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Development aid inertia:

An empirical study of the data and the literature

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Abstract: The aid volatility literature and many policy reports on aid argue that aid is too volatile. This paper provides an empirical assessment of the aid inertia/volatility proposition through two distinct methods. First, univariate time-series analysis of aid shares finds that inertia is approximately 0.82. Second, a systematic review of the literature finds 35 studies that report 212 estimates of inertia. The plain average of these estimates is approximately 0.46, while the more precise meta-average is approximately 0.70. The difference between the methods and two biases explain the gaps between the three averages: A publication selection bias caused by a theoretical prior against values larger than 1, and a unit root estimation bias. Their combined size is assessed to be about 0.3, so the true value appears to be close to 0.80. Aggregate aid to most countries is thus rather stable.

Jel: F35, F5, O19

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1. Introduction: Inertia or volatility?

The large policy literature on development aid often argues that high aid volatility harms development aid effectiveness, so that aid inflows should be more stable. Both bilateral and multilateral donors have policies to follow this advice. The purpose of this paper is to assess if aid flows are actually volatile or stable, i.e. to find the size of the *inertia* in aid share series, which are taken as the main measure of aid. Aid inertia, φ, is the first order autocorrelation in the aid share, or the coefficient to lagged aid in a relation explaining aid.

The study combines two distinct methods: A univariate data study and a meta study of the literature. The two methods produce three estimates of the average inertia: The univariate time-series analysis produces the first estimate $\varphi_u \approx 0.82$. The meta-analysis of the literature produces the second and third averages of the reported estimates: The plain average, $\underline{\varphi} \approx 0.46$, and the meta-average,[3] $\varphi_M \approx 0.70$. The three averages are quite different – if they can be reconciled it is an important finding.

Both methods have advantages and disadvantages. The univariate analysis uses the available data effectively, but in a narrow way. It does not distinguish between inertia itself and constancy of the variables determining aid. The meta analysis has the reverse characteristics as it put together estimates of the inertia as a part of larger models with many different variables explaining how aid is determined.

Two sets of empirical studies analyze the *causes* and *effects* of aid. These are the AAL, Aid Allocation Literature, and the AEL, Aid Effectiveness Literature, respectively.[4] Both literatures deal with aid inertia, though as a minor item. The AAL contains 35 papers that report 212 estimates of φ, which are the data of the meta study.

The AEL struggles with the aid ineffectiveness finding.[5] The aid volatility subset of the AEL claims that aid volatility is so large that it explains aid ineffectiveness. The volatility claim tallies well with the plain average, $\underline{\varphi}$, but not with the other two averages, φ_u and φ_M.

3. The meta average is a precision weighted estimate of the average corrected for publication selection bias. It is explained in section 5.3 below.
4. Christensen et al (2007, 2009) are bibliographies of 166 papers in the AAL, until 1/1-2006, and the 152 papers in the AEL, until 1/1-2009, respectively. Both bibliographies try to be comprehensive.
5. We have made a handful of meta studies of the AEL, summarized in Doucouliagos and Paldam (2009), which conclude that in spite of a large effort to prove aid effectiveness, the AEL has failed in so doing. Debate on the issue however continues. The present paper belongs to a set of meta studies of the AAL (see Doucouliagos and Paldam 2008 a, b and c).

Thus, it is important which of the three different averages is true. Our analysis concludes that truth is found in the high end of the range.

Section 2 discusses why the averages may differ, while section 3 contains the univariate time-series analysis of the data. Section 4 looks at the aid volatility papers listed in Part 1 of the references. Section 5 presents the meta-analysis of the AAL-papers analyzing aid inertia listed in Part 2 of the references. Finally, section 6 concludes. The appendix lists the countries covered by the aid data, and gives some descriptive statistics.

2. Three problems for finding the true value of total aid inertia

The *aid share* is defined as $h_{it} = ODA_{it} / GDP_{it}$, where ODA is the official development aid, and the denominator is the Gross Domestic Product or the Gross National Income. Both denominator and nominator are measured in the same current prices.[6]

Table 1 list the three average measures of aid inertia already mentioned. They differ considerably. In particular, it is amazing that the two averages of the 212 estimates of φ found in the literature differ so much (0.46 compared to 0.70). At a purely descriptive level the big gap between the plain average and the meta-average is caused by the strong *asymmetry* of the funnel plot showing the distribution of the results – see Figure 4 below. The distribution looks as if (nearly) all results above 1 have been censored. In section 3 we study the distribution of the φs estimated from different countries and time periods and show that properly estimated they are normally distributed and thus perfectly symmetrical. We thus need something that makes a normal distribution very skew. The two biases mentioned in Table 1 both have this effect. We should mention that neither bias is mentioned in the literature surveyed.

Table 1. A preview of the results reached, and the biases that may reconcile the results

Averages found		Section	Two likely bias	
Method	Average	of paper	Unit root bias	Censoring bias
Univariate time series result	$\varphi_u \approx 0.82$	3	Corrected	Not relevant
Plain average of literature	$\underline{\varphi} \approx 0.46$	5	Not corrected	Not corrected
Meta-average of literature	$\varphi_M \approx 0.70$	5	Unclear	Corrected

Note: The two biases are both assessed to be just below 0.2, but they are partly substitutes, so the effect of both combined is less than their sum.

2.1 A theory prior causing censoring of published φs at 1

From the analysis of economic development we know that absolute convergence of countries is insignificant both economically and statistically (see Jones, 2002, pp 63-71). Thus relatively poor countries may remain so for a long time.[7] Given this fact, and assuming that the motives for giving aid are constant, aid shares are likely to be almost constant in the long

6. The focus here is on aid shares. However, autocorrelation in aid allocations can be detected also if the absolute value of aid is considered. The aid share data are from the WDI home page (in references)
7. The two largest LDCs are converging rapidly to the DC-world, so it is important that the analysis in this paper deals with averages where each country has the same weight. The aid shares of India and Togo are taken to tell an equally interesting story.

run. A perfectly constant aid share would give φ = 1, but many reasons exist for some variation in aid shares. We also know that if φ > 1, the aid share will explode to ∞ or implode to 0. Consequently, theory suggests that the true coefficient of inertia $\hat{\varphi}$ < 1, but not much smaller than 1. This prior is consistent with the univariate result that φ_u = 0.82 and (barely) with the meta-average that φ_M = 0.70.

Consequently, it is a sound *theory prior* that 0 << φ < 1 in large data samples. Thus, if the large data sample is divided into many small samples, it will produce a distribution of estimated φs that includes a good many estimates above 1.

If the perfectly reasonable theoretical prior is applied to each of these *small samples* it turns unreasonable, as it will cause researchers, referees and editors to discriminate against the estimates above 1 and, hence, lead to some censoring of these estimates,[8] precisely as it looks on Figure 4 (below). This will cause the average published estimate, $\underline{\varphi}$, to be biased downward. This is the censoring bias mentioned in Table 1.

Table 2. The size of the theory prior bias – calculated as explained in the text

True value	Standard deviation of distribution					
of φ	0.25	0.3	0.35	0.4	0.45	0.5
1	-0.20	-0.24	-0.28	-0.32	-0.36	-0.42
0.9	-0.14	-0.18	-0.22	-0.26	-0.30	-0.35
0.8	-0.09	-0.13	-0.17	-0.21	-0.25	-0.30
0.7	-0.05	-0.09	-0.12	-0.16	-0.20	-0.31
0.6	-0.03	-0.05	-0.08	-0.11	-0.14	-0.18

Table 2 gives the potential size of this censoring bias. It is calculated as follows: Section 3.1 below demonstrates that (properly) estimated φs, are normally distributed, with standard deviations between 0.25 and 0.5 depending on country variation and sample size. We also know that the true value of φ must be between 0.6 and 1. With these assumptions we calculate the fraction of the normal distribution that is cut off if censoring is strict, and the bias it causes when the average is calculated from the non-censored part of the distribution. The un-shaded part of the table is the most likely part, as we will see. It has an average of about 0.21, but censoring is never complete, so it is likely to be a little less in practice.

The censoring bias is typical for a family of such biases found in meta-analysis, where a perfectly reasonable theoretical prior leads to censoring, which causes publication selection

8. We invite the reader to apply introspection to a situation where she/he finds an inertia estimate above 1, in a study where this concept is relevant.

bias (see Roberts and Stanley 2005). The meta-average has been developed precisely to pick up and correct such biases. However, it appears that the difference between φ_u and φ_M on the one side and $\underline{\varphi}$ on the other side is too large. The censoring bias can only fill some of the gap.

2.2 *The unit-root bias and the interaction between the two biases*

The preceding discussion suggests that the true value $\hat{\varphi}$ is close to 1. This means that some care has to be applied when it is estimated as it may have a *unit-root bias*, depending on the data generating process. We show that when φ is too close to 1 the level estimate becomes too small. We have corrected by calculating φ via the first difference. In section 3 we calculate the size of the bias from comparing the level and the first difference estimates. It turns out that the unit root bias is close in magnitude to the censoring bias, and it even looks a bit the same on the funnel plot.

The methods used to assess the two biases are fully independent. The censoring bias is calculated from censoring a normal distribution, while the unit root bias is the difference between uncorrected and corrected estimates using the data. Both calculations should give a rather precise estimate, but they give no estimate of the interaction.

The two biases are likely to interact so that they generate an aggregate bias that is smaller than their sum. The unit root bias causes the estimates to be smaller and, hence, reduces the need to censor. Censoring leads to the censoring of estimates with a unit root bias. As we find that both biases taken in isolation are around 0.2, so that: $0.2 \le abias \le 0.4$, where *abias* is the aggregate bias.

2.3 *Another reasons to expect deviation between the averages*

So far we have discussed *total* aid inertia, but as it is caused by a number of explanatory factors it might be divided in various components: The basic division is into two components: $\varphi = \varphi_b + \varphi_a$. They are:

Administrative inertia, φ_b, is due to deliberate policies to make aid stable, and to the convenience of the status quo. For many reasons it is cheaper to continue doing what you are already doing.

Allocation inertia, φ_a, is due to the persistence of the causal factors for aid allocation. Consider the following three examples of factors causing donor *D* to assist recipient *R*: (Ex1) *R* is a former colony of *D*; (Ex2) *R* is especially poor; and (Ex3) *R* has a strategic location. Neither of these factors is likely to change from year to year or even from decade to decade.

For some purposes it is important to try to sort out administrative and allocation inertia, but it is not easy, even at the theoretical level. Section 3 disregards the distinction.

Many of the models discussed in the meta-study of section 5 contain variables that explain aid allocation with variables that are rather stable (as the ones in the three examples) and thus some of the total φ becomes part of the coefficients to these variables. This may explain why the meta-average is a bit smaller than the average from in the primary study.

2.4 Aid inertia, pro- and counter cyclicality of aid and aid effectiveness

Two arguments about aid effectiveness hinge upon the size of aid inertia: (a) The simple volatility argument and (b) the pro-cyclicality argument. They are quite distinct, but both build upon the argument that high volatility in any exogenous variable cause low growth. This has been demonstrated in several studies, notably in the studies surveyed by Gavin and Hausmann (1998). The main chain of arguments stems from the idea that higher unpredictability reduces investments (see e.g. Aizenman and Marion, 1999).

(a) The simple aid volatility argument deals with the necessity of planning notably when it comes to public programs. Aid basically finances public consumption (see Boone, 1996) and thus causes ratchet-effects, if it is too volatile. This is known to be destabilizing and inflationary. The simple volatility argument suggests that inertia should be as close to 1 as possible, and the smaller it is the larger is the problem.

(b) The pro/counter-cyclicality argument is more complex as it claims that aid is pro-cyclical. This increases economic fluctuations, and as before this will cause lower growth. Conversely, if aid is counter-cyclical it will dampen economic fluctuations and thereby increase growth. As the aid share has aid in the nominator and GDP in the denominator one may argue that if $\hat{\varphi}$ is smaller than 1 it means that aid fluctuates less than GDP and, hence, aid is counter-cyclical. If aid fluctuates the same as GDP, so that $\hat{\varphi} \approx 1$, then aid is neutral as to economic fluctuations. To get pro-cyclical aid it has to fluctuate more than GDP, so we have to look for $\hat{\varphi} > 1$.

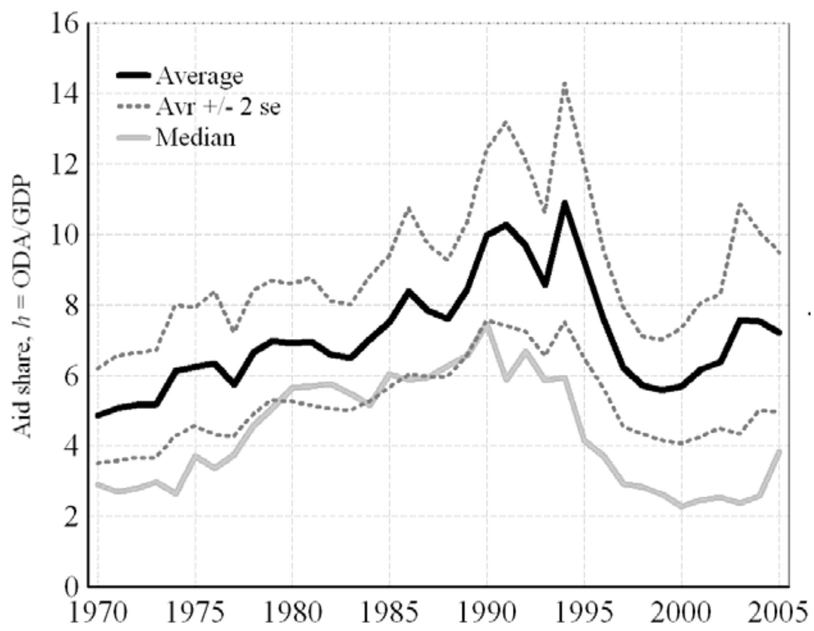
If we see the two arguments together, they suggest that optimal aid inertia should be high, but not as high as 1 and certainly not higher.

3. A univariate study of aid inertia in 70 countries with complete data

The World Development Indicators (WDI) covers 228 countries, of which 185 are characterized as LDCs. We omit middle income oil exporters, countries in transition from socialism, and we cannot include countries with no data. Appendix A lists the 115 remaining LDCs, of which 70 have complete data since 1970. A total of 4,226 observations of the aid share are available. We concentrate on the aggregate aid flows, but Table 4 also report results for bilateral and multilateral aid flows.

Most donors built their aid programs from 1960 to 1970, so here the aid shares have strong trends. However, since 1970, the aggregate aid share has no trend, as shown on Figure 1. Figure 1 surrounds the average by 2 standard errors, so it is clear that the 1970 aid shares are quite different and as the median is substantially below the average, the aid shares are much upward skewed: Some aid shares are even above 100%.[9] While the aggregate aid share is almost stationary in the period, many country series have deterministic trends, which are equally often up as down. After some experiments we decided that the results on the raw data were so close to the ones on the de-trended series that it was better to stick to the raw series.[10]

Figure 1. The path of the average aid share in 70 countries, 1970-2005



9. The most extreme cases are from São Tomé and Guinea Bissau. They are often deleted in aid studies.
10. Table 4 has been recalculated for the detrended series. It causes the results in columns (1) to (3) to decrease a little and the results in columns (4) to (6) to increase a little, but the general pattern is very much the same.

Table 3. The six models used to estimate φ

		Estimate of φ is done separately for each countries, $i = 1, \ldots, 70$
(1)	OLS1	$h_{it} = \alpha + \varphi h_{it-1} + \varepsilon_{it}$, where h is the aid share
(2)	OLS2	$h_{it} = \alpha + \varphi h_{it-1} + \beta A_i(h_t) + \varepsilon_{it}$, where $A_i(h_t)$ is the average h each year
(3)	OLS3	$\Delta h_{it} = \alpha + (\varphi - 1)\Delta h_{it-1} + \varepsilon_{it}$
(4)	ML1	The AR(1)-term in the ARIMA(1,0,0) process
(5)	ML2	The AR(1)-term in the ARIMA(1,0,1) process
(6)	ML3	1 + the AR(1)-term in the ARIMA(1,1,0) process

Note: ARIMA(n, j, k) is AR(n), integration I(j), and MA(k).

3.1 Six basic estimates

These data are used to estimate aid inertia in the six ways listed in Table 3. The results are reported in Tables 4 and 5 and on Figure 2. The averages are fairly similar, so the value in Table A2 (of the Appendix) for each country is only given for the average of the six estimates. Estimate (2) OLS2 includes a term to eliminate joint fluctuations in the aid share. It has a little collinearity to the lagged endogenous variable. The estimates (3) OLS3 and (6) ML3 are made to correct for the potential unit root bias.[11]

Table 4 shows the pattern in the $1260 = 3 \cdot 6 \cdot 70$ estimates. The "3" are (i) the total aid shares, (ii) the multilateral and (iii) the unilateral aid shares separately; the "6" are the six models listed in Table 3; and the "70" are the 70 countries. Table 4 reports cross-country averages, medians, standard deviations, and tests for normality. This section concentrates on the upper panel of the table, while the two lower panels are discussed in section 2.2 below.

Estimates of models (1) and (2) find average values of φ around 0.7, while Figure 2 shows the distribution of the individual φs. Some φs are small for reasons specific to one country or another. That is, some of the 70 countries have had aid interruption in periods of particularly bad regimes or during (civil) wars, often followed by a period of very high aid.[12] Thus, φ is higher in many countries in order for the average to reach 0.7, so that many aid shares are so close to a unit root that models (1) and (2) provide estimates that are too low. Indeed, OLS3 gives higher estimates (0.819).

The estimates of the ARIMA-models use the stepwise maximum likelihood estimator. Here the two level estimates (4) and (5) are slightly larger than the corresponding OLS estimates (1) and (2), while the first difference version (ML3) is similar to OLS (3).

11. As stated in 2.2 the properties of the estimates depend upon the (unknown) data generating process. We take it that the probit graphs of the estimates show that the level estimates have a unit root bias.
12. Two such cases are Uganda under Idi Amin and Zimbabwe in the sunset years of Robert Mugabe.

Figure 2 shows the probit-curves of the distributions of the 70 individual estimates of φ behind each of the 6 averages given in the top panel of Table 4. The 6 curves look precisely as they should in the presence of a unit root bias. The picture is much the same in the two parts of Figure 2, though it is clearest on Figure 2b: Two curves are rather similar while the third curve differs in the higher part of the range, i.e., for $\varphi > 0.8$. The similar pairs of curves are (1) OLS1 and (2) OLS2 on Figure 2a and (4) ML1 and (5) ML2 on Figure 2b. They show non-normality by bending upward as the curve approaches 1, while curves (3) OLS3 and (6) ML3 are linear (normal) as it should be. The Lilliefors test rejects normality in the two strongest cases (4) ML1 and (5) ML2.

Table 4. Estimates of the inertia in aid flows: Average results for 70 countries 1970-2005

Name in Table 3	(1) OLS1	(2) OLS2	(3) OLS3	(4) ML1	(5) ML2	(6) ML3
Estimator	OLS estimate of coefficient to lagged endogenous			AR(1)-term from ML estimate of ARIMA-process		
	Estimate of φ in the aggregate aid flows (from all donors)					
Average	0.726	0.668	0.819	0.743	0.782	0.819
Median	0.730	0.685	0.759	0.772	0.824	0.783
SD between	0.144	0.181	0.207	0.145	0.171	0.203
SD within	0.117	0.130	0.177	0.139	0.225	0.182
Lilliefors-test	0.67	0.61	0.64	0.88*	1.59***	0.67
	Estimate of φ in the multilateral aid flows (from all multilateral donors)					
Average	0.613	0.503	0.766	0.630	0.710	0.769
Median	0.659	0.552	0.753	0.659	0.774	0.754
SD between	0.216	0.243	0.227	0.227	0.267	0.227
SD within	0.126	0.141	0.166	0.147	0.280	0.167
Lilliefors-test	0.91**	0.84*	0.64	0.89**	3.14***	0.72
	Estimate of φ in the bilateral aid flows (from all donor countries)					
Average	0.705	0.661	0.824	0.722	0.740 [a)]	0.816
Median	0.727	0.657	0.833	0.731	0.814	0.823
SD between	0.158	0.179	0.200	0.162	0.345	0.180
SD within	0.122	0.132	0.177	0.147	0.232	0.194
Lilliefors-test	0.68	0.58	0.34	0.89**	5.82***	0.33
	t-test for difference between the estimates of φ for bilateral and multilateral donors					
t-statistic, f = 138	2.91***	4.43***	1.61*	2.80***	0.58	1.37*

Notes: The series are 36 years long. With a lag one year is lost, and in first differences another year is lost. See note to Figure 2 on the Lilliefors test. For large samples (as N = 70) the test limits are: $L_{80\%} = 0.74$; $L_{90\%} = 0.81$*; $L_{95\%} = 0.89$**; and $L_{99\%} = 1.03$*** (see Conover 1971). The t-tests assume that the joint standard deviation is the average of the two "between" standard deviations. It looks reasonable on the probit diagrams, but it is dubious when tested. The t-test tests if two means differ. It is accepted at the 10%, the 5% and the 1% levels if the t-ratio is provided with *, ***, *** respectively.

(a) The process did not converge for Paraguay, so this average covers 69 countries only.

Figure 2. Probit diagrams of the φs behind the six averages in the top panel of Table 4

Figure 2a. The 3 OLS-estimates

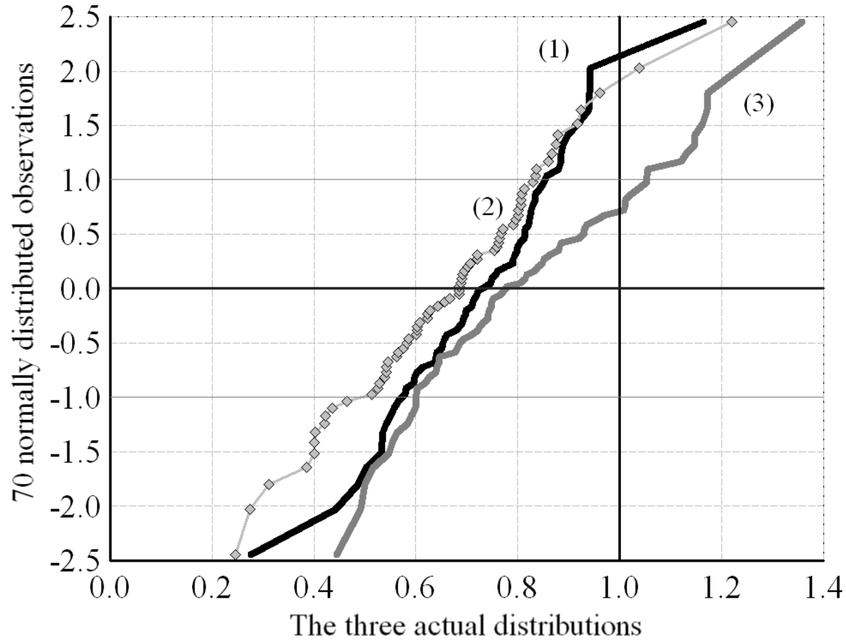
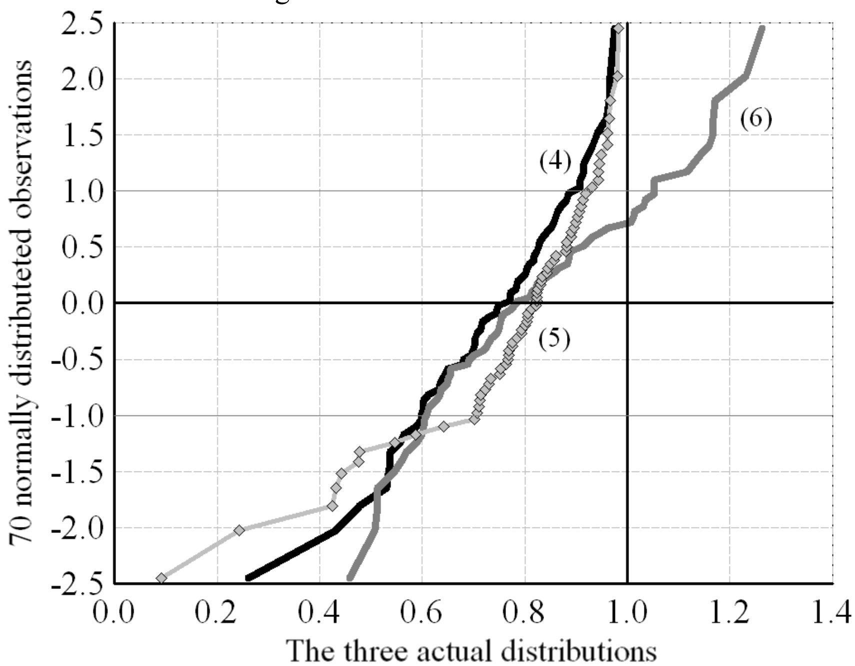


Figure 2b. The 3 ML-estimates



Note: The technique of the probit diagram is to plot the 70 sorted estimated (the φs for the 70 countries) against the normal distribution of 70 observations. If a straight line appears it is confirmed that the observations (the φs) are normally distributed. The family of Kolmogorov-Smirnov tests shows if the deviations from straightness are enough to reject normality. The Lilliefors test used in Table 4 is the family member for an unknown mean and standard deviation.

Table 5. The OLS and ML-results where the period is divided into two

Number	(1)	(3)	(4)	(6)	(1)	(3)	(4)	(6)
Name in Table 3	OLS1	OLS3	ML1	ML3	OLS1	OLS3	ML1	ML3
Estimator for φ	The period from 1970-87				The period from 1988-2005			
Average	0.672	0.826	0.663	0.860	0.586	0.814	0.585	0.812
Median	0.695	0.818	0.703	0.814	0.678	0.805	0.658	0.795
SD between	0.238	0.249	0.231	0.322	0.247	0.247	0.274	0.297
SD within	0.178	0.251	0.223	0.313	0.191	0.253	0.308	0.331
Lilliefors-test	1.17***	0.25	1.12***	0.80	1.19***	0.43	1.04***	0.76

Note: Se note to Table 4. The divided periods are 18 years long.

Table 5 shows the results when the calculation period is divided into two periods of 18 years each, and the regressions are run on the two periods. As expected, the standard deviation (within) increases in all eight cases compared to Table 4. While the average estimates for OLS1 and ML1 decrease, it remains constant for OLS3 and ML3. Also, the distributions of the results are normal for OLS3 and ML3, while they are not for OLS1 and ML1. It all serves to build confidence in the OLS3 and ML3 estimates.

Consequently, the coefficients for OLS3 and ML3 reported in Tables 4 and 5, are the best univariate estimates of the inertia in the aggregate aid share. They are close to $\varphi = 0.82$. These estimates show that if properly estimated, sets of φs are normally distributed. This was important for the argument in section 2.1 and it will be equally important for section 5.1.

3.2 Estimating the unit root bias

Our best estimate of φ is 0.82, which is corrected for the unit root bias. It is close to 1, so it is likely that the difference to the corresponding uncorrected estimates is due to the bias. Thus, the average size of the bias follows from the simple subtraction made in Table 6.

Table 6. Estimated size of the unit root bias from Tables 4 and 5

		(1) OLS1	(3) OLS3	Size of bias	(4) ML1	(6) ML3	Size of bias
		OLS-estimate, N = 34-35			ML-estimate, N = 34-35		
Table 4	All	0.726	0.819	**-0.093**	0.743	0.819	**-0.076**
Table 4	Multilateral	0.613	0.766	**-0.153**	0.630	0.769	**-0.139**
Table 4	Bilateral	0.705	0.824	**-0.119**	0.722	0.816	**-0.094**
		OLS-estimate, N = 16-17			ML-estimate, N = 16-17		
Table 5	First period	0.672	0.826	**-0.154**	0.663	0.860	**-0.197**
Table 5	Second period	0.586	0.814	**-0.228**	0.585	0.812	**-0.227**

The table gives the 10 estimates we have made of the unit root bias, each based on 2 *x* 70 calculations. The size of the bias is between 0.1 an 0.2 depending upon the number of observations *N*, so that it falls when *N* rises. When we turn to the literature it is mostly estimated on *N*s < 20, so we expect the bias is close to 0.2 in the typical article.

Section 2.1 estimated the censoring bias to a little less than 0.21. Due to their interaction, the aggregate bias is less than the sum as discussed in section 2.2. Later we also use the MRA-method of calculating the meta-average (in section 5). It is made to pick up and correct a censoring bias, not to correct unit root biases – and it is very unclear if it does so.[13]

3.3 Multilateral and bilateral aid flows

The three lowest panels of Table 4 contain a division of aid in two parts: Bilateral and multilateral.[14] One reason that the aid share has so much autocorrelation is that it is an aggregate of many flows with different explanations. So, by dividing in parts the autocorrelation should be slightly less in each part.

We note that the pattern in both parts of the aid flow is almost the same, but while the bilateral aid flows have almost the same autocorrelation as the total, the multilateral aid flows have a bit less. The difference tests borderline significant.

13. We have analyzed if the meta-average detect and correct the unit root bias simply by using the standard estimator on the 6 samples of 70 estimates of the top panel of Table 4. In all these cases the meta-average find values that are outside the range of averages shown, and go to both sides. Hence, it is not easy to predict how the meta-average will work on the aggregate bias. We shall return to this point later.
14. The WDI data does not contain this division, but it is found in the primary DAC-source.

4. A survey of the aid volatility studies

The aid volatility literature consists of only eight studies.[15] They are too few to submit to systematic quantitative analysis. Above we have argued that the study of φ provides a good reduced form estimate of aid volatility, which argues that aid is counter cyclical, though only marginally so. The aid volatility studies approach this in a different way.

4.1 A brief overview of the literature

The eight papers have two central themes: The first question is (i) Does aid increase or decrease economic fluctuations in the recipient countries? That is, can an important outcome variables, x, be found that has less volatility than aid and is positively correlated with aid? (ii) If aid increases fluctuations, in the sense of x, does this contribute to (explain) the aid ineffectiveness result?

The variable x that has been found is the domestic fiscal revenue. It was first found by (i) Pallage and Robe (2001), and led to the claim that aid is pro-cyclical, especially in Africa. Their result is confirmed by Bulíř and Haman (2003 and 2007) and Arellano, Bulíř, Lane and Lipschitz (2008). They demonstrate that aid is positively correlated to and more volatile than the fiscal revenue in many recipient countries. Thus, aid contributes to the fluctuations of the total revenue. As the total revenue is pro-cyclical it follows that aid is increasing, not dampening, economic fluctuations in most LDCs. Why this is not reflected in the real growth rate appears to need an explanation.

Their result is discussed in Chauvet (2005); Hudson and Mosley (2007); and Fielding and Mavrotas (2008). They show that aid is sometimes pro-cyclical and sometimes counter-cyclical. It appears that we are dealing with rather weak effects.

The key new finding is thus that aid volatility matters in itself – not whether aid is pro- or counter-cyclical. The reduced form relation between aid volatility and growth (ii) is made most explicit in Lensink and Morrisey (2000) that starts from the usual result that aid, h_t, has no effect on growth, but then, if a variable measuring aid volatility, $v(h_t)$, is added, it gets a negative coefficient and turns the coefficient to aid positive. However, this result has not been independently replicated, so it is still an unsubstantiated finding.

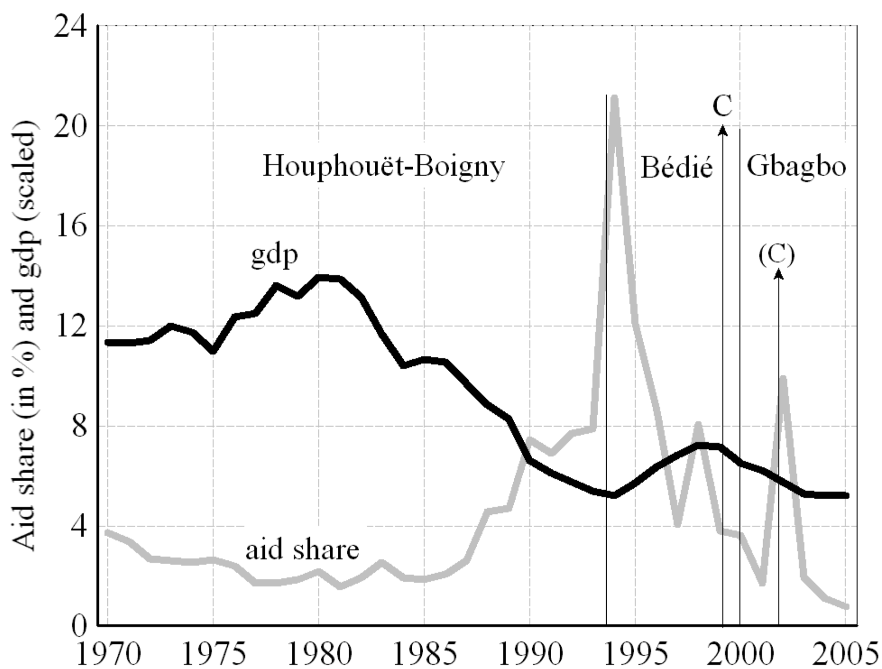
15. These are: Lensink and Morrissey (2000); Pallage and Robe (2001); Bulíř and Hamann (2003, 2007); Chauvet (2005); Hudson and Mosley (2007); Arellano, Bulíř, Lane and Lipschitz (2008); and Fielding and Mavrotas (2008).

4.2 Is aid volatility exogenous?

The main problem for the analysis of aid volatility is that it is rarely exogenous. We have studied aid volatility simply by drawing the path of the aid share in the 10 of the 70 countries where aid inertia is smallest, by the calculation reported in Appendix Table A2, and compared the path with the main political events and the path of gdp (that is GDP per capita) in the country. It appears that *all* major fluctuations in the aid share are closely related to political events in the recipient country.

Arellano, Bulíř, Lane and Lipschitz (2008) illustrate their analysis by the case of Côte d'Ivoire, which is one of the 10 countries, where aid has been most volatile. Figure 3 shows a simple interpretation of this case. For long the country was politically stable and growing quite satisfactory, but after 1982 (the year of the debt crisis), GDP per capita started to fall, and when President Hophouët-Boigny died in 1993 political stability deteriorated. His successor Bédié was overthrown by a military coup and an economic downturn followed. The junta allowed elections to be held the following year. They were won by Gbagbo, and later followed a failed coup, riots, a French intervention, etc.

Figure 3. The path of GDP per capita and the aid share in Côte d'Ivoire 1970-2005



Note: C is coup (C) is a failed coup. The aid share is ODA/GDP in the same prices, while the gdp series is GDP per capita, from Maddison (net). It is linearly scaled (gdp/100-5) to fit. The correlation between the two series is -0.54, which is an unusually large negative correlation (see Doucouliagos and Paldam 2007b).

It is clear that growth (and investment, not shown) has reacted negatively to the deterioration of political stability, and that aid has reacted too, but it would clearly be an exaggeration to explain the economic downturn of the Ivorian economy by the volatility of aid.

A similar story applies to Zimbabwe the last decade, where economic development has been very bad, and aid has ceased. Again, it would be a gross exaggeration to ascribe the economic debacle to the volatility of aid. Much the same story could be told of the volatility of aid in the two Congos and the other 6 countries considered.

Thus one may interpret the argument of Bulíř and Hamann to be that aid should disregard political events, such as the ones in Côte d'Ivoire, as they are transitory. By reacting to such events aid does increase the economic fluctuations resulting from the events. We think that this is serious argument, but that it is quite different from saying that aid volatility is a major factor in aid ineffectiveness.

In conclusion, we think that the aid inertia demonstrated in section 3 is so large that it can, at most, be marginally larger and, hence, we conclude that aid is on average stabilizing.

5. A meta-analysis of the aid allocation literature

Our literature search revealed 35 studies that report 212 estimates of aid inertia (see Part 2 of references). As the AAL consists of 166 studies, only 20% estimate the parameter of inertia. However, all 212 estimates relate to the lagged dependent variable in an aid allocation model, which typically includes also controls for humanitarian needs and donor interests.

The 212 estimates are averaged in two main ways:[16] as a *plain average*, $\underline{\varphi}$, and as a *meta-average*, φ_M, estimated by a MRA, as will be explained. Both estimates can be refined, by taking statistically dependencies into consideration. An author often uses the same dataset, but varies the specification. Accordingly, the estimates from each study are treated as a separate cluster in some of the data analysis.

5.1 The asymmetry of the funnel plot of the 212 estimates[17]

An informative way to display the distribution of a set of estimates is the funnel plot. It depicts the estimates, φ, over their precision, $p = 1/s$, where s is the standard error. The point scatter looks as a funnel that becomes narrower as precision rises. In the absence of bias, the plot is symmetric around the BAS (best axis of symmetry) that is parallel to the p-axis. The *meta-average*, φ_M, is defined as the intersection of the BAS, and the φ-axis – if the funnel is symmetric it is the same as the plain average. The MRA is an estimate of the meta-average even in the case where the funnel is censored. It does so by estimating a path of convergence to the hypothetical uncensored BAS as precision rises.

Figure 4 is the funnel of the 212 estimates. It has an obvious asymmetry (confirmed by the test in Part A of Table 8): It looks as the top part of the funnel with observations above 1 is (almost) missing.[18] We have argued that this asymmetry has two explanations:

(1) It is a publication selection bias *made* by the research/publication process through loops of result-based revisions of the results as explained in section 2.1. We here describe how a sound theoretical prior against inertia results above 1 may cause such censoring. In our case it would cause the funnel to look as it actually does.

---

16. The first step in the analysis is to convert all estimates to the same scale. In this case it is easy, as by definition, a lagged dependent variable is always in the same units as the dependent variable. In all cases, φ measures the proportion of aid that can be explained by past aid. Hence, all 212 estimates are comparable.
17. This section builds on two recent papers on funnel plots: Stanley and Doucouliagos (2009) and Callot and Paldam (2009). See also Roberts and Stanley (2005) for a comprehensive discussion of censoring biases.
18. It is possible that the funnel also misses observations below 1, so that there is a second censoring. However, this is less clear, and will not be discussed.

Figure 4. Funnel plots of 212 estimates of φ in the literature

Figure 4a. All reported estimates

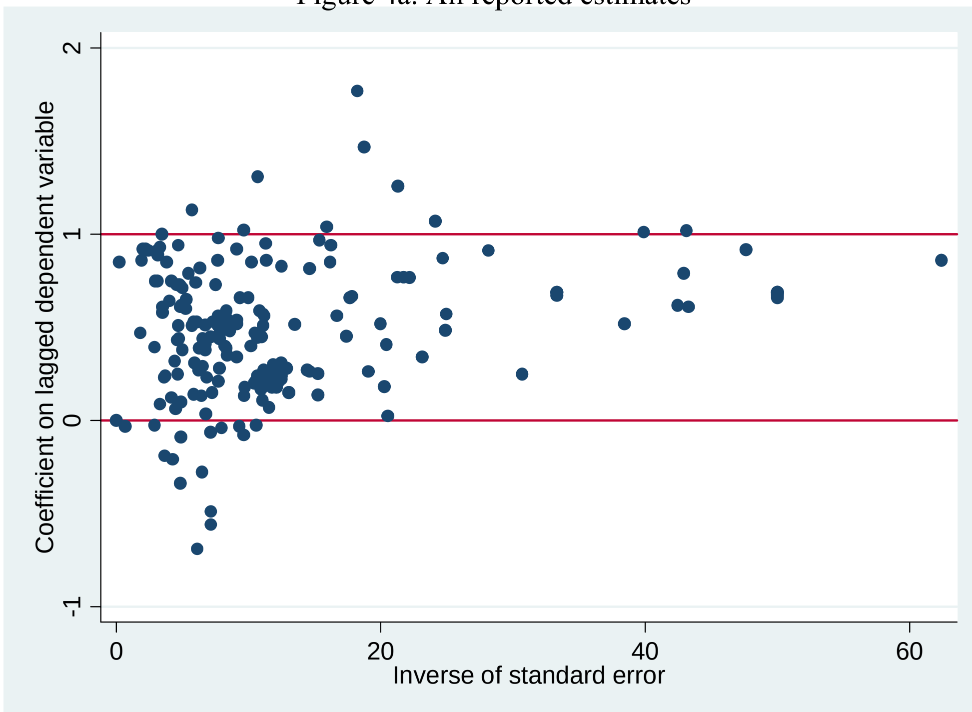
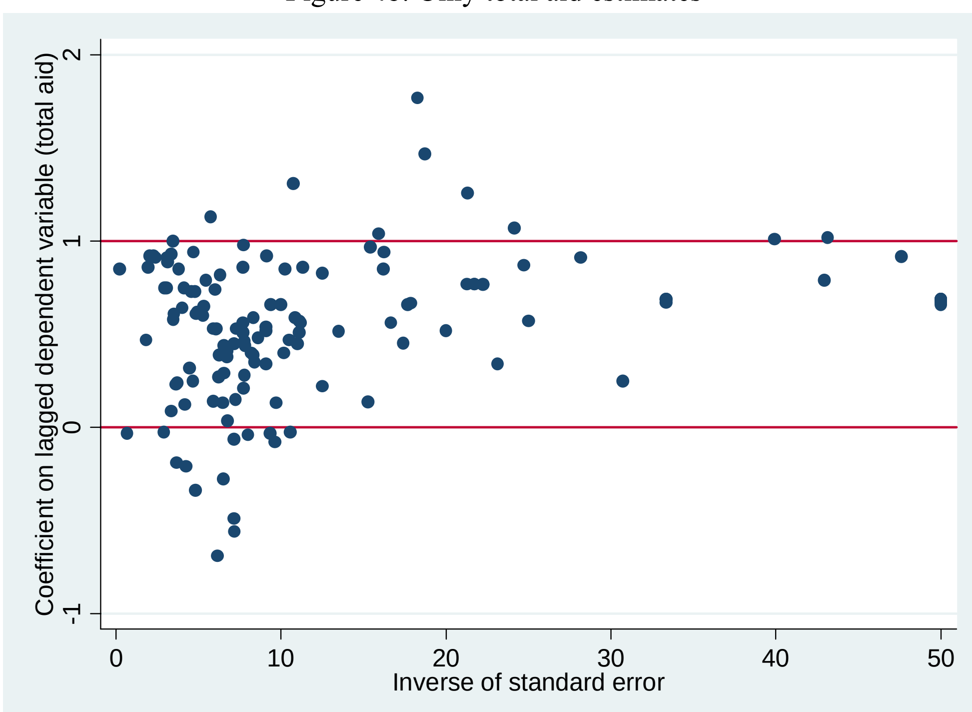


Figure 4b. Only total aid estimates



(2) It is a *natural* funnel asymmetry due to an undetected unit root bias.[19] Our analysis of this bias in section 3.2 shows that it occurs at the high precision end of the funnel, and keeps this part of the funnel too low. This is the high precision end of the funnel the MAR converges to, so we expect that the MRA give results that are too low (see however section 3.2 above).

5.2 *The plain average:* $\underline{\varphi} \approx 0.46$

Table 7 reports the distribution of reported estimated lagged dependent variable coefficients. The majority of estimates report a coefficient that is statistically significantly larger than zero. In addition, the results show a significant difference between bilateral and multilateral agencies: almost one in 5 estimates of multilateral agency aid allocations report an absence of an inertia effect, compared to only 2% of bilateral donors.

The table also presents three averages of the reported findings: The plain average, the median and the weighted average, $\underline{\varphi}_w$, which is calculated as $\underline{\varphi}_w = \Sigma N_i \varphi_i / \Sigma N_i$, where φ_i is the average estimate from the i[th] study and N_i is sample size associated with the i[th] study.[20] These averages are presented for bilateral and for multilateral donors as well. While the averages are rather similar for total aid and bilateral aid, the averages are much smaller for multilateral agencies. Note also that the weighted means are a little smaller than the plain averages.

Table 7. Distribution of aid-inertia effects, all-set

Reported value of φ	Percent of estimates: All estimates	Bilateral	Multilateral
$\varphi < 0$	1%	16%	14%
$\varphi = 0$	17%	2%	21%
$0 < \varphi < 1$	82%	82%	64%
$\varphi \geq 1$	Below 1%	Below 1%	Below 1%
Plain average $\underline{\varphi}$	0.46	0.46	0.13
Median φ	0.47	0.51	0.23
Weighted mean φ	0.41	0.42	0.11

Note: φ is the coefficient on the reported lagged dependent variable. Cells report the percentage of estimates that fall into each category.

19. The term "natural" means that it occurs without any censoring. We have found no case till now of a natural funnel asymmetry that is not due to bias.
20. Alternative weights such as the inverse of the estimate's variance and citations can also be used, and instead of clustering by paper, we tried clustering by author. Neither of these experiments changed the results significantly.

5.3 Correcting for censoring, a brief introduction to the technique

Typically, the MRA involves estimating some variant of the following model:

$$\varphi_i = \beta_0 + \beta_2 Z_i + v_i \tag{1}$$

here φ_i denotes the standardized estimate i and $\boldsymbol{Z}$ is a vector of study characteristics, such as data, specification and estimation differences. β_0 is the estimate of the population parameter of interest. That is, the sum of β_0 and β_2 give the literature's best estimate of the underlying population effect, in this case the size of the inertia effect.

Statistical analysis requires that the data-set is representative. When the data are censored this means that a part of the data is unavailable to the public. Consequently, the missing part of the distribution should be taken into consideration to reach a representative average. The FAT-PET MRA estimator has been developed to do precisely that.

The logic of this estimator is simple. Smaller samples tend to have larger standard errors. If publication selection bias is absent from a literature, no association between a study's reported effect and its standard error should appear. However, if there is publication selection bias, smaller studies will search for larger effects in order to compensate for their larger standard errors.[21] This suggests running the following regression:

$\varphi_i = \beta_M + \gamma s_i + \beta_2 Z_i + v_i$ (2a) or after division by s_i: $t_i = \beta_M p_i + \gamma + \beta_2 Z_i p_i + v_i$ (2b)

s_i is the standard error of the inertia estimate φ_i; $t_i = \varphi_i / s_i$; and $p_i = 1/s_i$ is the precision of the estimate. The two equations are equivalent; but (2a) gives an easier intuition, while (2b) is preferable to estimate as it is corrected for heteroskedasticity. As s falls and p rises the equation converges to β_M, which it is the meta-average previously discussed.

The term FAT (for Funnel Asymmetry Test) is used as the regression is related directly to the funnel plots and is designed to detect statistically funnel.[22] The coefficient, γ, is statistically significant if the funnel is asymmetric. Simulations show that the meta-average β_M in equation (2) does correct the φ-set rather well for censoring (Stanley 2007). Stanley calls this test (H_0: $\beta_0 = 0$) the PET (for Precision-Effect Test), and hence the meta-regression model equation (2) is known as the FAT-PET MRA.

21. This can be done by modifying specifications, functional form, samples and even estimation technique.

22. See Egger *et al.* (1997), Sutton *et al*. (2000), Rothstein *et al.* (2005) and Stanley (2005).

5.4 *The meta-average, $\varphi_M \approx 0.7$ to 0.8*

Table 8 presents 15 estimates of the meta-average. At the top are the detailed estimates, which are then re-estimated with robust regression to address the issue of outliers, and with clustered data analysis to correct the standard errors for statistical dependencies, where the estimates reported in each study are a separate cluster. To save space we only bring the key results for the two re-estimations – the rest of the table is virtually unchanged.

Table 8. FAT-PET MRA estimates on the 212 estimates of φ_i

	Variable	(1) All-donors	(2) All-donors	(3) All-donors	(4) Bilateral	(5) Multilateral
				full estimate presented		
Part A	γ	**-2.37**	**-2.38**	**-2.77**	**-2.39**	0.24
Asymmetry test		[4.4]***	[4.5]**	(6.20)***	(4.3)***	(0.3)
Part B	All aid	**0.72**	-	-	-	**0.09**
Estimate of φ_M		[24.9]***				(2.1)**
Aid aggregate	Aid share	-	**0.63**	**0.70**	**0.63**	-
			[5.2]***	(6.84)***	(5.14)***	
Part C	Share of aid	-	0.10	0.12	0.11	-
Correction terms			[0.6]	(0.87)	(0.6)	
for other aid	Per capita	-	-0.02	0.07	-0.03	-
definitions			[0.2]	(0.70)	(0.2)	
	Total aid	-	0.15	0.16	0.16	-
			[1.3]	(1.6)	(1.3)	
Part D	USA	-	-	**-0.18**	-	-
Other controls				(4.5)***		
	Multilateral	-	-	**-0.58**	-	-
				(8.7)***		
Re-estimation 1:		Robust regression – only estimate of φ_M presented				
Only Part B	Aid variable	**0.83**	**0.81**	**0.76**	**1.06**	0.09
		(38.6)***	(19.1)***	(19.3)***	(28.2)***	(1.8)
Re-estimation 2:		Clustered data analysis – only estimate of φ_M presented				
Only Part B	Aid variable	**0.72**	**0.63**	**0.70**	**0.63**	**0.09**
		(8.2)***	(3.5)***	(4.16)***	(3.5)***	(3.6)***
From the clustered	R^2 clustered	0.03	0.77	0.84	0.77	0.27
data analysis	*K* column	35	35	35	34	5
	N column	212	212	212	205	14

Absolute t-statistics reported in square brackets are derived from bootstrapped standard errors. All estimates derived from WLS regressions using precision $p_i = 1/s_i$ weights. Bold numbers are significant at the 5 percent level. *, **, *** denotes statistically significant at the 10%, 5% and 1% levels, respectively. Some observations are lost due to missing information. Coefficients and their level of significance are broadly similar if a fixed effects model is used. The R-squared relates to the clustered data analysis, and not to the mixed effects model.

The three first columns (1) to (3) are the estimates for total aid, done in 3 *x* 3 versions, giving 9 estimates of the meta-average: The three at the top are around 0.70, but as all corrections for other aid definitions are positive, the two lowest estimates are probably too low. The robust regression results are higher, but then the clustered analysis gives slightly lower results. All said, we cannot be sure that φ_M is larger than 0.70.

Hence it is probably less that the (univariate) time series analysis in section 2 (0.70 < 0.82). There are two explanations for this. Firstly, the aid allocation models may partial out the effects of other motives for allocating aid, such as humanitarian concerns, commercial interests, the recipient's human rights record which have inertia as well, etc. Secondly it is likely that the meta-average contains some unit root bias that was not corrected by the MRA.

Hence we believe that 0.70 underestimates aid inertia. So perhaps the univariate estimate of 0.82 is better.

The two last columns (4) and (5) of Table 8 break the total aid flows into bilateral and multilateral flows. It appears that the bilateral flow gives much the same result as the aggregate flow, while the multilateral flow shows much less inertia. He difference is much larger that it was in the univariate results. However, the meta-evidence is from only five studies offering only 14 observations. So all we can say is that the result confirms the impression that inertia is smaller in the multilateral aid flows than in the bilateral ones.

6. Conclusion

Both our own univariate time series analysis and the meta-analysis of the multivariate analyses reported in the aid allocations literature confirm the existence of a sizeable aid inertia effect. The two methods have different strengths and weaknesses as discussed, so it is no wonder that the results differ. However, we demonstrate that most of the difference may be explained by a censoring bias and a unit root bias, which are both estimated/assessed quantitatively. We conclude that the best value for φ is about 0.80. This large inertia can be explained in two ways:

(1) Deliberate policy and bureaucratic inertia. Many projects have an implementation period that exceeds a year, and an aid program is negotiated for a period of 3-5 years. Also, donors often negotiate longer run country-programs with selected recipients.

(2) The persistence of the factors explaining aid. The latter explanation means that some of the inertia may accrue to the explanatory factors.

When the aid flows are separated into multilateral and bilateral, the aid inertia turns out to be smaller for the multilateral donors. Here the literature is rather limited, so this is an area that warrants further attention from researchers.

The considerable inertia found means that we can reject the aid volatility claim. In general aid is not volatile, but has a stabilizing influence in the economies of the recipient countries. This does not mean, of course, that aid to all countries is stabilizing. To certain problem countries aid is cut in order to generate regime changes, so here aid is used as a deliberate destabilizer. However, such cases are rare.

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Appendix: Table A1. The aid data for 115 LDCs analyzed in section 2

Nr	Country	Avr	N	Nr	Country	Avr	N	Nr	Country	Avr	N
1	Afghanistan	7.94	27	41	**Ghana**	6.13	46	81	**Panama**	1.34	46
2	Angola	5.78	21	42	Grenada	5.64	22	82	**Papua New Guinea**	13.82	39
3	Antigua &	2.23	29	43	**Guatemala**	1.33	46	83	**Paraguay**	1.88	46
4	**Argentina**	0.07	44	44	Guinea	10.03	20	84	**Peru**	0.92	46
5	Aruba	2.86	8	45	Guinea-Bissau	41.18	34	85	**Philippines**	1.27	46
6	Bangladesh	4.87	33	46	**Guyana**	12.46	46	86	**Rwanda**	16.04	46
7	**Belize**	7.46	46	47	**Haiti**	6.56	46	87	Samoa	19.78	24
8	**Benin**	8.23	46	48	**Honduras**	6.05	46	88	Sao Tome &	70.35	26
9	Bhutan	16.10	26	49	**India**	1.07	46	89	**Senegal**	10.72	38
10	**Bolivia**	7.28	36	50	**Indonesia**	1.76	39	90	**Seychelles**	10.24	46
11	**Botswana**	9.42	46	51	**Jamaica**	2.60	45	91	**Sierra Leone**	12.96	42
12	**Brazil**	0.26	46	52	**Jordan**	12.87	41	92	Solomon Islands	25.60	34
13	**Burkina Faso**	10.28	46	53	**Kenya**	6.11	46	93	Somalia	28.41	31
14	**Burundi**	15.20	46	54	Kiribati	28.94	27	94	**Sri Lanka**	4.64	46
15	Cambodia	8.38	34	55	Lao PDR	13.67	22	95	St. Kitts &	4.92	29
16	**Cameroon**	4.16	45	56	Lebanon	2.07	17	96	St. Lucia	4.41	27
17	Cape Verde	25.25	20	57	**Lesotho**	11.16	40	97	St. Vincent &	7.71	33
18	**CAR**	10.73	46	58	Liberia	13.95	39	98	**Sudan**	4.13	46
19	**Chad**	9.66	46	59	**Madagascar**	8.06	46	99	**Suriname**	8.16	45
20	**Chile**	0.57	46	60	**Malawi**	17.44	46	100	**Swaziland**	7.98	46
21	China	0.32	27	61	**Malaysia**	0.51	46	101	**Syria**	3.57	46
22	**Colombia**	0.67	46	62	Maldives	9.27	21	102	Tanzania	17.63	18
23	**Comoros**	25.31	40	63	**Mali**	15.26	38	103	**Thailand**	0.78	46
24	**Congo, Bra**	7.48	46	64	Marshall Islands	40.29	8	104	Timor-Leste	48.34	6
25	**Congo, Kin**	7.06	46	65	**Mauritania**	17.63	46	105	**Togo**	8.53	46
26	**Costa Rica**	1.80	46	66	Mauritius	1.97	26	106	Tonga	19.50	24
27	**Cote d'Ivoire**	3.99	46	67	**Mexico**	0.09	46	107	**Trinidad &**	0.40	45
28	Djibouti	16.55	15	68	Micronesia	43.25	13	108	**Tunisia**	3.90	45
29	Dominica	12.69	29	69	**Morocco**	2.83	46	109	**Turkey**	0.43	38
30	**Dominican R**	1.88	45	70	Mozambique	30.23	26	110	**Uganda**	7.92	46
31	**Ecuador**	1.24	46	71	Namibia	3.57	22	111	**Uruguay**	0.41	46
32	**Egypt**	5.43	46	72	**Nepal**	6.35	46	112	Vietnam	4.02	17
33	**El Salvador**	3.46	46	73	Dutch Antilles	7.62	6	113	Yemen	5.01	16
34	Equatorial Guinea	21.37	22	74	New Caledonia	12.23	35	114	**Zambia**	12.07	46
35	Eritrea	30.35	13	75	**Nicaragua**	12.33	46	115	**Zimbabwe**	2.77	44
36	Ethiopia	9.82	25	76	**Niger**	10.76	46				
37	**Fiji**	3.05	46	77	**Nigeria**	0.79	46		Average	10.53	4226
38	French Polynesia	9.99	35	78	Oman	1.46	44		Median	7.48	
39	**Gabon**	2.71	46	79	**Pakistan**	3.76	46		SD	11.74	
40	**Gambia**	18.64	40	80	Palau	50.63	14				

Note: Some countries with double names are only give by first part and "&".
The bolded countries are the 70 countries used in most of estimations in section 2. The data for Chile, are zero for a long period, and the results are consequently not very interesting.

Table A2. Average inertia in the aid share for the 70 countries with full data 1970-2005

1	Congo. Bra	0.457	26	Mali	0.723	51	Nepal	0.847
2	Congo. Kin	0.469	27	Paraguay	0.729	52	India	0.852
3	Senegal	0.535	28	Guyana	0.730	53	Brazil	0.856
4	Rwanda	0.557	29	Sudan	0.734	54	Kenya	0.858
5	Argentina	0.567	30	Suriname	0.735	55	Costa Rica	0.862
6	Honduras	0.574	31	Pakistan	0.735	56	Lesotho	0.866
7	Zambia	0.581	32	Malawi	0.743	57	Botswana	0.872
8	Niger	0.584	33	Ghana	0.744	58	Seychelles	0.882
9	Cote d'Ivoire	0.596	34	Nicaragua	0.748	59	Colombia	0.894
10	Cameroon	0.609	35	Syria	0.758	60	Guatemala	0.903
11	Fiji	0.618	36	Philippines	0.768	61	Burkina Faso	0.918
12	Trinidad &	0.621	37	Gabon	0.773	62	Indonesia	0.919
13	Dominican R	0.625	38	Jordan	0.774	63	Sierra Leone	0.927
14	Uruguay	0.629	39	Papua New Guinea	0.777	64	Uganda	0.936
15	Morocco	0.637	40	Bolivia	0.781	65	Egypt	0.942
16	Mauritania	0.639	41	Turkey	0.787	66	Burundi	0.974
17	CAR	0.642	42	Panama	0.788	67	Tunisia	0.981
18	Madagascar	0.643	43	Togo	0.790	68	Jamaica	0.995
19	Peru	0.676	44	Zimbabwe	0.797	69	El Salvador	1.029
20	Benin	0.694	45	Chad	0.800	70	Nigeria	1.065
21	Haiti	0.697	46	Thailand	0.803			
22	Mexico	0.706	47	Comoros	0.807		Average	0.760
23	Belize	0.706	48	Sri Lanka	0.817		Median	0.763
24	Gambia	0.708	49	Ecuador	0.827		SD	0.132
25	Malaysia	0.719	50	Swaziland	0.832			

Note: The average of the 6 measures: (1) OLS1, (2) OLS2, (3) OLS3, (4) ML1, (5) ML2, (6) ML3, from the top panel of Table 4, which are also shown on Figure 2. The countries are sorted by average.