[4] It is evident that the research intensity has escalated. The new studies are authored by 65 researchers, 50 of them entirely new to this literature. For these new researchers at least, aid effectiveness remains an unresolved issue. An important driver for the literature seems to be to try out new estimators, while the underlying model specifications are fairly stable. The research effort matches the growth of aid from about $80 billion US in 2004 to $120 billion US in 2009. As regard (S1), section 2 demonstrates that the aid ineffectiveness result is even *stronger* after recent years of intense scrutiny.

As regard (S2), the old *causality assumption* in this literature was that causality from aid to growth dominated these data, so that simultaneity could be disregarded. The new literature has made a large effort to adjust the aid-growth relation for simultaneity bias. Section 3 shows that this effort has confirmed the old causality assumption. As regard (S3), we find that the literature at present has produced some promising aid effectiveness results, but to date there has been very little independent replication to allow a firm conclusion.

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Figure 1

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Figure 1 displays the data used by the 106 studies. It shows a weak (but insignificant) negative correlation between the data. Given the distribution of the data, it is not surprising that empirical studies have failed to produce a strong and robust aid effectiveness effect.[5] We show in this paper that all along the result of this research effort would have been perfectly clear, if the literature had been *quantitatively summarized* by the appropriate tools: According to all the available evidence, total aid was and remains ineffective in generating economic growth.

2. Estimation and results

Empirical studies estimate some variant of a generic growth model:

$$g_{it} = \alpha + \mu\, h_{it} + \gamma_1\, x'_{1it} + \varepsilon_{it} \tag{1}$$

where the variables g and h denote the real growth rate and the aid share, respectively, i and t index country and time, x is a vector of controls, and ε are the residuals. The key measure of interest is aid effectiveness: $\partial g/\partial h = \mu$. Following standard practice in meta-analysis, we collect estimates of μ that are conceptually comparable within and between the 106 studies. These are converted into *partial correlations*, μ_r, in order to reach a common unit of measurement of the strength of the association between aid and growth.[6]

A standard tool for drawing statistical inferences from the results of empirical studies is meta-regression analysis (MRA).[7] This is a secondary data analysis, applying regression analysis to the results of primary data regression analysis. A frequent problem in any regression analysis is sample selection, which can distort inference. Our dataset consists of all comparable estimates of the effect of aid on growth reported in 106 empirical papers. However, it is possible that there are missing observations, especially if estimates are chosen on the basis of statistical significance (De Long and Lang 1992).

Equation (2) combines comparable estimates of the effect of aid on growth while controlling for the effects of sample selection:[8]

$$\mu_{rij} = \beta_\mu + \beta_p SE_{ij} + u_{ij} \tag{2}$$

where μ_{rij} is the i^{th} partial correlation of aid and growth from the j^{th} study, SE is the standard error of each estimate, and u denotes errors. The constant β_μ is the 'meta average' of the μ_r, which is the average effect of aid on growth controlled for asymmetric sample selection. If there is no publication bias in a literature, there should be no association between SE and μ_r and, hence, $\beta_p = 0$.[9] Equation 2 may have heteroscedasticity. Hence, Stanley (2008) recommends estimating the weighted least squares (WLS) version, which is derived from dividing equation (2) by SE. Accordingly, we estimate the following equation:

$$t_{ij} = \beta_p + \beta_\mu/SE_{ij} + v_{ij} \quad (3)$$

where $t_{ij} = \mu_{rij}/SE_{ij}$ and $v_{ij} = u_{ij}/SE_{ij}$. As before, β_μ is the meta average, while β_p measures the bias due to publication selection. Studies typically report more than one estimate, so clustered data analysis is used to correct the standard errors.

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Table 1

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Our key results are presented in table 1. The old results are reported for comparison purposes. Columns 1 and 2 present the MRA using unadjusted and clustered standard errors, respectively. The accumulated evidence suggests a very small partial correlation of aid on growth (β_μ = +0.02) which is insignificant once data dependence is controlled for (column 2).[10] Table 1 also presents the MRA for all of the estimates of individual components of aid, such as technical assistance, project aid, and program aid. When all estimates from these diverse measures are pooled, there is again no evidence of aid having any effect on growth, once data dependence is controlled for (columns 3 and 4).

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Table 2

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The MRA for the individual components in table 2 shows positive effects from short term aid and project aid, while program aid appears to be detrimental to growth. These results are promising and raise the hope that aid might be made to work. However, the number of estimates is small and, hence, it might be premature to conclude that the case for these types of aid is proven: More independent replication is needed. Also, many ways exists to disaggregate aid, se e.g., Nunnenkamp, Weingarth and Weisser (2009) for a division into state-run bilateral and NGO aid.

As the average μ_r of aggregate aid on growth is effectively zero, it is not obvious how we should interpret the result that some components of aid might have a positive effect. It suggests that reforms of present aid policies are possible. However, it might be related to the micro-macro paradox, which has been known since Mosley (1987), that half of all aid projects work and few harm the recipient, but still the aggregate has no effect. This clearly needs to be explored further.

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Table 3

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An alternative way to view this literature is to compare the evolution of the literature over time. Column 1 of table 3 traces the exponential growth in the number of studies and estimates reported in the literature over time. Column 2 reports the estimated meta average β_μ of aid and growth, derived from estimating equation 3 for different time periods. This average has always been statistically insignificant. The β_μ of aid and growth has fallen from +0.23 in the pre-1980s literature to +0.02 when the newer studies are included. In all cases, β_r is not statistically significant different to zero. *With the accumulation of more evidence, the effect of aid on growth is converging to zero.*

Column 3 reports the associated unweighted average, while column 5 reports the average μ_r using the estimate's precision (1/SE) as weights.[11] In all cases, μ_r is falling over time, instead of rising, as it should if donors learn by doing. In the first decade of the new century, the size of the reported aid effectiveness fell by 61% (column 4). The accumulated evidence reflected in the uncorrected averages (columns 3 and 5) shows an aid on growth effect that is now so small that it is little practical significance. This stands in sharp contrast to statements that the new estimates show that aid works: They show the exact opposite.

The difference between columns 2 and 3 (or 2 and 5) is the estimated publication bias – column (6) gives its size in per cent of the unweighted average. Once the number of estimates reaches a certain minimum the bias stabilizes to between 60% and 75%. Consequently, we are dealing with a substantial problem. Doucouliagos and Paldam (2009b) show that there is reluctancy in this literature to report aid ineffectiveness. This reluctancy has been so strong in the past that it gave the appearance of larger aid on growth effects. As more and more research has been generated, the aid ineffectiveness is revealed with greater clarity.

Bias in research is not a new discovery. Harry G. Johnson (1975, p. 92) famously remarked that: "… the 'testing of hypothesis' is frequently merely a euphemism for obtaining plausible numbers to provide ceremonial adequacy for a theory chosen and defended on a priori grounds."[12] Given the emotional dimensions involved in aid, poverty, and growth, and the strong presence of the 'aid industry' in the research, bias in this literature is understandable. The techniques of meta-analysis allow inferences to be drawn from the accumulated evidence, even in the face of such biases.

3. A note on causality: does the old causality assumption hold?

We now turn to the claim that aid ineffectiveness results estimated by OLS suffer from simultaneity bias. It is a fairly common claim in the literature, and many attempts have been made to substantiate the claim. Two bodies of evidence about reverse causality will be examined.

One body of literature (of 30 papers with 211 estimates) analyzes the reverse causality of the effect of growth in the recipient country on the aid it is allocated.[13] Applying equation 3 to the growth-to-aid literature produces a small *positive* partial correlation of +0.013, with a t-statistic of 1.22. Of course, the growth-to-aid literature may have a simultaneity bias, generated by the aid-to-growth relation.[14]

The second body of literature consists of studies that try to adjust the estimates (of μ) for simultaneity. In the newer studies this has become a standard procedure, which has been applied in 40 studies that provide 219 estimates of aid effectiveness corrected for simultaneity bias using a variety of instruments and estimators.

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Table 4

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Table 4 reports the effect of these efforts on the partial correlations. The table demonstrates that the studies which have attempted to control for simultaneity have found no effect on the aid-to-growth estimate. Though most studies find a positive bias others find a negative, so no clear picture emerges. The small positive bias suggested by the growth-to-aid literature, turns out to be insignificant.

It is notoriously difficult to find good instruments, so maybe the lack of results simply reflects the low quality of the instruments tried.[15] However, until some evidence to the contrary is found, we have to treat the aid effectiveness literature to be what it claims: A set of estimates of the causal effect of aid on growth.

4. Conclusion

Our study analyzes the avalanche of new studies of aid effectiveness on growth. There are now 106 papers which have reported 1,217 estimates. The average result is positive but of no economic significance. We use meta-regression analysis to correct the average finding for the effect of publication selection – this further decreases the average result, and makes it statistically insignificant. This analysis of the results of decades of research suggests that, *on average*, aggregate development aid flows are ineffective in generating growth. This result is not driven by the particular meta-regression model used: Aid ineffectiveness is obvious from just simple raw averages of the reported estimates.

Also, we confirm a striking pattern in the results: As the number of estimates has increased, the partial correlation of aid and growth keeps declining. All donors have the stated goal of increasing aid effectiveness. We have yet to see any donor (or NGO) state that aid is now less effective than in the past. Indeed, their common belief is the opposite. We conclude that the falling trend is due to publication bias. Our earlier meta-analysis had detected this declining aid effectiveness. It is remarkable that the predictions from that meta-analysis have proven to be robust to the doubling of the reported estimates.

It is a thought provoking observation that the literature on the one side keeps expanding and on the other side keeps showing the same result. All the literature seems to be doing is to confirm aid ineffectiveness more and more strongly. The marginal contribution of another aggregate aid on growth estimate is minimal. It is useful to ask at what point research effort should be redirected. The efficient allocation of scarce resources requires moving resources to activities of higher value. It appears to us that the growing interest in total aid effectiveness runs the real danger of resource misallocation.

It has often been claimed that this literature suffers from simultaneity bias, but the meta-analysis shows that to date the many attempts to find such a bias have failed. We consider also the effects of different components of development aid. Here the results are more promising though they require independent replication. Our analysis suggests that researchers should refocus their attention away from aggregate measures of aid to more disaggregate ones.

Aid ineffectiveness does not mean that there will not be individual countries and time periods where aid is effective. It also does not mean that aid is never effective, e.g. food aid given for emergency relief, aid given to reduce debt, see Bjerg, Bjørnskov and Holm (2010). That total aid does not generate growth, on average, is an important finding. It suggests that policy makers and aid donors should look elsewhere, in order to effectively assist the development of poor countries. It contrasts strongly to the standard finding (since Cassen 1986) of a success rate of about 50% for the projects financed by the aid. Many reasons for aid ineffectiveness have been given:[16] However, perhaps one point has been insufficiently stressed. Aid appears to have considerable fungibility so that the projects *financed* by aid are different from the projects *caused* by aid. If aid permits a recipient government to provide what it has promised its population, it might feel free to seek rents from the funds set free.

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Notes:

1. The claim the aid works was first made by Papanek (1973). Few of the new studies (as Rajan and Subramanian 2008a) explicitly say that aid is ineffective. Also, some new surveys by ‘insiders’ of the ‘aid industry’, such as Arndt, Jones and Tarp (2009) and Feeny and McGillivray (2010), claim that the (new) literature shows that aid works.

2. See Doucouliagos and Paldam (2008 and 2009b) for the empirics and a more detailed discussion of the biases.

3. It is difficult to assess the weight of the two priors as they overlap. Many authors fail to report their conflict of interest and few authors are critical of the ideology of aid, and none, of course, disagree with the stated purpose of aid.

4. Christensen, Doucouliagos and Paldam (2010) provide a bibliography of the 106 papers. It is posted on http://www.martin.paldam.dk together with the coding of the papers. We are aware of newer studies, e.g. Nowak-Lehman *et al.* (2009), which use a range of new techniques, but find the usual results.

5. The estimated kernel-curve shows why the many attempts in the last decade to fit a non-linear curve through the data has produced unstable results, as demonstrated in Doucouliagos and Paldam (2010).

6. The use of partial correlations is common in meta-analysis; see Djankov and Murrell (2002). Unfortunately, there is insufficient information in many studies from which to calculate elasticities.

7. The tools of meta-analysis are surveyed in Hunter and Schmidt (2004). The MRA model was first proposed by Stanley and Jarrell (1989). Applications in economics include Görg and Strobl (2001), Roberts and Stanley (2005), Mookerjee (2006), and Disdier and Head (2008).

8. To test the validity of combining the studies, the precision of each estimate (the inverse of the standard error, 1/SE) was regressed on the Social Science Citation Index Impact Factor of the journal in which the estimate is reported. We find no difference in the precision of estimates on the basis of this index of journal quality (coefficient of -1.50 and a t-statistic of -0.98).

9. For details on this regression see Card and Krueger (1995) and Stanley (2001, 2008).

10. Following Cohen’s (1988) guidelines, a correlation less than |0.10| is regarded as small. Consequently, the meta average of the correlation of +0.02 is both statistically and economically insignificant. The uncorrected averages in columns (3) and (5) of Table 3 are ‘only’ economically insignificant.

11. The table reports three averages of the μ_r’s: Column (3) is the simple unweighted average. It treats all estimates equally. Column (5) weight the average with the precision of the estimate. These averages might be

biased by sample selection. Column (2) is our preferred average. It is the meta average that both uses precision weights, and corrects for sample selection.

12. Posner (1999) discusses the parallel situation of "witness shopping" in evidence presented to courts.

13. These results are analyzed in Doucouliagos and Paldam (2009a).

14. The world may be so mischievous that the aid-to-growth and the growth-to-aid effects are of the same size, but with opposite signs, so that they cancel out each other, and the picture on Figure 1 results. This implies that aid is countercyclical, a property of aid that has never been confirmed. In fact, a small body of literature exists, since Pallage and Robe (2001), showing that aid is procyclical.

15. Some believe that one day a perfect method to correct for simultaneity will be discovered, and that it will show that the whole AEL-literature is wrong and that aid does indeed cause growth. We have even experienced a referee who demanded that we reverse our conclusion – based on that *belief* – hereby confirming the argument of Frey (2003). The whole purpose of meta-analysis is to show what the literature has actually found, and not what we believe that it should have found.

16. See Rajan and Subramanian (2008b) and Doucouliagos and Paldam (2009b) for comprehensive discussions concentrating on recipient countries. Other explanations concentrate on donor motives for aid, where aid effectiveness may not enter. Many papers discuss strategic and commercial interests of donors; see e.g., Younas (2008). A few papers consider the utility (warm glow) obtained by donors from giving. To the extent the utility is purely expressive it is independent of the eventual results of the gift; see Hillman (2010).

Figure:

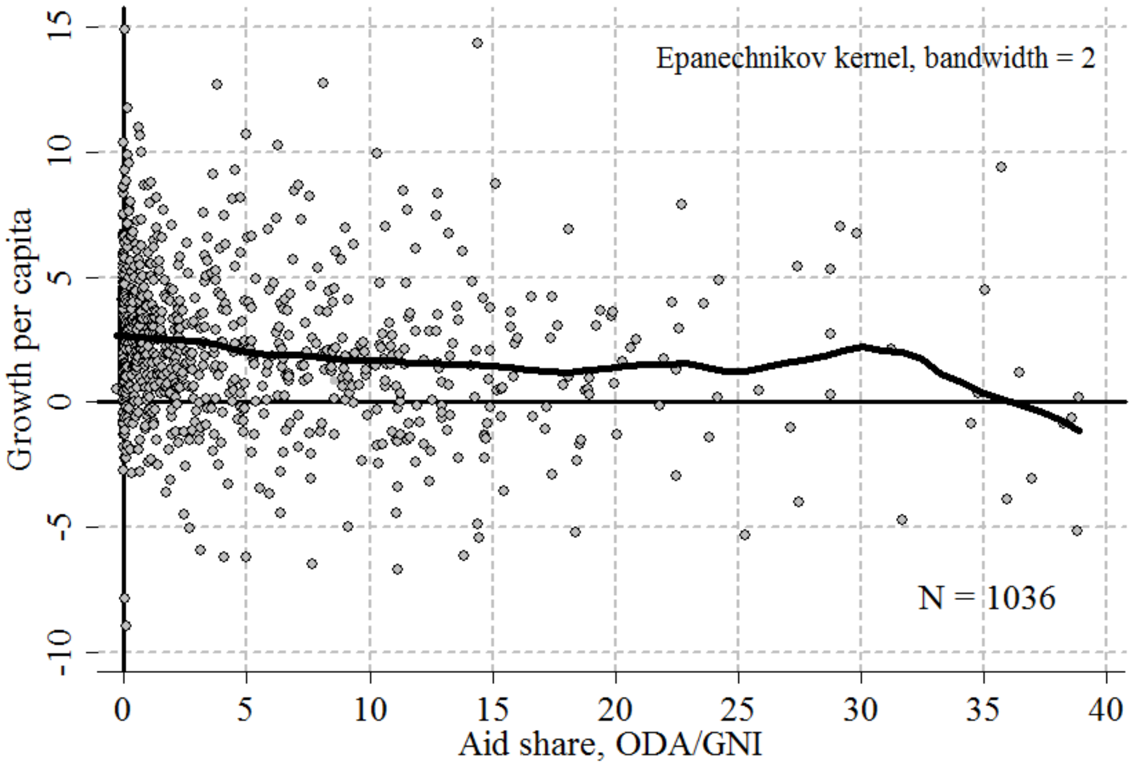

Figure 1: Development aid and economic growth, 1960-2005. *Notes:* The figure shows 1,036 of the 1,052 observations available between 1960 and 2005 divided in intervals of 5 years (1960-65, 1965-70, …, 2000-2005). 16 extreme observations (outside the frames) have been removed: They do not change anything of substance. The real growth rate per capita is from the Maddison data and the share of aid (ODA) is in percent of the GNI. The solid line is a kernel regression showing the best "moving average" with a fixed bandwidth.

Tables:

Table 1.

The effect of development aid on economic growth

	Doucouliagos and Paldam (2008)	Aggregate measure of aid		Disaggregate measure of aid	
		(1)	(2)	(3)	(4)
	WLS, CDA	WLS	WLS, CDA	WLS	WLS, CDA
β_{μ}, aid effectiveness	0.03	**0.02**	0.02	**0.07**	0.07
	(1.00)	(3.86)	(1.13)	(3.02)	(1.45)
Unweighted average	0.11	0.06	0.06	0.05	0.05
Number of studies	68	103	103	15	15
Number of estimates	541	984	984	233	233

Notes: The dependent variable is the set of partial correlations of aid on growth. All estimates based on equation 3. WLS is weighted least squares. CDA is clustered data analysis. Figures in bold are statistically significant at the 5% level of significance. Brackets hold t-ratios. The 984 + 233 = 1,217 estimates are drawn from the comparable studies of aid effectiveness mentioned in the text. The unweighted average is the simple average partial correlation from the reported estimates.

Table 2.

The Effect of Disaggregate Measures of Aid on Economic Growth

	(1) Grants	(2) Technical assistance	(3) Short term aid	(4) Project aid	(5) Program aid	(6) Multilateral aid
WLS	**+0.14** (2.55)	-0.06 (-0.52)	**+0.22** (3.47)	**+0.28** (4.94)	-0.14 (-1.15)	-0.16 (-1.01)
WLS, CDA	+0.14 (1.80)	-0.06 (-0.39)	**+0.22** (14.95)	**+0.28** (4.10)	**-0.14** (-5.37)	-0.16 (-1.53)
Number of estimates	27	24	27	55	30	9

Notes: See notes to Table 1. The data come from 15 studies that report estimates of the components.

Table 3.

The evolution of the estimated aid effects for aggregate aid

	(1) Number of estimates [studies]	(2) Meta average, β_μ from equation 3	(3) Unweighted average	(4) % change in unweighted average	(5) Precision weighted average	(6) Publication bias [a)]
Pre 1980	24 [7]	0.231 (0.71)	0.266 (1.49)	-	0.258 (1.21)	13%
Pre 1990	88 [15]	0.080 (0.70)	0.204 (3.07)	-23%	0.164 (1.96)	61%
Pre 2000	245 [34]	0.041 (0.67)	0.153 (4.33)	-25%	0.119 (3.08)	73%
Pre 2009	984 [103]	0.023 (1.13)	0.059 (2.94)	-61%	0.036 (2.99)	61%

Notes: See notes to Table 1. Figures in round brackets denote t-statistics using standard errors that are robust to heteroskedasticity and data clustering. Estimated coefficients are converted to partial correlations. (a) Calculated as ((3) – (2))/(2).

Table 4.

The Effect of Simultaneous Estimation Techniques on the Results

	(1) Column (2) From Table 3	(2) Meta average, β_μ aid to growth	(3) β_b bias dummy	(4) R^2	(5) Number of estimates	(6) Adjusted for bias
Pre 1980	0.231 (0.71)	0.237 (0.74)	0.148 (0.77)	0.03	24	1
Pre 1990	0.080 (0.70)	0.080 (0.69)	-0.152 (-1.06)	0.03	88	11
Pre 2000	0.041 (0.67)	0.073 (1.25)	**-0.176** (-2.76)	0.07	245	24
Pre 2009	0.023 (1.13)	0.024 (1.19)	-0.013 (-0.74)	0.02	984	219

Notes: See notes to Table 1. The regression run is $t_{ij} = \beta_p + \beta_\mu/SE_{ij} + \beta_b S_{ij}/SE_{ij} + v_{ij}$, where S_{ij} is a binary dummy that is one for estimates done with simultaneous estimators, while it is zero elsewhere. Note that a positive (negative) estimate of β_b indicates a negative (positive) bias in the estimates disregarding simultaneity.