Working Paper No. 2012/35

Consequences of Aid Volatility for Macroeconomic Management and Aid Effectiveness

John Hudson*

March 2012

Abstract

This paper reviews both the literature on aid volatility and also adds to that literature. In general, the focus of this literature has been on the volatility of overall aid, while we focus more on the volatility of the individual aid sectors, e.g., education aid. In doing this, detailed use is made of the Creditor Reporting System (CRS) database on aid commitments and disbursements, particularly the latter. Key aid sectors in explaining total aid volatility relate to debt, programme assistance, infrastructure and government. This reflects both these sectors' volatility and their size. The most volatile aid sectors *per se* are debt, industry, humanitarian, NGO and programme assistance. The least volatile are education, health, other social infrastructure and multi-sector aid. We also find evidence that the volatility of different aid sectors saw a peak around 2006, which

…/.

Keywords: aid volatility, sector aid, school completion rates, internet users

JEL classification: F35, O11, L31

*Department of Economics, University of Bath, Bath; email: j.r.hudson@bath.ac.uk

This working paper has been prepared within the UNU-WIDER project 'Foreign Aid: Research and Communication (ReCom)', directed by Tony Addison and Finn Tarp.

UNU-WIDER gratefully acknowledges specific programme contributions from the governments of Denmark (Ministry of Foreign Affairs, Danida) and Sweden (Swedish International Development Cooperation Agency—Sida) for the Research and Communication (ReCom) programme. UNU-WIDER also acknowledges core financial support to UNU-WIDER's work programme from the governments of Finland (Ministry for Foreign Affairs), the United Kingdom (Department for International Development), and the governments of Denmark and Sweden.

ISSN 1798-7237 ISBN 978-92-9230-498-0

was about when debt aid volatility was at its highest. In an asymmetric VAR, we find that both positive and negative aid volatility tend to be corrected for in the following period, rather than there simply being a return to trend. There are also cross-sector effects by which volatility in one sector has subsequent impacts on other sectors. These tend to revolve around government aid and programme assistance. Finally we examine the impact of aid and aid volatility on very specific targets, finding both to be significant. There are several lessons we draw from this: first, in analysing aid's impact, for example, on social targets such as school completion rates, social sector aid rather than overall aid is the relevant variable although not necessarily just education aid. Second, we argue that a complete understanding of aid's impact can only be obtained by an analysis such as this, across a range of targets and then analysing the impact of these targets on the macroeconomy itself. This leads to the further conclusion that it is not the volatility of total aid which matters so much as the sum of sector and subsector volatilities.

Acknowledgements

I would like to acknowledge the extraordinarily detailed and helpful comments of an anonymous referee.

Acronyms

CRS	Creditor Reporting System
CV	coefficient of variation
ODA	official development assistance

The World Institute for Development Economics Research (WIDER) was established by the United Nations University (UNU) as its first research and training centre and started work in Helsinki, Finland in 1985. The Institute undertakes applied research and policy analysis on structural changes affecting the developing and transitional economies, provides a forum for the advocacy of policies leading to robust, equitable and environmentally sustainable growth, and promotes capacity strengthening and training in the field of economic and social policy making. Work is carried out by staff researchers and visiting scholars in Helsinki and through networks of collaborating scholars and institutions around the world.
www.wider.unu.edu *publications@wider.unu.edu*

UNU World Institute for Development Economics Research (UNU-WIDER)
Katajanokanlaituri 6 B, 00160 Helsinki, Finland

Typescript prepared by Liisa Roponen at UNU-WIDER

1 Introduction

In recent years the impact of aid has been more favourably viewed in the literature. One negative aspect, however, has been aid volatility, and indeed a key pledge from the Paris Declaration of 2005 was to make aid more predictable. Celasun and Walliser (2008) argue that unexpected aid shortfalls can force governments to disproportionately cut investment, including in human capital, while aid windfalls can disproportionately boost government consumption. The issue is relatively new to the literature. Pallage and Robe in 2011 observed that aid is highly volatile with an average volatility of about 25 per cent in African recipients and 29.5 per cent in non-African recipients. But perhaps it was the work of Bulíř and Hamann (2003, 2008) which had most early influence. They argue that the volatility of aid is (i) greater than that of government revenue, (ii) increasing over time and (iii) procyclical (i.e., aid flows are inversely correlated with the level of government expenditures in any particular year). Others have since built on and modified their conclusions. For example, Hudson and Mosley (2008a) find that volatility as a whole reduces growth given the level of aid, but not in a uniform way, differentiating between upside and downside volatility.

The majority of this work focuses on the totality of aid and its impact on key macroeconomic variables such as growth and government expenditure. Indeed this is also the case with the impact of aid itself. This is problematic. Why should health aid promote growth as equally as infrastructure aid, or vice versa with respect to targets such as infant mortality? Why, too, should volatility in these two sectors have the same impact? In this paper we seek to examine the impact of aid and aid volatility of different aid sectors. The database we use is the OECD's Creditor Reporting System (CRS) on the DAC website. This gives detailed information on aid disbursements, and, over a longer time, commitments, by 50 different sectors and subsectors. The data on the former are only available in a reliable form since 2002, but on a panel data basis this is now sufficient to allow meaningful analysis.

We are also interested in analysing the impact of aid on specific, and in some cases fairly narrow, targets. It is important to realize that much of aid works not so much on the macroeconomy, although there may, for example, be exchange rate effects and policy environment effects for all aid, but rather on individual aspects of the economy. The road built between A and B facilitates trade between those two locations, a new hospital in location C facilitates healthcare in that location, the promotion of secondary education does just that. Aid and aid volatility then impact on those projects, and, spillover effects apart, not on others. Now if there is a temporary switch in aid from healthcare to secondary education, this will not show up in the overall aid figures as volatility. The two will cancel each other out. But the healthcare project will have suffered from negative volatility and the education project from positive volatility. In this respect, a better guide to the impact of volatility can be found by summing the volatility of the individual aid sectors rather than by looking at the volatility of total aid. Similarly the impact should be judged by the impact on specific, almost micro, target variables as much as on macroeconomic ones.

The paper proceeds as follows. In the next section, we review the literature, after which we discuss methodological and theoretical issues. The literature review is wide covering many aspects of aid volatility. Section 4 introduces the data, presenting summary statistics on the relative variability of the different aid sectors. The empirical analysis follows. We first decompose overall volatility into its constituent, sector parts. We then analyse the extent to which volatility is a dynamic process. Are shocks temporary? Do they persist more than one year? Is there over-correction with a positive shock being compensated for in the following period by a negative one? And to what extent are there cross-sector effects, with lagged shocks impacting on other aid sectors? Finally we examine the impact of the different aid sectors and associated volatility, on selected 'micro targets', i.e., death rates, primary school completion rates, internet usage and mobile phone subscriptions. Finally we conclude the paper. Table 1 defines some key concepts and the measures of volatility we make use of in this paper.

Table 1
Key definitions and measures of volatility

Aid sector	This is the sector, or subsector, at which the aid is identified. Examples include health and programme assistance. The term 'sector' is the one employed on the CRS database. The different aid sectors we use are defined in the Appendix Table. They are chosen to be a comprehensive summary of total aid and also to reflect important social and productive sectors.
Aid target	This is the specific identifiable variable on which the aid is designed to impact. It could be literacy rates, internet usage, or at a local level, access to safe drinking water in a specific location.
	Measures of volatility
Coefficient of variation (Table 2)	The standard deviation of the aid variable as a proportion of GDP divided by its mean. This reflects variations between and within countries over time.
Adjusted coefficient of variation (Table 2)	The standard deviation of the difference between the aid variable, as defined above, and the average value for each country. This reflects variations within countries over time, but not between countries. It is found by taking the error term from a fixed-effects regression of aid, with no explanatory variables other than the fixed effects. It gives an insight into aid variability over time, but not volatility as a steady increase, e.g., along a trend is not regarded as volatility *per se*.
Aid volatility (Table 3)	This represents the mean of the square of the error term from regressing aid disbursements on a trend and trend squared for each country. If predicted aid from this regression is negative, then a lower bound of zero is imposed and the error adjusted accordingly.
Mean adjusted CV of aid volatility (Table 3)	Mean adjusted CV (coefficient of variation) divides the standard error of aid volatility, as defined above, in each year by the mean value of aid in all years. In some years, particularly for debt aid, disbursements are low, which would lead to very large CVs as normally calculated.
The aid error term (Tables 4 and 5)	In Table 4 we represent the results of an 'asymmetric VAR' based on the error term from the trend regression described above. This error term when squared is aid volatility, but is, in its original form, more suitable for analysis in a VAR. This is also used in the impact analysis of Table 5.
The volatility measure Figures 1 & 2)	In Figures 1 and 2 the square root of aid volatility is regressed on a time trend and trend squared to fit trends in volatility. The square root was used as this more closely relates to the error itself and is less affected by outliers.

Source: See text.

2 Literature review

2.1 Measuring aid volatility

Revenue volatility can present problems to developing countries. Rodrik (1990) argues that the volatility of revenue inflows, a high proportion of which for the poorest countries is aid, may result in volatility of expenditure and instability of policy. There is a growing, if relatively recent, literature which focuses on the role of aid in this respect. Mosley and Suleiman (2007) show that the ability of the recipient country's public sector to implement coherent investment programmes and fiscal policies is reduced by aid volatility. Lensink and Morrissey (2000) conclude that volatility damages the macroeconomic effectiveness of aid. However, the key initial work in this area is by Bulíř and Hamann (2003, 2008) as described above. Their empirical work (ibid. 2008) is based on a sample of 76 countries from 1975 to 2003. They measure the residuals by taking a Hodrick-Prescott filter.[1] The square of those residuals[2] then measures volatility in a specific year for an individual country.

Critical in all this is how one scales aid, particularly when comparing volatilities between different variables. Bulíř and Hamann specify aid in US dollars and government revenue in domestic currency. Both series were transformed into proportions of nominal GDP, PPP GDP, and constant US dollars per capita. This was done in part to remove the impact of scale on variability—clearly a variable with a large mean will tend to have a large variance. But when this is done, the resultant ratio is affected by both the variance of GDP, the variance of the revenue variable, e.g., aid, and the covariance between the two. If the two are perfectly negatively correlated so that changes in the one neutralizes changes in the other, then the variance of the ratio will equal zero. The normalization process that Hudson and Mosley (2008a) employ involved defining all variables as a proportion of their mean value for the whole estimation period, multiplied by 100. By normalizing around an arbitrary mean of 100 they remove the scale factor from the variance, i.e., the tendency for low ratios of aid or expenditure to GDP to have low variances. Hudson and Mosley also prefer to use the median, rather than the mean, as a measure of the relative volatility of aid and domestically-generated revenue.[3] They find that the measurement of aid volatility is more or less invariant with respect to the choice of units; but this was not the case for government revenue. Least volatility is evident for government revenue expressed as a ratio of GDP, slightly more when expressed, not as a ratio, but simply in terms of the local currency, and substantially more when government revenue is expressed in US dollars. Indeed in US dollars, volatility is approximately 60 per cent greater than when defined in terms of the GDP ratio. Hence in comparing the volatility of different variables, the choice of unit is critical.

---

1 This includes using a value for lambda of seven (see Bulíř and Hamann 2008 for clarification).

2 Or the square root of this squared term.

3 Bulíř and Hamann take the average as defined by the mean and also the median. We argue that the latter is preferable in this case because of the properties of a ratio. Given two countries, one with government volatility twice that of aid volatility and the other with the opposite scenario, relative volatility defined as the ratio of aid to government revenue volatility will be 0.5 and 2.0 respectively with a mean value of 1.25, misleadingly implying that volatility is greater for aid than for government revenue.

In their original paper, Bulíř and Hamann found that volatility was highest in the countries which are most aid-dependent, which are generally the poorest and most vulnerable. However, in their 2008 paper, they find that the pattern is more complex, and that both country groups—those that are little dependent on aid and those that are heavily dependent on aid—display high aid volatility relative to government revenue. Hudson and Mosley (2008a) in a subsequent paper find no evidence for highly aid dependent countries to have higher volatility. Indeed, they conclude that volatility declines as the aid-revenue ratio increases. But to a large extent they are able to confirm the work of Bulíř and Hamann. Thus they find that the ratio of aid to government revenue volatility was in excess of one for almost all countries. The volatility of overseas aid is also noted to be severe (in relation to the volatility of domestic revenue) and increasing over time.

2.2 The impact and causes of aid volatility

In a work which parallels that of Fielding and Mavrotas (2005), Hudson and Mosley (2008a) examine the link between volatility and donor concentration. There was a tendency for countries with high two-donor concentration ratios, i.e., the share of aid provided by the two biggest donors, to have relatively high volatility. They also find that in part, volatility was in response to recipient need, e.g., the famines in Ethiopia, but in part it was impacted on by donor coordination. There was a tendency for donors to be positively coordinated in giving aid to specific countries, which suggests that they tend to respond to common signals and/or are impacted upon by common factors such as a global economic cycle. In terms of impact, they find that volatility as a whole reduces growth given the level of aid, but not in a uniform way. The initial impact of both positive/upside and negative/downside volatility is to reduce the impact of aid. But subsequently some of this adverse impact is reversed, although only for upside volatility. With downside volatility there is no such reversal. This may reflect problems of absorptive capacity being short term only. Upside volatility may also be reacting to emergencies and reflect an element of flexibility inherent in 'reactive' forms of aid. The high incidence of this type of aid is, therefore, in principle an asset rather than a liability. Even negative volatility might feasibly have longer-term beneficial impacts in persuading recipients to move towards policy reform, which are not apparent within the relatively short time-horizon Hudson and Mosley looked at. The question as they visualized it was, therefore, not to try and reduce the volatility of aid to zero, but rather to reduce those elements in volatility which cause harm, or, to take the approach extensively developed by Eifert and Gelb (2008), to seek to neutralize the harmful effects in some other way.

Other work has expanded upon these original themes. On the theoretical side, Agenor and Aizenman (2010) study the impact of aid volatility in a two-period model focusing on self-insurance, taking the form of a first-period contingency fund financed through taxation. Unsurprisingly, an increase in aid volatility is shown to raise the optimal contingency fund. But if future aid also depends on the size of the contingency fund (as a result of a moral hazard effect on donors' behaviour), the optimal recipient policy may entail no self-insurance. On the empirical side, Chauvet and Guillaumont (2009) show that aid, even if volatile, is not clearly as procyclical as is often argued, and, even if procyclical, it is not necessarily destabilizing. Unlike much of the literature, they measure aid volatility with respect to exports. The stabilizing/destabilizing nature of aid is measured by the difference in the volatility of (i) exports and (ii) aid plus export flows. Then, in order to take into account the diversity of shocks to which aid can respond, they consider the effect of aid on income volatility and again find that aid is making growth more stable, while its volatility reduces this effect. Finally through growth regressions, they show that the higher effectiveness of aid in vulnerable countries is, to a large extent, due to its stabilizing effect. Eifert and Gelb (2008) look at what can be done more from the donor's side. They argue that the costs of aid volatility can be dramatically reduced by a flexible pre-commitment rule which adjusts aid flows in response to improvements or deteriorations in country performance ratings. They also suggest that a buffer stock of around 50–100 per cent of annual aid-financed spending might enable a corrective feedback loop, with the necessary buffer depending on the size and variability of aid flows.

Arellano et al. (2009) examine the effects of aid and its volatility on consumption, investment, and the structure of production in the context of an inter-temporal, two-sector general equilibrium model. They argue that a permanent flow of aid mainly finances consumption rather than investment. Aid volatility results in substantial welfare losses to consumers, equivalent to 8 per cent of the aid budget. Hudson and Mosley (2008b) analyse the impact of aid volatility on GDP/GNP shares of expenditure. Negative volatility reduces investment and government expenditure shares and also the import share. This may be because of the type of aid which is subject (a donor effect) to volatility, or because consumers are better able to absorb shocks by drawing on savings and/or borrowing than other agents. The results also suggest a limited ability of governments to rearrange revenue flows to reduce the impacts upon their own expenditure priorities. Positive volatility also reduces investment and government expenditure shares, as well as increasing the consumers' expenditure share. These results suggest that absorptive capacity constraints particularly limit aid's effectiveness with respect to both investment and government spending. Thus, in both cases, volatility impacts most consistently and adversely on investment and the government.

2.3 A more micro-based approach to the impact of aid volatility

The vast majority of the aid effectiveness literature has been devoted towards understanding the effects of aid flows on macroeconomic aggregates, particularly economic growth. Some studies have examined other macroeconomic factors such as public sector behaviour in developing countries (Mavrotas and Ouattara 2006a, 2006b). But there have been few attempts to focus the attention more finely. This perspective very much views aid from a macroeconomic viewpoint, ignoring what the aid is actually for, i.e. frequently very specific projects or sectors. In addition, much of the literature tends to treat all aid as the same. Clemens, Radelet and Bhavnani (2004) question this and argue that different types of aid impact on growth over different time frames, and to lump it all together in cross-country growth regressions is inappropriate. They focus on aid which could stimulate growth in a four year time-horizon. This includes budget and balance-of-payments support, investments in infrastructure, and aid for productive sectors such as agriculture and industry. Neanidis and Varvarigos (2009) make the distinction between tied and 'pure' aid. They find that scenarios in which aid can hurt the recipient's growth rate emerge only in cases where foreign aid is volatile.

Fielding and Mavrotas (2005) also depart slightly from this general approach and distinguish between sector aid and total aid in examining aid volatility in 66 countries over 1975-2004. Their paper built on the conclusion by Levin and Dollar (2005) that aid is more volatile in countries identified as having weak political institutions and historically poor macroeconomic policies. Consistent with this, Fielding and Mavrotas conclude that institutional quality and macroeconomic stability affect aid volatility, as does reliance on a small number of donors. However, the relative importance of these effects varies across different aid types. Reflecting this, countries that have recently agreed to IMF conditionality experience higher total aid volatility, but not higher sector aid volatility. This suggests that having agreed to such conditionality is a sign of weakness in existing macroeconomic policy. Fielding and Mavrotas (2008) find that the factors driving up sector aid volatility are different to those impacting on total aid volatility. In addition, a number of individual donors (in particular, Germany, the United States and the European Commission) appear to be associated with relatively high volatility sector aid flows.

Wolf (2007) and Stuckler, Basu and McKee (2011) are more focused on the effects of aid volatility on more micro-targets. Wolf analyses the effects of the volume and volatility of aid on education, health, water and sanitation outcomes. Overall the share of official development assistance (ODA) that is provided for education and health seems to have a positive impact on outcomes in these sectors, whereas total aid seems to be negatively associated with these. Aid volatility is associated with *better outcomes* in sanitation, water, and infant mortality, contrary to expectations. The merits of this paper are in its focus and the use of sector aid as well as total aid. But the research measures aid volatility as the coefficient of variation for total aid between 1980 and 2002, whilst the regressions themselves relate to just 2002. Hence, this is entirely different to the concept of volatility as used by most of the literature and it is not really clear what this is picking up. Stuckler, Basu and McKee focus on one of the possible reasons for volatility with respect to health. They note that there is evidence that aid money intended for health is often accompanied by a decline in other health spending by recipient governments, whereas similar assistance routed via private NGOs has a positive impact. They further find that for each \$1 of development assistance for health, about \$0.37 is added to the health system. However, evaluating IMF-borrowing versus non-IMF-borrowing countries reveals that non-borrowers add about \$0.45 whereas borrowers add less than \$0.01 to the health system. This, they argue, could be because World Bank and IMF macroeconomic policies specifically encourage governments to divert aid to reserves to cope with aid volatility.

The possibility that different types of aid may have different impacts on the recipient has been noted by, e.g., Chatterjee, Sakoulis and Turnovsky 2003; Clemens, Radelet and Bhavnani 2004; Reddy and Minoiu 2006; Mavrotas (2002) for Kenya and India, Mavrotas (2005) for Uganda and Mavrotas and Ouattara (2006a) for Côte d’Ivoire. Mavrotas and Ouattara (2007) find that both project aid and financial programme aid exert a positive, significant effect on total expenditure, but that project aid also appears to increase capital expenditure while financial programme aid is associated with an increase in government consumption. The results related to capital expenditure suggest that project financing is more likely to be growth enhancing than programme aid, possibly because donors have more control over it. They find no evidence that aid flows are associated with a reduction in taxation effort. Indeed, project aid flows are associated with an increase in trade tax. However, Neanidis and Varvarigos (2009) argue that the extent to which the volatility of various forms of foreign assistance may have different implications for recipients’ growth rates has not been the subject of much discussion. Using the CRS database, they find that aid disbursements used for productive sectors have a positive effect on growth, while pure transfers reduce growth.

Aid volatility is found to hurt growth only when aid is used productively, while the volatility of pure aid disbursements is associated with higher growth.

3 Theory and methodology

3.1 The micro-macro adding up problem

The relationship between j'th sector aid (A_j) and the i'th target (Y_i) can be written as:

$$Yi = fi(Aj, A^*j, \mathbf{X}i) \tag{1}$$

where A^*_j is aid volatility and $\mathbf{X_i}$ a vector of other variables relevant to the i'th target. The impact of volatility on (Y_i) is then approximately:[4]

$$A^*_j \partial Y_i / \partial A^*_j \tag{2}$$

For most aid sectors and targets, this will, arguably, be zero. We would expect education aid to impact on primary school completion rates, rather than energy sector aid. But primary school completion rates may also depend upon socioeconomic factors and hence other aid sectors may impact on this. The total impact of aid volatility on the economy is then found by summing across all I targets:[5]

$$\sum_{i=1}^{I} A_j^* \frac{\partial Y_i}{\partial A_j^*} \tag{3}$$

The total impact on a variable such as growth (g) will then be:

$$\sum_{i=1}^{I} \frac{\partial g}{\partial Y_i} \frac{\partial Y_i}{\partial A_j^*} \tag{4}$$

and similarly for other 'macro variables' such as infant mortality, governance and the balance of payments. The full impact of aid volatility on growth is then found by summing (4) across all J aid sectors:

$$\sum_{j=1}^{J} \sum_{i=1}^{I} A_j^* \frac{\partial g}{\partial Y_i} \frac{\partial Y_i}{\partial A_j^*} \tag{5}$$

The total impact of aid, ignoring volatility, can be defined in a similar manner.

Simply focusing on the impact of total aid volatility on a single macroeconomic variable such as growth misses the two different effects contained in (5). First, aid in sector j may switch between (micro-) targets, that is, education aid, for example, switches from one locality to another. This will not be reflected in overall aid volatility, but will result in positive volatility for one (micro-) target and negative volatility for another (micro-) target. Second, and more the concern of this paper, aid may switch between sectors.

---

4 Assuming that the impact is symmetric between positive and negative volatility. The term 'target' is defined in Table 1.

5 This assumes that the different targets are measured in such a way that they can be sensibly combined.

Again, overall aid will show no volatility, but the individual sectors will be affected. In addition, it may be the case that some $\partial Y_i/\partial A_j < 0$, i.e., an aid sector has negative impacts on some targets. For example, aid, by focusing on one target, may divert resources from another. This could be aid for one locality having negative spillover effects on other localities, or with limited resources, aid for one target such as health, diverting resources from another target such as industry. In this case, volatility may have limited positive effects in neutralizing the negative ones of aid *per se*. Hence simply focusing on overall aid and its volatility potentially misses much that is relevant, and is possibly one of the factors behind much of the criticism of cross-country regressions.[6]

3.2 The donor's allocation problem

We can assume donors tend to maximize some form of welfare function subject to a budget constraint. They will be aware that volatility is potentially damaging to both the recipient country and its own credibility as a donor. But nonetheless, aid may still be volatile for a number of reasons. First, volatility may be a response to recipient behaviour. A failure to implement previous commitments, or a perceived corrupt bureaucracy or political system, may see aid fall below intended disbursements. Similarly an emergency elsewhere may lead to a tightening of budgets to other countries. In this case the donor will juggle the aid budget as best they can. *They will reduce the aid most in those sectors which are least important to the donor*[7] *and where, for example, it can be substituted between t and t+1 with relatively little adverse impact.* Similarly there may be a need to switch aid between sectors within countries, quite independently of what is happening elsewhere. This can occur in response to an emergency in the country or unforeseen developments possibly associated with existing aid spending. However, as already indicated, having diverted aid away from sector j in period t, the donor may respond by increasing it above trend in the following period and vice versa in a sector which saw an aid surge. In this way aid shocks can have ripple effects. In addition aid between sectors may be complementary, for example, increasing humanitarian aid may foretell an increase in programme assistance aid.

3.3 Measuring volatility

Previous studies have used the Hodrick-Prescott filter to derive a trend and deviations from this trend, or its square, to represent volatility. We prefer not to do this in this present study as, particularly with respect to disbursements, we have relatively few data points to work with for each country.[8] Instead we regress aid in sector j on a time trend and its square to calculate the trend. Deviations from this, or the square of these

---

6 Although this is not to say that the macro approach with cross-country regressions is without value as it does provide information on the overall picture and is relatively straightforward to do.

7 Or alternatively they will seek to protect those sectors which are of most importance.

8 Bulíř and Hamann note that the Hodrick–Prescott filter may create (i) spurious serial correlation in de-trended data and (ii) end-period observations have larger mean square errors than observations in the middle of the sample (Cogley and Nason 1995). Bulíř and Hamann also note that there is relatively little difference between different methods of identifying residuals and that, e.g., a first difference operator gave similar results to those using the Hodrick-Prescott filter.

deviations suitably defined, are then assumed to represent positive and negative volatility. However, this leaves us with the possibility that some predicted aid values may be negative; we therefore impose a lower bound of zero and adjust the measures of volatility accordingly.[9] Each trend is fitted for one country at a time. Thus, in common with the literature, we fit a trend over a period t1 to t2. Deviations from this trend, or the square of, represent volatility. This assumes that in early periods close to t1, recipient countries are aware of this trend; that if aid, for example, rises steadily over the period, they are aware of this right at the beginning of the period and it does not take them by surprise. It is not obvious this is the case and certainly at the beginning of a sustained period of growth or decline in the aid budget, the recipient country may be surprised, or at least partially surprised. Even if not surprised, even if the change is anticipated, they may well have difficulties in responding to change or harbour doubts as to whether donors will fulfil commitments.[10]

4 Data

The DAC has been tracking aggregate information about aid since 1960. The CRS was established in 1973 to collect more detailed information about individual aid loans, and later grants, to complement the recording of aggregate flows. There are two sets of data on aid, relating to commitments and disbursements. Commitments represent ‘a firm obligation, expressed in writing and backed by the necessary funds, undertaken by an official donor to provide specified assistance to a recipient country or a multilateral organization’. On the DAC website it further clarifies that ‘bilateral commitments are recorded in the full amount of expected transfer, irrespective of the time required for the completion of disbursements’. Disbursements are the ‘release of funds to or the purchase of goods or services for a recipient; by extension, the amount thus spent. They record the actual international transfer of financial resources, or of goods or services valued at the cost to the donor’.

The CRS has been used in many of the recent analyses on aid volatility and aid impact (e.g., Fielding and Mavrotas 2008; Neanidis and Varvarigos 2009; Clemens, Radelet and Bhavnani 2004). But there are doubts about its suitability in early years. The completeness of CRS commitments for DAC members has improved from 70 per cent in 1995 to over 90 per cent in 2000 and reached nearly 100 per cent starting from the 2003 flows. With respect to CRS disbursements, before 2002 the annual coverage was below 60 per cent, while it has been around and over 90 per cent since 2002 and reached nearly 100 per cent starting with the 2007 flows. Thus the OECD warns against using the earlier data for sectors of analysis and these data on the main database are available only since 1995 for commitments and since 2002 for disbursements. As a consequence, 2002 represents the start date for the sample period we use in this paper.

The term ‘aid sector’ signifies the sector of the recipient’s economy that the aid activity is designed to assist, e.g., health, energy and agriculture. Some contributions are not targeted to a specific sector, e.g., balance-of-payments support, debt relief, emergency

---

9 With relatively little data on disbursements, we had problems in estimating Tobit regressions for individual countries.

10 We note these issues, but in this paper do not explore them any further.

aid. These are called ‘non-sector allocable aid’. But all the data are derived from the section of the database termed ‘sector’, which is why we use this generic term in this paper. The aid activity database registers information on the purpose of aid using a sector classification specifically developed to track aid flows and to permit measuring the share of each sector or other sector category in total aid. For activities cutting across several sectors, either a multi-sector sector code or the code corresponding to the largest component of the activity is used.

We analyse all the main sectors, or their constituent parts, but not all of the subsectors. Instead we focus on the social and production subsectors. Specific details on the data can be found in an appendix. In order to be able to make valid comparisons between countries, we need to normalize aid in some manner. In this paper we choose to do this by taking aid as a proportion of recipient country GDP. The pros and cons of the various alternatives are discussed in Hudson and Mosley (2008a). However, in this case we are focused on comparing aid volatility between different aid sectors rather than between aid and some other revenue variable such as government expenditure. In this case, in relative terms, the various differences between different normalization procedures are less important. We focus our analysis on disbursements rather than commitments, as these represent actual aid flows rather than the promises of flows. The data are available for different donors as well as different types of aid. We focus on ODA for all donors.

Table 2 shows us information on both disbursements and commitments over the shorter time period for which disbursements are available. Judged by the coefficient of variation, the most volatile aid sectors are refugee, debt, humanitarian, NGO and industry. Among the most stable are the three social infrastructure categories, together

Table 2
Summary data on variability, 2002-09

	Commitments					Disbursements				
	Coeff of variation	Mean	Skewness	Median	Adj. coeff of variation	Coeff of variation	Mean	Skewness	Median	Adj. coeff of variation
Total	1.474	9.502	4.173	4.284	0.868	1.655	10.002	4.477	3.719	0.974
Health	2.138	0.576	4.771	0.11	1.664	1.784	0.606	3.624	0.155	0.891
Education	2.053	0.853	5.034	0.249	1.486	1.704	0.866	3.723	0.325	0.742
Other social	2.035	1.249	6.988	0.407	1.277	1.940	1.194	7.935	0.449	0.982
Industry	3.487	0.142	8.507	0.011	3.039	2.760	0.124	7.174	0.019	2.169
Other prod.	1.863	0.654	4.467	0.176	1.463	1.680	0.497	4.597	0.172	0.978
Infrastructure	1.903	1.446	4.612	0.335	1.548	1.583	0.977	3.175	0.313	0.887
Government	2.811	0.892	14.870	0.185	2.135	2.885	0.873	16.956	0.231	2.162
PA	2.630	1.210	7.176	0.100	2.175	2.977	1.078	9.571	0.082	2.432
Debt	5.605	0.813	16.570	0.000	5.165	4.379	2.107	7.734	0.001	3.878
Humanitarian	3.693	0.682	7.336	0.028	2.506	3.510	0.637	7.403	0.034	1.927
Multi-sector	2.517	0.805	6.789	0.219	1.889	2.826	0.720	7.002	0.215	1.441
Refugees	7.186	0.034	15.677	0.000	6.658	7.691	0.055	22.008	0.000	7.089
NGOs	3.477	0.022	6.926	0.001	2.666	2.230	0.065	5.386	0.011	1.302

Notes: For definitions, included the adjusted coefficient of variation, see Table 1. PA denotes programme assistance. Some small sectors have been omitted from the table, e.g., rated to administration costs.

Source: Compiled by the author based on data from the CRS database as detailed in the Appendix.

with ‘other production’ (relating to non-industry production), in which agriculture figures prominently. Agriculture is often seen as a vehicle to help the poor, as of course are the three social infrastructure categories. This tentatively suggests that this is a factor influencing donors’ decisions on what sectors to protect from volatility. Aid to refugees, and governments is also heavily skewed to the right, suggesting that large positive shocks are more frequent than negative ones. These figures may reflect differences between, rather than within, countries. Hence, the adjusted coefficient of variation, defined in Table 1, corrects for this focusing on variations within countries. The remaining columns give information on median aid and skewness. It is apparent that volatility with respect to disbursements is slightly greater than that for commitments for total aid. But for most sectors the reverse is the case; that is, actual sector volatility is less than ‘planned volatility’, as reflected by commitments. Of course it must be borne in mind that lumpy commitments may be smoothed out over a several year disbursement period. But it does tentatively suggest that planned donor volatility is constrained by reality. As already emphasized, the measures in this table give an indication of the variability of aid, but not volatility as defined in the literature. It is to this we now turn.

5 Results

In this section we seek to (i) disaggregate aid volatility into its different sectors, (ii) then analyse the volatility of individual sectors, (iii) identify any trends, albeit over a very short time period and (iv) analyse the extent to which different aid sectors impact on different target variables.

5.1 The makeup of overall volatility

We begin by examining the causes of volatility in terms of linking overall volatility with its component parts. As Fielding and Mavrotas (2008) emphasize, the variance of a variable made of n components is the sum of the n variances plus twice each of the covariances. Hence for three components, it is $\sigma^2_1 + \sigma^2_2 + \sigma^2_3 + 2\sigma_{12} + 2\sigma_{13} + 2\sigma_{23}$. Thus the overall variance can exceed or fall short of the sum of each of the components, or sector, variances depending upon the signs of the covariances.

Table 3 shows the average volatility of total disbursements in the first column and the sum of the sector volatilities in the final column. The figures in this final column relate to the mean of this composite variable. This is different to the sum of individual sector means, which is partly why the sum of individual columns differs from this final column.[11] There are substantial differences between the first and the final columns, but the correlation between the two is very high. Hence in an OLS regression of total aid volatility on summed sector volatility across all years and countries, the R^2 is 0.89. The difference between the two is due to the covariances between the different sectors impacting on total aid volatility. It is not a simple story of one being consistently greater than the other, indicating that in some years the net effect of the covariances is negative

11 In addition, these aid sectors do not sum to total aid as some small sectors have been omitted, e.g. related to refugees.

Table 3
Volatility: Aid disbursements, 2002-09

	Total aid	Total aid net debt	Debt	Humani-tarian	Education	Health	Other social	Infrastruc ture	Industry	Other production	Multi-sector	Govern-men	PA	Sum of sector variances
Mean														
2002	20.282	2.842	20.602	0.242	0.073	0.02	0.613	0.118	0.025	0.058	0.067	0.044	0.222	22.168
2003	41.441	3.014	47.356	0.308	0.236	0.05	0.445	0.22	0.049	0.091	0.396	0.106	1.519	51.019
2004	24.926	4.113	19.759	1.011	0.227	0.11	0.955	0.29	0.025	0.215	0.418	0.325	2.178	25.648
2005	49.738	7.45	39.836	1.471	0.122	0.18	0.355	0.429	0.034	0.056	0.191	1.652	0.362	45.406
2006	132.19	7.371	123.33	0.491	0.078	0.09	0.279	0.12	0.028	0.057	0.179	1.906	0.608	127.3
2007	31.94	13.268	29.846	0.536	0.129	0.11	0.828	0.387	0.109	0.217	0.095	16.603	1.229	50.168
2008	96.562	4.67	69.365	0.133	0.044	0.07	0.176	0.418	0.035	0.077	0.38	1.699	9.438	81.85
2009	41.963	5.489	21.944	0.263	0.05	0.07	0.266	0.148	0.019	0.049	0.129	0.49	2.869	26.326
90th percentile														
2002	32.302	2.98	24.261	0.059	0.081	0.05	0.237	0.237	0.016	0.064	0.077	0.122	0.405	28.856
2003	24.59	6.001	11.829	0.202	0.198	0.092	0.466	0.466	0.043	0.102	0.148	0.226	0.633	24
2004	59.55	4.48	35.416	0.267	0.189	0.09	0.671	0.671	0.023	0.094	0.078	0.258	0.741	65.693
2005	85.808	9.568	74.398	1.468	0.196	0.084	0.474	0.474	0.013	0.108	0.158	0.247	0.587	84.566
2006	415.27	3.664	405.729	0.37	0.221	0.066	0.317	0.317	0.007	0.07	0.105	0.269	0.948	427.11
2007	96.419	6.73	71.407	0.541	0.141	0.092	0.279	0.279	0.012	0.114	0.103	0.172	1.684	83.105
2008	29.789	3.667	22.632	0.08	0.075	0.11	0.593	0.593	0.018	0.113	0.155	0.18	0.856	28.027
2009	19.678	3.822	7.721	0.085	0.042	0.059	0.394	0.394	0.012	0.046	0.08	0.112	0.608	14.387
Mean adjusted CV														
	0.274	0.199	1.031	0.34	0.162	0.191	0.18	0.237	0.509	0.25	0.212	0.307	0.344	

Notes: For definitions see Table 1. PA denotes programme assistance. The final column relates to the sum of volatility in the individual aid sectors, not all of whom are included in the previous columns. Some small sectors have been omitted from the table, e.g., related to refugees and NGOs

Source: Compiled by the author based on data from the CRS database as detailed in the Appendix.

and in others it is positive. Thus in 2004 individual sector volatilities compensated each other to reduce total volatility, whereas in 2009 the reverse was the case. It is a mute question as to which is the better indicator of aid volatility, that relating to total aid or that to the sum of its constituent parts. However, as already indicated, it seems reasonable to argue that it is more the latter, as the damage done to health, education and industry cannot really be reduced/increased because they are negatively/positively correlated with each other. If this is accepted, then it follows that a measure of aid volatility based on total aid is limited. Indeed arguably the problem is worse than this, as a single sector in itself is likely to be made of multiple subsectors, for example, in different localities.[12]

The remaining columns relate to individual sector volatility. The most important sectors in explaining total volatility are debt aid followed by government aid and programme assistance aid. Debt volatility in particular goes a long way to explaining total volatility. Take this out of the picture, as in the second column, and aid disbursements appear substantially less volatile. However, being averages the figures are misleading to an extent, as they are substantially affected by outliers. This is reflected in the figures for the 90th percentile. The peak year for total volatility as measured by the mean is 2006, followed by 2008. But for the 90th percentile it is the cluster of years 2005 to 2007. The dominant factor in both 2006 and 2008 is the volatility of debt aid. However in 2007 aid to government also showed considerable volatility.

These data tell us the most important sectors in determining overall volatility, but do not tell us which sectors are most volatile. To find this, we need to remove the scale factor. Dividing the square root of the error squared term[13] for aid sector A by the average level of A's aid over all years, in a manner similar to the coefficient of variation, achieves this. The result is shown in the final row of Table 3. We now get a very different picture. Debt aid is still the most volatile. But aid for the social sectors, including education and health, tends to exhibit low volatility, indeed now less than overall volatility. Apart from debt aid, the most volatile sectors are industry, programme assistance (PA) and government aid.

5.2 Trends in volatility

Finally, in this section we examine whether there are any visible trends in volatility. We again focus on disbursements. We regress the square root of volatility[14] on a trend and squared trend, and use the coefficients to calculate a nonlinear trend. We use country fixed effects to allow for systematic country differences. The curves for total debt, with aid netted out, and infrastructure, are shown in Figure 1. The trend variables are jointly significant at the 5 per cent level. We can see volatility appears to increase until about 2006 after which it begins to decline. This nonlinear pattern, although not necessarily with the same turning point, is repeated for education and humanitarian aid, as can be seen from Figure 2. The trend variables were jointly significant at the 1 per cent level in

---

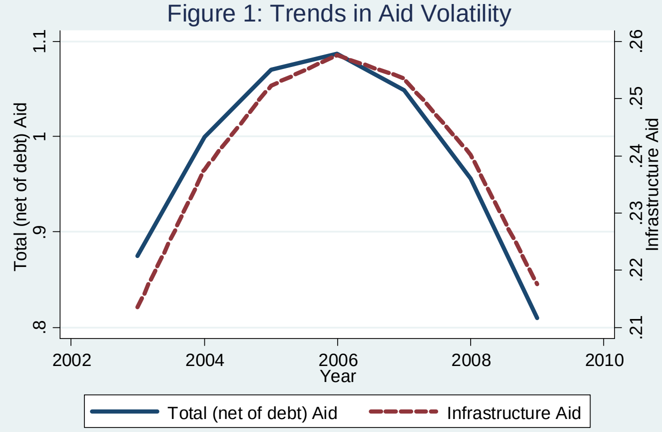
[12] This does not mean that the sum of the variances will increase as we get an increased number of more finely defined sub-categories as the variances of these sub-categories will also decline.

[13] From the regression of aid on a trend and trend squared term for each individual country. Thus it is the square root of volatility.

[14] That is, the square root of the squared error term from the trend regression as defined in Table 1.

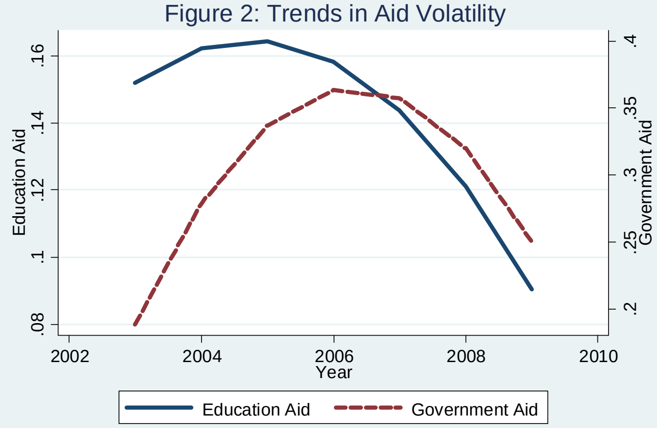
both of these equations. However, there was no significant trend in government, programme assistance or industry aid. We noted earlier that 2006 was a peak year for debt aid volatility and it is possible that this had ripple effects on other aid sectors. This is not something we explore in more depth than in the VAR regressions which follow in the next section. Nor do we have a long enough run of data to discern any more general trends. But certainly there is no evidence that aid volatility is increasing.

Figure 1: Trends in Aid Volatility



Notes: See Table 1 for definitions. Compiled by the author based on data from the CRS data base as detailed in the appendix.

Figure 2: Trends in Aid Volatility



Notes: See Table 1 for definitions. Compiled by the author based on data from the CRS data base as detailed in the appendix.

5.3 The dynamics of aid volatility

In this sector we show the dynamics of aid volatility via a modified VAR on aid volatility with respect to disbursements. Underlying these regressions is the behaviour of donors trying to allocate aid to maximize its impact, given an objective function which contains multiple objectives including health, education, economic development, governance and social development, subject to a budget constraint. In addition, an aid surge, for example, in one sector may foretell a subsequent aid surge in other sectors. We do not regress volatility on lagged volatility as in a standard VAR, but in what we term an asymmetric VAR, distinguishing between positive and negative volatility; that is, we regress the error term, rather than the error term squared, on lagged positive and negative errors terms[15] as two separate variables. The rationale is that positive aid volatility and negative aid volatility are separate concepts, with separate causes and impacts. Thus there is reason to anticipate that they will have different impacts on future volatility within a VAR structure. If the coefficients are the same, then it is equivalent to a standard VAR. We have only a limited time dimension, but the cross-section element gives a reasonable number of observations. However, because of this we utilize only a first order VAR.

The results are shown in Table 4. We use as our benchmark the 1 per cent level of significance. Focusing first on the own effects, i.e., the impacts of the twin lagged dependent variables, there is a tendency for errors in period t to be at least partially corrected for in the following period. This is the case for five of the 12 negative volatilities and seven of the positive volatilities. There are no significant positive auto-coefficients, indicating an absence of shock persistence. It is thus not simply a matter of volatility being limited to a single period and then to return to trend, it is that a positive injection of aid above trend tends to be partially compensated for in the following period by a below-trend level of aid and vice versa for aid below trend. There are also 21 cross-sector impacts, nine relating to positive lagged error terms. Five of these impacts have negative coefficients, indicating a positive error term in sector A spills over to a negative one in sector B. Three of these relate to PA. Of the four positive impacts, all are linked to the government, either government aid *per se* or PA. Turning to the 12 significant cross-impacts pertaining to negative lagged error terms, four relate to government or PA and three each to other social sector and multi-sector aid. The latter is particularly subject to misrecording and also changes in recording. There are no significant spillover effects from health, education, and debt. In terms of the variables affected, there are five significant spillovers in the PA equation, three in the infrastructure equation and two each in the humanitarian, debt, other production and education aid equations. Spillovers thus seem primarily linked to government aid, broadly defined to include PA, both in terms of impact and being impacted upon.

Is the use of an asymmetric VAR justified? Just focusing on the own lagged impact, there is a significant difference in the two coefficients in one equation at the 1 per cent level of significance. It is, however, often more difficult to prove a significant difference between two variables than significance per se, and two other equations have significantly different coefficients at the 5 per cent level of significance and three at the 10 per cent level. The use of an asymmetric VAR thus seems justified.

15 Where the lagged positive/negative error term takes a value equal to the error term if that is positive/negative, otherwise it takes a value of zero. The dependent variable being the error term is strictly speaking not volatility, but the results give us insights on the dynamic behaviour of positive and negative volatility. The term asymmetric VAR has been used in the literature both in the sense we are using it and where there are variable lag lengths.

Table 4
Dynamic impacts of volatility

LHS variable		Education	Health	Other social	Debt	Humani-tarian	Industry	Other production	Infrastruc-ture	Multi-sector	Government	PA
Lagged variables												
Education	–	-0.4627*	-0.0004	0.2554	-1.152	0.2222	-0.0246	0.1881	0.1337	-0.0074	-0.6084	0.9651
		(3.28)	(0.00)	(1.11)	(1.70)	(1.24)	(0.49)	(1.39)	(0.81)	(0.03)	(1.23)	(2.42)
Education	+	-0.0853	0.0939	-0.1507	-0.9494	0.336	0.0173	0.2122	-0.2754	0.0937	-0.1273	-0.6803
		(1.21)	(1.33)	(0.61)	(1.34)	(1.45)	(0.60)	(1.82)	(2.14)	(1.15)	(0.70)	(2.41)
Health	–	0.1205	0.107	-0.2018	0.0839	0.3477	-0.0324	-0.003	-0.3098	0.3934	0.503	-0.2494
		(0.41)	(0.30)	(0.68)	(0.05)	(1.18)	(0.62)	(0.02)	(1.50)	(1.02)	(1.30)	(0.85)
Health	+	-0.0028	-0.4597*	0.3172	-0.4254	0.3342	-0.0258	-0.1146	-0.1717	0.00085	-0.3474	-0.136
		(0.03)	(2.80)	(1.03)	(0.41)	(1.79)	(0.71)	(1.65)	(2.35)	(0.01)	(1.12)	(0.67)
Other social	–	0.0421	0.0517	0.302	-0.8973	0.0612	0.0655	-0.0088	-0.2533*	0.1746*	0.7257	-0.3028*
		(1.31)	(0.57)	(1.02)	(1.82)	(0.35)	(2.17)	(0.32)	(4.43)	(4.06)	(2.18)	(4.08)
Other social	+	-0.0326	0.0308	-0.1894*	-0.4004	-0.1137	-0.0094	0.0224	-0.0659	-0.0643	0.1048	-0.0944
		(2.05)	(2.16)	(4.00)	(1.52)	(1.65)	(0.33)	(1.21)	(1.32)	(1.71)	(0.22)	(1.46)
Debt	–	0.0017	0.0011	-0.0041	-0.6628*	0.0032	-0.0019	0.0045	0.0059	-0.000046	-0.0622	0.0145
		(0.63)	(0.32)	(0.58)	(4.53)	(0.55)	(0.55)	(1.88)	(1.18)	(0.01)	(1.78)	(1.16)
Debt	+	0.00047	0.0016	0.00038	-0.2557*	-0.001	-0.0018	-0.00076	-0.0031	-0.00066	-0.0158	-0.0133
		(0.19)	(0.70)	(0.10)	(3.75)	(0.27)	(0.59)	(0.38)	(0.47)	(0.18)	(1.66)	(1.71)
Humanitarian	–	-0.0334	-0.0914	0.0255	1.343	-0.3259	0.0159	0.095*	0.0365	-0.0635	0.5506	-0.0847
		(1.32)	(1.85)	(0.14)	(1.57)	(1.13)	(0.40)	(2.90)	(0.68)	(1.53)	(1.04)	(0.88)
Humanitarian	+	0.00031	0.0188	0.1599	0.1691	-0.2756*	-0.0548	0.0446	-0.0601	0.0583	-0.4252	-0.0399
		(0.08)	(0.39)	(0.90)	(0.51)	(2.61)	(2.40)	(1.03)	(2.11)	(2.18)	(1.63)	(0.64)
Industry	–	-0.0463	0.0731	0.1443	0.7789	0.0426	-0.4395	-0.3611	0.3038	0.3452	0.4575	-0.0223
		(0.29)	(0.56)	(0.17)	(0.24)	(0.12)	(2.47)	(2.13)	(0.73)	(0.94)	(0.46)	(0.10)
Industry	+	-0.0306	-0.1158	-0.2117	-2.416	0.8729	-0.3532*	0.0642	-0.7077*	0.3762	-0.5672	-0.1642
		(0.37)	(1.27)	(0.69)	(0.81)	(1.48)	(5.15)	(0.81)	(3.04)	(1.45)	(1.08)	(0.57)

Table 4 con't

Table 4 (con't)
Dynamic impacts of volatility

LHS variable	Education	Health	Other social	Debt	Humani-tarian	Industry	Other production	Infrastruc-ture	Multi-sector	Government	PA
Other production –	-0.1451	0.0229	-0.1856	-1.032	0.0632	0.0296	-0.3265	-0.3726	-0.0399	0.1063	-0.4116
	(1.12)	(0.28)	(1.92)	(1.09)	(0.40)	(0.91)	(2.09)	(1.88)	(0.22)	(0.25)	(2.54)
Other production +	-0.1249*	0.1352	-0.1986	-1.987	-0.1234	0.0114	-0.2501	0.046	-0.0304	-0.1399	-0.1074
	(2.86)	(1.11)	(1.35)	(1.01)	(0.84)	(0.43)	(2.34)	(0.25)	(0.56)	(0.74)	(0.79)
Infrastructure –	0.1311	0.1393	0.1538	0.944	-0.2063	-0.0371	0.1756	-0.3043*	0.1178	-0.5952	-0.4538*
	(2.00)	(1.88)	(0.97)	(1.34)	(1.52)	(0.78)	(1.22)	(2.67)	(0.63)	(0.98)	(3.32)
Infrastructure +	0.053	0.00029	0.0627	-0.3614	-0.1301	-0.000026	-0.0017	-0.1878	-0.029	0.1735	0.1523
	(1.21)	(0.01)	(0.75)	(0.62)	(1.11)	(0.00)	(0.04)	(2.13)	(0.42)	(0.82)	(1.28)
Multi–sector –	-0.1657*	-0.1785	-0.0471	0.2203	-0.0163	-0.0465	-0.1093	0.0442	-0.6722*	-0.2619	0.7136*
	(2.77)	(1.76)	(0.74)	(0.49)	(0.23)	(1.65)	(1.24)	(0.71)	(5.55)	(1.19)	(4.02)
Multi–sector +	-0.1249	0.1662	0.4938	1.617	0.2043	-0.0042	0.0228	-0.1932	-0.2189	-0.0894	-0.0594
	(0.69)	(0.87)	(1.93)	(1.49)	(1.28)	(0.14)	(0.36)	(1.78)	(1.01)	(0.26)	(0.13)
Government –	0.0446	0.0654	-0.2077	1.631*	0.0342	-0.0519	0.0255*	0.0499	-0.0334	-0.9692*	0.5257*
	(1.62)	(1.44)	(2.20)	(5.33)	(0.59)	(2.21)	(2.69)	1.58	(0.62)	(4.71)	(6.06)
Government +	-0.0095	-0.0083	-0.0017	1.606*	-0.0882	0.0064	0.0163	0.0493	-0.0487	-0.2625*	0.6807*
	(0.87)	(1.11)	(0.04)	(6.39)	(1.93)	(0.99)	(1.58)	(1.69)	(1.64)	(6.21)	(15.46)
PA –	-0.0943	-0.0996	0.076	0.0769	0.2403*	0.00041	0.0301	-0.1322	-0.1243	-0.3273	-0.2146
	(1.88)	(1.68)	(1.58)	(0.20)	(2.90)	(0.01)	(1.26)	(2.01)	(2.18)	(1.08)	(1.38)
PA +	0.0206	0.0353	-0.0987*	0.1496	0.0839*	-0.0379*	0.0077	0.0463*	-0.0135	-0.4141*	-0.316*
	(1.38)	(2.29)	(4.10)	(0.75)	(3.73)	(4.31)	(0.91)	(2.80)	(0.66)	(6.00)	(4.91)
Asymmetry	5%	ns	10%	5%	ns	ns	10%	ns	10%	1%	ns
Observations	957	957	957	957	957	957	957	957	957	957	957
X^2	1672	2052	1861	1100	3450	1300	288.3	1244	7905	1100	5600

Notes: Regressions based on aid disbursements, regressing the errors on lagged positive and negative errors. Regressions estimated by random effects over the period 2003-09. * denotes significance at the 1% level of significance. Standard errors estimated using the correction for clustering at the country level. PA denotes programme assistance. Asymmetry relates to whether the coefficients on the two lagged dependent variables are significantly different. ns denotes 'not significant'. X2 denotes the likelihood coefficient. The +/- after the variable name indicates whether it relates to positive or negative volatility.

Source: Compiled by the author based on data from the CRS database as detailed in the Appendix.

5.4 The impact of volatility

In this section we analyse the impact of volatility on several aspects of a country, which in general have not been the subject of much research, at least with respect to the impact of aid. In part this is because some of the data, such as that relating to internet usage, are available only over a limited timeframe. But this timeframe tends to match our data from the CRS database, and in any case with the cross-section data supplementing the timeseries data, there are now sufficient observations to make analysis plausible, even if slightly constrained. In general these target variables tend to show substantial variation over time, albeit often along a trend. The choice of our variables is, in part, dictated by data availability and in part by the fact that they represent a combination of social targets and targets more related to economic efficiency.

Aid is, of course, a flow variable, but many of the variables we analyse have more of the characteristics of a stock variable. Internet usage, e.g., over a limited timeframe will tend to increase and seldom decline. If aid impacts on internet usage, the impact is unlikely to be temporary, but longer lasting, as once someone is a user, they will stay a user. The same is true, to varying degrees, of the other variables we are analysing, Hence, including aid in a normal regression with internet usage as the left hand side variable is not satisfactory as it will only capture a temporary impact.[16] For this reason, we model these variables in a similar manner to the impact of aid on GDP or GDP per capita in growth regressions. As with the growth regressions, we include the base year value of the variable, e.g., for death rates, the death rate in the first year of our sample. The coefficient on this will measure convergence and is expected to be negative. We also include year dummy variables to capture general movements in time caused, for example, by technical progress or the diffusion of a new technology. The estimations are done using random effects[17] with a correction for heteroscedasticity using the robust or sandwich estimator of the standard errors. In the regressions we use both total aid disbursements and sector specific disbursements.

The results are shown in Table 5. The first equation relates to death rates. Social infrastructure aid, which includes aid for health and education as well as water sanitation, is negatively significant at the 1 per cent level of significance. Positive error terms, however, neutralize this impact. There is, however, no impact from negative error terms. Total aid disbursements were not significant, but base year death rates were with the anticipated negative coefficient indicating convergence across countries. This pattern was repeated in the next two equations linked to male and female primary school completion rates. In both equations social infrastructure aid is significant at the 1 per cent level with a sign which indicates it increases completion rates. As with death rates social infrastructure aid produced better results than aid for specific social sectors such as education aid. This is not surprising: completion rates, e.g., are impacted upon by social factors as well as purely education facilities. For males, the impact of aid is again

---

16 Essentially this would be the case even with a lag structure.

17 Random effects was preferred over fixed effects because most of the variation in aid disbursements is between countries, whilst fixed effects only captures within country variations. Bias is unlikely as we are dealing with growth rates, not levels.

Table 5
The impact of aid on specific targets

	Target variables: changes in:				
		Completion rate:			
Aid disbursements	Death rate	Male	Female	Internet usage	Mobile phone
Social infrastructure	-0.000770** (3.59)	0.0047** (3.51)	0.0052** (2.87)		
Positive error	0.0011** (2.63)	-0.0245* (2.08)	-0.0192 (1.22)		
Negative error	-0.00018 (0.44)	0.0159** (2.76)	0.0167* (2.55)		
Industry				0.7624* (2.56)	
Positive error				-1.173** (3.18)	
Negative error				0.501** (2.69)	
Infrastructure					0.2449* (1.96)
Positive error					-0.4604 (1.21)
Negative error					0.0115 (0.05)
Total disbursements	0.000047 (1.42)	0.000025 (0.09)	0.00021 (0.57)	-0.0006 (0.35)	0.0062 (0.69)
Base year value of dependent variable	-0.0011** (5.50)	-0.0464** (3.04)	-0.046* (2.10)	-0.0057 (1.46)	-0.007** (2.87)
Constant	0.0037 (1.56)	0.004 (0.39)	0.0075 (0.76)	0.1736** (5.28)	-0.1092 (0.81)
Observations	1032	642	642	1047	1046
X^2	96.71	31.27	26	80.91	119.6

Notes: Regressions estimated by random effects over the period 2002-9 across potentially 154 countries, although missing observations reduced this, for example to 120 countries for completion rates. (.) denotes t statistics, */** significance at the 5% and 1% levels respectively. Standard errors have been corrected for heteroscedasticity. X2 represents the likelihood ratio test statistic. Year dummy variables have been included.

Source: Compiled by the author based on data from the CRS database as detailed in the Appendix.

neutralized by both positive and negative error terms, representing aid volatility.[18] The signs on the error terms for female completion rates are similar, but only that the negative error term is significant at the 5 per cent level of significance.

The next two equations relate to economic rather than social variables. The first is that for internet usage. Our initial expectation was that it would be infrastructure aid which would be significant, but in practice it was industry aid. Both this and the two error terms are significant with the anticipated signs. This suggests both that many people in developing countries access the internet via their firms and that industry aid has facilitated the adoption of the internet by firms. Internet usage, of course, has social benefits as well as economic ones and is an indication on just how complex the impact of aid can be on an economy and its people. The final column related to mobile phone

18 The negative error term takes the value of the error term when negative and is otherwise zero. Hence the positive coefficient on this variable *reduces* completion rates.

subscriptions. In this case it was infrastructure aid which was significant, at the 5 per cent level, although neither of the error terms were significant.

In all the equations, apart from internet usage, the base year variable was significant and indicated convergence, most rapidly for primary school completion rates. The insignificance for internet usage, and perhaps the small coefficient for mobile phone usage, may reflect that there was relatively little variation in the base year values across countries, as with new technologies most were close to zero. In none of the equations were total aid disbursements significant, nor were variations on this, e.g., total disbursements less debt aid. Nor indeed was government or programme assistance aid. It is the relevant aid sector which tends to matter when dealing with these very specific targets. These results are of interest, but they assume, for example, as is standard in the cross-country growth regressions, that the impact of aid is the same for countries with high and low death rates, which may be problematic. Nor does the analysis illuminate the long-run determinants of the various targets. In an appendix we suggest an alternative, two stage estimation technique, which although demanding in terms of data requirements, helps with these problems.

6 Conclusions

In this paper we have explored a new, or at least a newly updated, dataset on aid disbursements and commitments, focusing on the former and issues surrounding volatility. We have taken the issue of aid volatility and expanded it to cover the different aid sectors. It is apparent that total volatility is often less than the volatility of the individual aid sectors. Ignoring debt and humanitarian aid, the most volatile aid sectors as they relate to recipient countries are linked to government, industry and PA. Aid for health, education and other social sectors have relatively low volatilities. This, however, is not the case with respect to aid for industry, which raises the question as to whether this reflects the donor's relative priorities. Much of the total aid volatility in recent years has been caused by debt aid. Humanitarian, infrastructure and aid for governments are also a significant part of overall volatility. This reflects both the volatility of these aid sectors as well as their size. However, we have also put forward the case that the impact of volatility on an economy cannot best be judged in terms of overall aid volatility, but rather by the sum of the volatility of its constituent sectors. If, for example, education aid and industry aid are volatile, it is not obvious why their impact on the recipient country should be substantially reduced if they are negatively correlated with each other.

In general, positive/negative aid volatility in a particular sector tends not to be simply short lived with a return to trend, but also compensated for with negative/positive volatility in the following period. In addition there is also evidence of cross-sector impacts. The dominant cross-sector impact tends to be negative, that is, e.g., a positive shock is adjusted for not just in the sector the shock occurred in, but also in other aid sectors too. The exceptions to this are the positive cross-sector effects, which, in our analysis, tend to involve either government, programme assistance or humanitarian aid. This suggests that aid donors adjust in a fairly complex manner the different aid to the different sectors and that a shock in one can have spillover effects in subsequent periods.

In the final section we examined the impact of aid on selected variables. These were more micro-focused variables than typically is the case. The regression results suggest that what matters for social targets is social infrastructure aid and for communications, infrastructure, and also industry, aid. Despite the relatively few years at our disposal, it is also apparent that volatility impacts even on these fairly focused variables. Hence positive infrastructure aid volatility impacts on the speed of adjustment for mobile phones, and primary school completions are affected by social infrastructure aid volatility.

As more observations become available, many aspects of this dataset warrant further analysis, for example, on the different aid volatilities of different donors and more finely focused on the different aid subsectors. In addition it will become possible for more detailed analysis of the lagged impact of aid disbursements. Work also needs to be done analysing the different impacts of volatility as we have defined it and sustained trends. Is it really the case that a sustained and anticipated increase/decrease in aid has no added impact over and above that of aid itself? In spatial terms do donors tend to shift the aid budget within regions such as sub-Saharan Africa, and to what extent is aid volatility within a country correlated with that of near neighbours? Related to this, are there regional spillovers of aid volatility, whereby the impact is not limited to one country, but involves multiplier effects on adjacent countries? Finally we need more analysis of the impact of aid, subsector aid and associated volatility on specific targets. Development economics used to be a data poor area, where researchers strived heroically with inadequate observations both in terms of time periods and variables. That is rapidly changing and the CRS database is helping to make development economics data rich, facilitating analysis and understanding.

References

Agenor, P. R., and J. Aizenman (2010). 'Aid Volatility and Poverty Traps'. *Journal of Development Economics*, 91(1): 1–7.

Arellano, C., A. Bulíř, T. Lane, and L. Lipschitz (2009). 'The Dynamic Implications of Foreign Aid and its Variability'. *Journal of Development Economics*, 88: 87–102.

Bulíř, A., and J. Hamann (2003) 'Aid Volatility: An Empirical Assessment'. *IMF Staff Papers*, 50: 64–89.

Bulíř, A., and J. Hamann (2008). 'Volatility of Development Aid: From the Frying Pan into the Fire?'. *World Development*, 36(10): 2048–66.

Celasun, O., and J. Walliser (2008). 'Predictability of Aid: Do Fickle Donors Undermine Aid Effectiveness?'. *Economic Policy*, 55: 546–94.

Chatterjee, S., G. Sakoulis, and S. J. Turnovsky (2003). 'Unilateral Capital Transfers, Public Investment, and Economic Growth'. *European Economic Review*, 47(6): 1077–103.

Chauvet, L., and P. Guillaumont (2009). 'Aid, Volatility, and Growth Again: When Aid Volatility Matters and When It Does Not'. *Review of Development Economics*, 13(s1): 452–63.

Clemens, M., S. Radelet, and R. Bhavnani (2004). 'Counting Chickens when They Hatch: The Short-Term Effect of Aid on Growth'. CGD Working Paper 44 Washington, DC: Center for Global Development.

Cogley, T., and J. W. Nason (1995). 'Effects of the Hodrick–Prescott Filter on Trend and Difference Stationary Time Series: Implications for Business Cycle Research'. *Journal of Economic Dynamics and Control*, 19(2): 253–78.

Eifert, B., and A. Gelb (2008). 'Reforming Aid: Toward More Predictable, Performance-Based Financing for Development'. *World Development*, 36(10): 2067–81.

Fielding, D., and G. Mavrotas (2005). 'The Volatility of Aid'. WIDER Discussion Paper 2005/06. Helsinki: UNU-WIDER.

Fielding, D., and G. Mavrotas (2008). 'Aid Volatility and Donor-Recipient Characteristics in "Difficult Partnership Countries" '. *Economica*, 75(299): 481–94.

Hudson, J., and P. Mosley (2008a). 'Aid Volatility, Policy and Development'. *World Development*, 36(10): 2082–102.

Hudson, J., and P. Mosley (2008b). 'The Macroeconomic Impact of Aid Volatility'. *Economics Letters*, 99(3): 486–9.

Lensink, R., and O. Morrissey (2000). 'Aid Instability as a Measure of Uncertainty and the Positive Impact of Aid on Growth'. *Journal of Development Studies*, 36(3): 31–49.

Levin, V., and D. Dollar (2005). 'The Forgotten States: Aid Volumes and Volatility in Difficult Partnership Countries'. Paper prepared for DAC Learning and Advisory Process on Difficult Partnerships, 13-14 January. London.

Mavrotas, G. (2002). ‘Foreign Aid and Fiscal Response: Does Aid Disaggregation Matter?’ Weltwirtschaftliches Archiv/*Review for the World Economy*, 138(3): 534–59.

Mavrotas, G. (2005). ‘Aid Heterogeneity: Looking at Aid Effectiveness from a Different Angle’. *Journal of International Development*, 17(8): 1019–36.

Mavrotas, G., and B. Ouattara (2006a). ‘Aid Disaggregation, Endogenous Aid and the Public Sector in Aid-Recipient Economies’. *Review of Development Economics*, 10: 432–49.

Mavrotas, G., and B. Ouattara (2006b). ‘Public Fiscal Behaviour and Aid Heterogeneity in Aid-Recipient Economies’. *Journal of Developing Areas*, 39(2): 1–15.

Mavrotas, G., and B. Ouattara (2007). ‘Aid Modalities and Budgetary Response: Panel Data Evidence’. *Review of World Economics*, 143(4): 720-41.

Mosley, P., and A. Suleiman (2007). ‘Aid, Agriculture and Poverty’. *Review of Development Economics*, 11(1): 139–59.

Neanidis, K. C., and D. Varvarigos (2009). ‘The Allocation of Volatile Aid and Economic Growth: Theory and Evidence’. *European Journal of Political Economy*, 25(4): 447–62.

Pallage, S., and M. A. Robe (2001). ‘Foreign Aid and the Business Cycle’. *Review of International Economics*, 9(4): 636–68.

Reddy, S. G., and C. Minoiu (2006). ‘Development Aid and Economic Growth: A Positive Long-Run Relation’. DESA Working Paper 29. New York: United Nations Department of Economic and Social Affairs.

Rodrik, D. (1990). ‘How Should Structural Adjustment Programmes Be Designed?’. *World Development*, 18(7): 933–47.

Stuckler, D., S. Basu, and M. McKee (2011). ‘International Monetary Fund and Aid Displacement’. *International Journal of Health Services*, 41: 67–76.

Wolf, S. (2007). ‘Does Aid Improve Public Service Delivery?’. *Review of World Economics*, 143(4): 650–72.

World Bank (n.d.). World Development Indicators, on line. Washington, DC: World Bank.

Appendix Table: Data definitions

Sector aid (Source: CRS database available at: www//stats.oecd.org/Index.aspx?DatasetCode=CRSNEW)	
Education	Primary, secondary and post-secondary education.
Health	General and basic health.
Other social sector	Population, water supply and sanitation and 'other social infrastructure and services'.
Social infrastructure	The sum of education, health and other social sector.
Government (and civil society)	Includes general activities (e.g., anti-corruption, judiciary) as well as conflict and security areas; note in the CRS this is part of social infrastructure and services, we analyse it separately.
Programme assistance (PA)	Un-earmarked contributions to the government budget; support for the implementation of macroeconomic reforms (structural adjustment programmes, poverty reduction strategies); general programme assistance (when not allocable by sector). Also includes developmental food aid/food security assistance.
Industry	Industry, mining and construction.
Other production	Agriculture forestry and fishing, tourism and trade policy and regulations.
Infrastructure	Includes transport, communications, energy, banking and financial services and business services.
Humanitarian	Comprises emergency response, reconstruction relief and rehabilitation and disaster prevention.
Multi-sector	Multi-sector and cross cutting, includes general environmental protection.
Debt	Includes debt forgiveness, rescheduling, buy backs, etc.
NGOs	Aid to non-governmental organizations.
Refugees	Refugees in donor countries (not analysed).
Administration	Administration costs (not analysed).
Residual	Aid not included in above sectors and subsectors, includes promotion of development awareness (not analysed).
	The target variables
Internet usage	Internet users (per 100 people): people with access to the worldwide network. Source: World Development Indicators (WDI) based on the International Telecommunication Union (ITU).
Mobile phones	Mobile cellular subscriptions (per 100 people): subscriptions to a public mobile telephone service using cellular technology. Post-paid and prepaid subscriptions are included. Source: WDI based on data from the ITU.
Death rate	Crude death rate indicates the number of deaths occurring during the year, per 1,000 population estimated at midyear. Source: WDI
School completion rate	The total number of students in the last grade of primary school, minus the number of repeaters in that grade, divided by the total number of children of official graduation age. Source: WDI based on UNESCO Institute for Statistics.

Note: Further details on the definitions with respect to the CRS data can be found in www.oecd.org/document/32/0,3343,en_2649_33721_42632800_1_1_1_1,00.html#Commitment

Appendix: a two stage estimation approach

We illustrate this for female primary school completion rates (PSCRF). First, we estimate a long-run equation using random effects, as fixed effects will obscure whether the particular country is above or below trend, which is the key factor we are attempting to capture. Bias is not a problem as we are not so much interested in the values for specific coefficients, but in deviations (Z) of the variable from its long-run value. The second stage involves regressing the change in the dependent variable on adjustments to lagged Z as well as other more direct impacts:

$$\Delta Y_t = \beta_0 + \gamma_1 A_{1t} + \gamma_2 A^e_{1t} + (\lambda_0 + \lambda_1 A_{1t} + \lambda_2 A^e_{1t})Z_{t-1} \tag{A1}$$

This is a form of error adjustment model. A_1 represents aid for a specific sector or group of sectors. It can impact on changes in Y via both a direct impact ($\gamma_1 A_{1t}$) and by impacting upon the speed of error adjustment ($\lambda_1 A_{1t}$). The key difference is that $\gamma_1 A_{1t}$ has a given impact upon Y regardless of how far from trend it is, whereas $\lambda_1 A_{1t}$ has a bigger impact the greater is $|Z_{t-1}|$, and the nature of its impact will depend upon the sign of Z_{t-1}. It could speed up adjustment of, e.g., a low primary school completion rate, but also theoretically, that of a high usage country downwards. A^e_{1t} is the error term in aid. In the regressions we again distinguish between positive and negative error terms.

The first stage regression includes population density, GDP per capita and dummy variables for each year. The purpose of this regression is not to provide a full explanation of the determinants of PSCRF. The average level of education, for example, may well impact on this. But aid can impact on education levels and hence we wish to exclude them from the long-run equation. The resulting equation, with errors corrected for heteroscedasticity and t statistics in (.) is:

$$\Delta \text{Log(PSCRF)} = \underset{(4.83)}{0.238} \text{ log(population density)} + \underset{(4.40)}{0.241} \text{ Log(GDP per capita)} + \text{year dummies}$$

$$\text{Overall } R^2 = 0.29 \tag{A2}$$

The equation relating to first differences of the log(PSCRF), which is the growth rate of PSCRF, is

$$\text{Log(PSCRF)} = \underset{(3.20)}{0.0032} A_S - [\underset{(2.05)}{0.021} + \underset{(2.67)}{0.0064} A_S \; \underset{(2.54)}{-0.073} A^{e-}_S]Z_{t-1} + \text{Year dummies}$$

$$\text{Overall } R^2 = 0.14 \tag{A3}$$

where (.) denotes t statistics. A_S is as social infrastructure aid and Z_{t-1} the lagged error term from (A2). The results indicate that aid impacts on growth directly, as in γ_1 in (A1) and indirectly via the adjustment mechanism, as in λ_1 in (A1). Aid volatility, in this case the negative error term (A^{e-}_S), retards adjustment. The two aid terms in [.]are only operative if Z_{t-1}<0, i.e. aid stimulates adjustment upwards, but not downwards.

These results and the methodology are preliminary. The main purpose of this appendix has been to emphasize that the impact of aid and aid volatility may be more complex than is generally modelled and to suggest an alternative modelling strategy. This strategy does, however, make considerable demands on the data. In addition some aspects could be changed, e.g., a stochastic frontier function approach could be used to estimate Z_t.