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Aid Absorption and Spending in Africa: A Panel Cointegration Approach

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Abstract: This paper focuses on the macroeconomic management of large inflows of foreign aid. It investigates the extent to which African countries have coordinated fiscal and macroeconomic responses to aid surges. In practice, we construct a panel dataset to investigate the level of aid 'absorption' and 'spending'. This paper departs from the recent empirical literature by utilising better measures for aid inflows and by employing cointegration analysis. The empirical short-run results suggest that, on average, Africa's low-income countries have absorbed two-thirds of (grant) aid receipts. This suggests that most of the foreign exchange provided by the aid inflows has been used to finance imports. The other third has been used to build up international reserves, perhaps to protect economies from future external shocks. In the long-run, absorption increases but remains below its maximum ('full absorption'). Moreover, we also show that aid resources have been fully spent, especially in support of public investment. There is only weak evidence that a share of aid flows have been 'saved', i.e. substituted domestic borrowing. Overall, these findings suggest that the macroeconomic management of aid inflows in Africa has been significantly better than often portrayed in comparable exercises. The implication is that African countries will be able to efficiently manage a gradual scaling up in aid resources.

JEL Classification: C23, F35, O23, O55
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1. Introduction

Foreign aid is often provided with the twin objectives of financing domestic expenditures and increasing the availability of foreign exchange. In Africa's low-income countries, external grants and concessional loans provide crucial resources to support the expansion of public investment programmes – e.g. building important socio-economic infrastructure that contributes to fostering economic growth and alleviating poverty. Moreover, these flows provide foreign exchange resources that allow countries to increase imports of capital goods, which stimulate economic output and are often associated with productivity gains.

This paper is mainly concerned with the fiscal and macroeconomic management challenges arising from large foreign aid inflows. For that purpose, we use the analytical framework proposed by the IMF (2005) and Hussain et al (2009) to investigate whether African countries have pursued a coordinated strategy in terms of their fiscal and macroeconomic responses to large aid inflows. The lack of coordination between the government and the central bank may undermine the effective use of foreign aid resources, often contributing to inflationary pressures, the appreciation of the nominal exchange rate, high interest rates and accumulation of public debt (Buffie et al, 2004).

We construct a new panel dataset for African countries, covering the period 1980-2005. An important emphasis is placed on the definition, source and construction of the main variables. Although the vast literature on the macroeconomic impacts of foreign aid inflows predominantly uses OECD-DAC data on aid, we argue that this is not appropriate. One reason is that donor-reported statistics often overestimate the 'true' amount of aid. For example, costs relating to technical assistance are included in foreign aid statistics (e.g. OECD-DAC's) even though many of these payments never actually leave the donor country's banking system. Since these activities have no clear impact on the balance of payments or the fiscal budget, they should not be included in the analysis. Moreover, off-budgets are not likely to have significant fiscal effects. Therefore, we favour the use of official data from recipient countries to assess the questions at hand. In this study we use balance of payments (BOP) data for the macroeconomic variables (including external grants) and government data for the fiscal variables. The former is reported in the IMF's Balance of Payments Statistics (BOPS) by the respective central banks, whilst the latter is reported in the World Bank's Africa Database by World Bank country economists. This actually entails the construction of two different measures of foreign aid.

This paper also strives to use appropriate panel data methodologies. Despite the popularity of dynamic panel data (DPD) methods in applied research, these seem to be more suitable for panels with large N (e.g. countries) and small T (observations through time). For panels that incorporate both a significant number of cross-sections and annual observations – like this one – non-stationarity becomes a major concern for inference. Therefore, we use recently developed methods that have strong foundations in the analysis of time series data, namely, panel unit root tests, cointegration tests, and efficient estimators for assessing long-run relationships.

The next section provides a brief overview of the literature on the macroeconomic effects of aid. Moreover, it introduces the analytical framework that provides the background for this study and presents the few existing empirical results. Section 3 introduces the empirical methodologies to be utilised in this study. Section 4 explains the construction of the variables, whereas section 5 presents the empirical findings. Section 6 concludes the paper.

2. Literature Review

The Macroeconomic Management of Aid

There is a growing literature on the macroeconomic challenges associated with large foreign aid inflows. White (1992) is an important and often cited early contribution. The author critically surveys the debates relating to the impact of aid on domestic savings, the fiscal response, the real exchange rate and ultimately economic growth, thus providing an excellent synthesis of the theoretical and empirical contributions to the topic. However, academic interest in these lines of investigation may have suffered from the marked reduction in aid flows to developing countries during the 1990s. This declining trend was partly due to: (i) the collapse of the Soviet Union, eliminating the geo-political justification for providing aid inflows; (ii) rising concerns about the effectiveness of aid in achieving desired outcomes, namely policy reform, economic growth and poverty reduction ('aid fatigue'); and (iii) the economic recession that affected several donors in the early 1990s.

Nonetheless, the early 2000s witnessed a renewed interest from the international donor community. The United Nations Millennium Declaration (and the subsequent Millennium Development Goals) provided the impetus that was quickly followed by promises to increase the availability of external finance to developing countries – in particular to Africa.[1] Naturally, this led to the revival of many debates concerning the impact of 'scaling up' aid inflows. The International Monetary Fund took a decisive lead, with publications such as Isard et al (2006), Heller (2005) and Gupta et al (2006). These works revisit the main foreign aid debates and provide an overview of current knowledge.

We can subdivide the main issues concerning the macroeconomics of aid into two main areas: (i) the fiscal sphere, which is influenced by recipient governments; and (ii) the monetary and exchange rate sphere, which is usually under the responsibility of central banks. The first incorporates questions about the impact of aid on the size and composition of public spending, domestic revenues, fiscal deficit, debt sustainability and aid dependency. This leads to policy decisions such as how much aid the government should spend and whether it should save some of the aid resources (e.g. to smooth the expenditure pattern when resources are scarce). The second area focuses on concerns of exchange rate appreciation, rising price inflation and high interest rates. This often leads to debates about the optimal level of sterilisation (e.g. Prati et al, 2003) and effective exchange rate regimes (e.g. Buffie et al, 2004). Nonetheless, these two areas of interest are interdependent and should be considered in tandem. Fiscal decisions crucially depend on macroeconomic circumstances (e.g. the interest rate on domestic public debt), while central bank objectives (e.g. low inflation) are partly influenced by the government's policy stance. This interdependence has led to the development of the analytical framework that we will now discuss.

Analytical Framework

The starting point of this empirical investigation is the analytical framework proposed by Hussain et al (2009).[2] The framework is used to investigate the macroeconomic management challenges and optimal policy responses to increases (surges) in foreign aid inflows. This is a crucial policy issue for low-income countries, which are often aid-

[1] These were embedded in the 2002 Monterrey Consensus – an outcome of the United Nations International Conference on Financing for Development – and the 2005 Gleneagles G8 summit.
[2] Earlier versions of this paper are Berg et al (2007) and IMF (2005).

dependent and may suffer from the volatility and unpredictability of aid flows. Hence, the framework emphasises the need to coordinate fiscal policy with monetary and exchange rate policy in order to minimise potential adverse effects and improve its efficiency. Hussain et al (2009) suggest the use of the following two interrelated concepts: (i) 'absorption', which is defined as the widening of the current account deficit (excluding aid) due to the aid surge; and (ii) 'spending', which is defined as the widening of the fiscal deficit (excluding aid) following an aid surge. Absorption can be seen as a measure of the degree of 'real resource transfer,'[3] whilst spending assesses "the extent to which the government uses aid to finance an increase in expenditures or a reduction in taxation" (Gupta et al, 2006:10). In the special cases of aid-in-kind and 'tied aid' (i.e. imports directly financed by aid), spending and absorption are equivalent.

In order to understand the implications of these concepts, we can make use of the relevant macroeconomic and fiscal identities. In terms of aid absorption, we start with the following balance of payments identity:

$$\Delta R = CAB + KAB$$

where ΔR stands for changes in international reserves, *CAB* is the current account balance, and *KAB* the capital account balance. If we pull out aid inflows from both accounts,[4] we obtain:

$$\Delta R = NACAB + NAKAB + Aid$$

where *NACAB* is the non-aid current account balance, *NAKAB* the non-aid capital account balance, and *Aid* is the net aid inflow. Taking differences and rearranging, we obtain the following expression:

$$\Delta Aid = -\Delta NACAB - \Delta NAKAB - \Delta\Delta R$$

[3] "It measures the extent to which aid engenders a real resource transfer through higher imports or through a reduction in the domestic resources devoted to producing exports" (IMF, 2005:3).
[4] Some aid inflows are included in the current account (e.g. current grants) while others are incorporated in the capital account (e.g. capital loans) – see Aiyar and Ruthbah (2008).

This identity provides some insights into the possible uses of additional aid inflows: (i) to widen the non-aid current account deficit (usually through higher imports); (ii) to widen the non-aid capital account deficit (potentially through capital outflows); and (iii) to increase the accumulation of international reserves. We can now express aid absorption as the deterioration of the non-aid current account balance that is attributed to aid (Aiyar and Ruthbah, 2008):

$$Absorption = -\frac{\Delta NACAB}{\Delta Aid}$$

Assuming that $\Delta Aid>0$, 'full absorption' is achieved when the non-aid current account deficit increases by the same amount of the extra aid inflow (the measure equals 1). A value close to 0 indicates a low level of absorption, and suggests that the additional foreign exchange provided by the aid inflow is used to increase international reserves and/or widen the non-aid capital account deficit.

In terms of aid spending, we start from the usual budget constraint facing the government:

$$I_G + C_G = T + Aid + B + L$$

where I_G stands for public investment, C_G public recurrent expenditures, T domestic revenue, B domestic borrowing and L external (non-concessional) loans. Re-arranging the budget constraint and differencing we obtain:

$$\Delta Aid = -\Delta NAGOB - (\Delta B + \Delta L)$$

where *NAGOB* is the non-aid government overall balance, i.e. domestic revenues (T) minus total expenditures ($I_G + C_G$). Hence, the potential uses of the additional aid inflows are: (i) to widen the non-aid current account deficit (through higher public spending and/or lower domestic revenues); and (ii) reduce the need for deficit financing (either domestic or external). We can now express aid spending as:

$$Spending = -\frac{\Delta NAGOB}{\Delta Aid}$$

Similarly, 'full spending' is achieved when the additional aid inflows are utilised to expand the non-aid fiscal deficit (the measure equals 1), whereas a value close to 0 suggests that aid has not been significantly spent.

Table 1: Possible Combinations in Response to a Scaling Up of Aid

	Absorbed	Not Absorbed
Spent	• Government spends the aid • Central Bank sells the foreign exchange • Current account deficit widens	• Fiscal deficit widens (expenditures are increased) • Central Bank does not sell foreign exchange • International reserves are built up • Inflation increases
Not Spent	• Government expenditures are not increased • Central Bank sells the foreign exchange • Monetary growth is slowed; nominal exchange rates appreciate; inflation is lowered;	• Government expenditures are not increased • Taxes are not lowered • International reserves are built up

Source: Gupta et al (2006:12)

When we take these two concepts together, there are four potential scenarios to be considered:

(i) *Absorb and spend aid*. The government spends the extra aid inflow – either through higher public spending, lower domestic revenue (e.g. cutting taxes), or a mixture of both – while the central bank sells the foreign exchange in the currency market. The fiscal expansion stimulates aggregate demand, which in turn contributes to a higher (public and private) demand for imports. This effect does not create balance of payments problems since the aid inflow finances the increase in net imports – as more foreign currency becomes available to importers. Hence, the foreign exchange is absorbed by the economy through the widening of the non-aid current account deficit (Gupta et al, 2006). This policy combination leads to aid-financed widening deficits, while the central bank's balance sheet remains unaltered (see table below). However, some real exchange rate appreciation may take place to enable this reallocation of resources. The choice of exchange rate regime will affect the mechanism through which the (potential) real exchange rate appreciation may occur – nominal appreciation in a 'pure float' versus higher domestic inflation in a 'fixed peg' (Hussain et al, 2009). This absorb-and-spend combination is often considered to be the ideal policy response to a surge in aid inflows.

(ii) *Absorb but not spend aid*. The government decides not to spend the aid inflow,[5] while the central bank sells the foreign exchange. Foreign aid is thus used to reduce the government's seigniorage requirement since it substitutes domestic borrowing in financing the government deficit (Buffie et al, 2004). Moreover, the central bank sterilises the monetary impact of domestically financed fiscal deficits (Gupta et al, 2006). This policy scenario usually leads to slower monetary growth and alleviates inflationary pressures. Hussain et al (2009) suggest that this could be an appropriate policy response in countries that have not achieved stabilisation – hence facing high domestic deficits and high inflation – or have a large stock of domestic public debt. A reduction in the level of outstanding public debt could 'crowd in' the private sector (both investment and consumption) through its effect on interest rates (Hussain et al, 2009).[6] This increase in aggregate demand would then feed into higher net imports, which would then be financed by the additional foreign exchange available in the currency market.

(iii) *Spend and not absorb aid*. The government spends the additional aid inflow (non-aid fiscal deficit widens), while the central bank allows its foreign exchange reserves to increase. In this case, the extra foreign exchange is not made available to importers but instead is used to build up international reserves. This policy response is similar to a fiscal stimulus in the absence of foreign aid (Hussain et al, 2009). The increase in government spending must be financed by either: (i) monetising the fiscal expansion (i.e. printing domestic currency), which increases money supply and therefore inflation; or (ii) sterilising the monetary expansion (by issuing securities, usually treasury bills), which could lead to higher interest rates and potentially crowd out the private sector (Hussain et al, 2009). There is no real resource transfer due to the absence of an increase in net imports. The IMF (2005) argues that this is a "common but problematic response, often reflecting inadequate coordination of monetary and fiscal policies." The net effect on the real exchange rate is uncertain: higher (unmet) demand for net imports contributes to depreciation (via the nominal exchange rate), whilst higher inflation works in the opposite way.

[5] It is assumed that neither public spending is increased nor revenues lowered (through tax cuts), which means that aggregate demand remains unchanged. However, a 'balanced budget' approach (i.e. a combination of higher/lower spending and taxes that leaves the non-aid fiscal deficit unchanged) is compatible with this result and can have significant impact on aggregate demand via the fiscal multiplier.

[6] "When debt reaches low levels, however, there are typically limits to the extent to which the financial system can effectively channel additional resources to the private sector. Further attempts to absorb without spending may amount to 'pushing on a string', increasing excess liquidity or even causing capital outflows rather than increased domestic activity" (IMF, 2005:4).

(iv) *Neither absorb nor spend aid*. The government does not use the additional aid inflow to widen the non-aid fiscal deficit, while the central bank increases its foreign exchange reserves. In this scenario, the government 'saves' the incremental aid and the availability of foreign exchange in the currency market is not increased. Once again, this could be a viable (short-run) strategy if the government needs to retire onerous debts (or smooth volatile aid inflows) and foreign reserves are at a precariously low level (Gupta et al, 2006). In the absence of a fiscal expansion, aggregate demand is not affected and there are no pressures on the exchange rate or domestic prices (Hussain et al, 2009). In the long-run, however, this may not be a politically viable strategy due to external and domestic pressures.

The following table provides an example of an aid inflow of 100 monetary units, which formalises the discussion presented above.

Table 2: Example with Aid Inflow of 100 Monetary Units

	Absorbed				Not Absorbed			
Spent	Central Bank Balance Sheet				Central Bank Balance Sheet			
	NIR	0	RM	0	NIR	+100	RM	+100
	NDA	0			NDA	0		
	Fiscal Accounts				Fiscal Accounts			
	EF	+100	DEF	+100	EF	+100	DEF	+100
	DF	0			DF	0		
Not Spent	Central Bank Balance Sheet				Central Bank Balance Sheet			
	NIR	0	RM	–100	NIR	+100	RM	0
	NDA	–100			NDA	–100		
	Fiscal Accounts				Fiscal Accounts			
	EF	+100	DEF	0	EF	+100	DEF	0
	DF	–100			DF	–100		

Obs.: 'NIR' net international reserves, 'NDA' net domestic assets, 'RM' reserve money, 'EF' external financing, 'DF' domestic financing, and 'DEF' deficit (excluding aid).
Source: Adapted from Berg et al (2007:8)

A final observation is warranted with regard to aid absorption. The central bank can choose to build up reserves or sell foreign exchange under any exchange rate regime (IMF, 2005:9). Consider the 'corner solutions'. In a pure float, the central bank sells the full amount of foreign exchange ($\Delta R = 0$), so that aid is absorbed and/or exits through the capital account. However, this is an extreme and unusual case. Many African countries operate a de facto managed float, where the central bank intervenes in the foreign exchange market (e.g. accumulation of reserves) due to a 'fear of floating' (Calvo and Reinhart, 2002:388). For this reason, any combination of the three uses of aid would be possible. In a fixed regime (e.g. CFA Franc Zone), the central bank accumulates the foreign exchange to defend the fixed peg ($\Delta R = \Delta Aid$) and none of the aid is absorbed. However, as the fiscal stimulus contributes to higher demand for net imports the central bank may decide to sell the foreign exchange to defend the peg – nominal depreciation pressures in 'spend and not absorb' – which may lead to full absorption (IMF, 2005:9). Hence, one could argue that while the exchange rate regime may condition the short-term response to aid, in the long-run, countries with different exchange rate and monetary frameworks may adopt similar policy responses. This assumption supports the main empirical framework proposed by this paper (pooled mean group estimator), which constrains the long-run impacts to be identical across countries but allows for short-run heterogeneous effects.

The aim of this section was to briefly introduce the analytical framework and concepts that are going to be used in the empirical assessment. The next section presents the empirical findings of the relevant literature.

Empirical Results

Hussain et al (2009) apply the framework described above to five African countries with the objective of examining their policy responses.[7] The countries that have recently experienced a surge in aid inflows and are included in the sample are Ethiopia, Ghana, Mozambique, Tanzania, and Uganda. The table below presents the results.

Table 3: Aid Absorption and Spending (% GDP)

Country	Period		ΔNACAB	ΔAid	Aid Absorbed?	ΔGE	ΔT	ΔAid	Aid Spent?
	Pre-Surge	Aid Surge							
Ethiopia	1999-00	2001-03	–1.6	8.0	20%	0.7	1.5	5.9	0%
Ghana	1999-00	2001-03	10.0	5.5	0%	2.3	1.9	6.0	7%
Mozambique	1998-99	2000-02	–3.9	5.9	66%	6.7	1.3	5.0	100%
Tanzania	1998-99	2000-04	2.3	2.2	0%	4.0	0.4	3.9	91%
Uganda	1999-00	2001-03	–1.3	4.7	27%	2.5	0.1	3.2	74%

Source: Adapted from Hussain et al (2009:499-501). All variables are defined as a percentage of GDP. The results are truncated at 0 and 100. The actual 'absorption' value for Ghana and Tanzania is negative. Moreover, the actual 'spending' value for Ethiopia is –14 percent, whereas for Mozambique is 108 percent.

The results suggest that, with the exception of Mozambique, foreign aid inflows were not significantly absorbed. In Ethiopia and Uganda, only 20 and 27 percent of the additional aid was absorbed, respectively. Moreover, Ghana and Tanzania have not used the extra aid inflow to widen the current account deficit. In fact, these countries experienced an improvement in the non-aid current account balance. With regard to aid spending, the estimate for Mozambique suggests that all aid was 'spent', meaning that the non-aid government balance deteriorated by the full amount of aid. In Ethiopia, however, none of the additional aid was 'spent'. In fact, there was an improvement of the non-aid government deficit, since revenue collection increased by more than the increase in government expenditures. The conclusion would be that Ethiopia is saving aid resources, possibly to substitute for domestic borrowing or even to retire public debt. Most of the additional aid inflows were spent in Tanzania and Uganda, whereas in Ghana most of the aid resources were saved. As a result of these findings, the usual policy prescription is that African countries need to significantly improve the management of aid inflows – through better coordination between the government (e.g. treasury) and the central bank.[8]

Foster and Killick (2006) also follow this approach to explore the consequences of scaling up aid flows in four African countries: Mauritania, Sierra Leone, Mozambique and Tanzania (the latter two overlapped with the IMF study). They conclude that aid has been fully absorbed and spent in Mauritania, whereas in Sierra Leone it has been mostly absorbed and partly spent (54 percent, if debt relief excluded).

However, this methodology has a few limitations. For example, the estimates from the absorption and spending equations will be very sensitive to the point in time in which they are evaluated. Defining the pre-aid surge and the surge period will be critical for the results and perhaps the policy conclusions. Moreover, this simple methodology ignores potential dynamic effects. Absorption and spending may well increase after the surge period (time lag). Finally, one needs to use these concepts with caution, since full 'spending' can be achieved through a total displacement of domestic revenues, in which case aid flows cause a proportional decrease in domestic revenues with no increase in government expenditures. The concept does not distinguish between what would be a desired outcome (e.g. increased developmental expenditures), and a potentially perverse effect that increases aid dependency and threatens long-term sustainability. For that purpose, we will also investigate the impact of aid on public investment.

[7] The same results can be found in IMF (2005).
[8] McKinley (2005) suggests that countries may not fully spend aid inflows due to a 'fear of inflation', while a 'fear of appreciation' hampers full absorption by the central bank.

More recently, Aiyar and Ruthbah (2008) have employed a panel econometric approach to investigate these issues in more detail. Their sample consists of 95 countries, distributed over three categories: sub-Saharan Africa (45), Latin America and Caribbean (19), and Other (31). Annual data for the period 1970-2004 is collected from the World Development Indicators (WDI), Global Development Finance (GDF) and the World Economic Outlook (WEO). The aid variable is taken from the WDI, which is in fact compiled by the OECD-DAC. Most variables in their analysis are measured as a share of GDP. The authors use a system Generalised Method of Moments (system GMM) estimator to evaluate the level of aid absorption and spending. The logarithm of average income per capita (LYPC) and the volatility of aid flows are used as country-specific time-invariant control variables. The logarithm of the terms of trade (LTOT) and inflation are country- and time-specific determinants.

Table 4: Aid Absorption and Spending Regressions

	NACABY			NAGOBY		
	Full	Africa	A/Y>0.1	Full	Africa	A/Y>0.1
Lagged Dep. Var.	0.64***	0.63***	0.60***	0.65***	0.62***	0.63***
AIDY	–0.31***	–0.41***	–0.45***	–0.56***	–0.79***	–0.68***
LTOT	–0.20	1.09	2.28			
LYPC	1.34**	1.17*	2.21	–1.63***	–1.72	–0.75
Autocracy Index	–0.01	–0.04	0.21	0.04	0.41***	0.02
Aid Volatility	–0.35***	–0.36***	–0.40***	–0.02	0.13	–0.22*
Inflation				–0.29	–0.91*	–1.35**
Observations	2218	1087	535	1290	539	241
Countries	72	37	18	62	31	15

Source: Compiled from Aiyar and Ruthbah (2008). Aid-dependent countries are those where foreign aid is higher than 10 percent of GDP. The asterisks represent significance at the 10 percent (*), 5 percent (**), and 1 percent (***) confidence levels.

Their results suggest that aid absorption is statistically significant in the short-run, with a coefficient ranging for –0.31 to –0.45. Technically, this means that a 1 percentage point increase in the aid-GDP ratio will lead to about a third of a percentage point increase in the non-aid current account deficit (as a share of GDP).[9] The results are stronger for the African and aid-dependent samples. Moreover, income per capita seems to have a positive impact on the non-aid current account balance, whilst aid volatility contributes to its deterioration. The results for aid spending appear to be stronger than for absorption. This is not an unexpected result, since countries are often blamed for spending more aid than they absorb (no real resource transfer). In this case, the impact for Africa appears to be stronger than for aid-dependent countries. Finally, the autocracy index appears to improve the government balance while inflation has the opposite effect. For aid-dependent countries, only inflation and aid volatility seem to be statistically significant.

To complement their analysis, Aiyar and Ruthbah (2008) also estimate the impact of foreign aid inflows on the accumulation of international reserves and total domestic investment. Their results suggest that aid has no impact on the accumulation of foreign reserves. Moreover, income per capita and the terms of trade may have a positive impact. Finally, foreign aid contributes to a modest increase in total domestic investment, when controlled for public investment.

Table 5: International Reserves and Investment Regressions

	dRY			INVY		
	Full	Africa	A/Y>0.1	Full	Africa	A/Y>0.1
Lagged Dep. Var.	0.02	0.04	–0.05	0.48***	0.43***	0.42***
AIDY	0.05	0.01	0.06	0.14***	0.15***	0.19***
L(ToT)	0.54	0.61*	0.52	–1.79**	–1.70*	–0.59
L(YPC avg)	0.37	0.52*	0.28**	0.60	0.39	0.16
Autocracy Index	–0.02	0.04	0.04	–0.01	0.08	–0.04
Aid Volatility	–0.05	0.01	–0.02	0.20***	0.23***	0.25*
INVPY				0.54***	0.60***	0.68***
Observations	2073	1007	485	1813	888	389
Countries	72	37	18	72	37	18

Source: Compiled from Aiyar and Ruthbah (2008). The asterisks represent significance at the 10 percent (*), 5 percent (**), and 1 percent (***) confidence levels.

The table below summarises the short- and long-run effects of an increase in aid inflows. The long-run coefficients are obtained by dividing the estimated (short-run) coefficient by 1 minus the coefficient of the lagged dependent variable. The long-run results indicate that aid has a more than proportional effect on the non-aid current account balance and the non-aid government balance. Although there is no impact on the accumulation of international reserves, aid seems to contribute to a modest increase in total investment. Finally, the authors argue that the unabsorbed aid is leaving the countries through the capital account.

This study will revisit the empirical evidence on aid absorption and spending, with a special focus on low-income countries in Africa. For that purpose we compiled data from several international sources and constructed a new (balanced) panel dataset. Contrary to

[9] The authors interpret these results differently. For the first column they suggest that (in the short-run) “about 30 cents out of every dollar is absorbed” (Aiyar and Ruthbah, 2008:10).

what is common practice in this field of research, we do not use the OECD-DAC's dataset on aid flows, but instead collect consistent aid data as reported by the recipients. Furthermore, we use alternative panel data methodologies, which we argue are more appropriate to deal with this type of macroeconomic dataset.

Table 6: Impact of a 1 percentage point increase in the Aid-GDP Ratio

	Full Sample		Africa		A/Y > 0.1	
	Short-Run	Long-Run	Short-Run	Long-Run	Short-Run	Long-Run
Absorption	0.30***	0.83***	0.41***	1.11***	0.45***	1.13***
Spending	0.56***	1.60***	0.79***	2.14***	0.68***	1.48***
Reserves	0.05	0.05	0.01	0.00	0.06	0.00
Investment	0.14***	0.26***	0.15***	0.26***	0.19***	0.33***

Source: Aiyar and Ruthbah (2008:13) for full sample and author's calculations for remaining samples. The asterisks represent significance at the 10 percent (*), 5 percent (**), and 1 percent (***) confidence levels.

3. Methodology

This paper uses (linear) panel data regression methods to evaluate how African countries have managed foreign aid inflows. Panel data is a special case of pooled time-series cross-section, in which the same cross-section (e.g. individual) is surveyed over time. In this paper, the cross-section includes African countries, for which annual observations of a number of variables were collected. Baltagi (2008:6-11) provides a good summary of the advantages and disadvantages of using panel data. Here we focus on the aspects that contrast macro panels to time series regressions. Some of the advantages include: (i) controlling for individual heterogeneity;[10] (ii) more informative data, variability, degrees of freedom and efficiency, as well as less collinearity among the variables; (iii) allowing the construction and testing of more complicated behavioural models; and (iv) panel unit root tests that have more power and have standard asymptotic distributions.

In terms of its limitations, the most serious are: (i) the 'poolability' (homogeneity) assumption, although there are formal tests to evaluate its validity; (ii) potential cross-sectional dependence, which complicates the analysis; (iii) some tests and methods require balanced panels; and (iii) cross-country data consistency. With these features in mind, we now proceed to the presentation of two important methodological approaches – dynamic panel data (DPD) methods and cointegration analysis.

[10] Unobserved heterogeneity or time-invariant variables that are correlated with explanatory variables (such as history, institutions and political regimes) may cause omitted variable bias in time series regressions.

3.1 Dynamic Panel Data

Economic relationships often incorporate some degree of dynamic behaviour. To capture this feature, dynamic panel data (DPD) models – which include a lagged dependent variable – are usually considered (Baltagi, 2008:147):

$$y_{it} = \delta y_{i,t-1} + \beta x_{it} + u_{it}$$

where δ is a scalar, x_{it} is a 1 x k vector of explanatory variables and β is a k x 1 vector of coefficients. For the purpose of illustration, assume that u_{it} is a one-way error component model:

$$u_{it} = \mu_i + v_{it}$$

where $\mu_i \sim \text{IID}(0,\sigma^2_\mu)$ and $v_{it} \sim \text{IID}(0,\sigma^2_v)$ independent of each other and among themselves.

This DPD model is characterised by two sources of persistence over time: (i) autocorrelation due to the lagged dependent variable; and (ii) individual effects capturing country heterogeneity (Baltagi, 2008:147). Estimation of DPD models raises several problems in both fixed- and random-effects. For example, the lagged dependent variable is correlated with the disturbance term (since $y_{i,t-1}$ is a function of μ_i), even if the v_{it} is not serially correlated (Greene, 2003:307). The OLS estimator is biased and inconsistent in finite samples, especially if T is small. In fact, the coefficients of the explanatory variables will be subject to a downward bias in absolute terms (i.e. biased towards zero). Even for T=30 the fixed-effects (FE) estimator can present a significant bias (Baltagi, 2008:148). The solution is thus to use instrumental variables (IV) regressions or generalised method of moments (GMM) estimators (Greene, 2003:308-14).

Arellano and Bond (1991) developed one- and two-step GMM estimators for dynamic panels (‘difference GMM’). They obtain additional instruments by using orthogonality conditions between the lagged dependent variables and the disturbance terms. The difference GMM does not require any prior knowledge of the initial conditions or even the distribution of v_i and μ_i. However, if the dependent variable is very persistent (close to a random walk), then the lagged levels are poor instruments for first-differences and difference GMM performs poorly. Blundell and Bond (1998) develop a ‘system GMM’ estimator for DPD models to solve the problem of ‘weak instruments’. The Blundell-Bond estimator combines moment conditions for the model in first-differences with those for the model in levels. The procedure uses lagged differences of y_{it} as instruments for the equation in levels and lagged levels of y_{it} as instruments for the equation in first-differences. Moreover, it requires a stationary restriction on the initial conditions process (Baltagi, 2008:161). The validity of the moment conditions imposed are usually assessed by a test of over-identifying restrictions (either Hansen’s or Sargan’s).

The main advantages of these GMM estimators relate to their perceived robustness to heteroscedasticity and non-normality of the disturbances. Moreover, the use of instrumental variables helps address biases arising from reverse causality. Nonetheless, there are some remaining concerns about the efficiency of such methods. The violation of moment conditions (e.g. presence of non-stationarity), will yield inconsistent estimates. Moreover, Roodman (2009) argues that the number (and quality) of instruments generated by difference and system GMM methods can affect the asymptotic properties of the estimators and specification tests. In samples with large T, instrument proliferation can be particularly serious, inducing two main types of problems: (i) overfitting endogenous variables; and (ii) imprecise estimates of the optimal weighting matrix. Greene (2003:307) provides another strong criticism. He argues that introducing a lagged dependent variable to an otherwise long-run (static) equation will significantly change its interpretation, especially for the independent variables. In the case of a DPD model, the coefficient on x_{it} merely represents the effect of new information, rather than the full set of information that influences y_{it}. Finally, it is often argued that while DPD methods are appropriate for panels with a small T, but when T is sufficiently large other methods should be preferred. Hence, we now turn to panel data methods that were specifically developed for ‘long’ panels.

3.2 Panel Cointegration

Traditional panel data econometrics rests on micro panels that usually include thousands of households or hundreds of firms (large N), which are tracked over a few survey rounds (small T). This study, however, uses macroeconomic variables that are collected for several African countries over a significant number of years. The use of panel datasets with these characteristics – large N and large T – presents new challenges to researchers. Panels with a significant temporal dimension are subject to spurious relationships, especially since macroeconomic variables are often characterised by non-stationarity. According to Baltagi (2008:273), the accumulation of observations through time generated two strands of ideas: (i) the use of heterogeneous regressions (one for each country) instead of accepting coefficient homogeneity (implicit in pooled regressions), e.g. Pesaran et al (1999); and (ii) the extension of time series methods (estimators and tests) to panels in order to deal with non-stationarity and cointegration, e.g. Kao and Chiang (2000) and Pedroni (2000).[11] We will pursue both strategies in this paper.

Cointegration analysis in a panel data setting entails similar steps to those usually employed in time series analysis: (i) unit root testing; (ii) cointegration testing; and (iii) estimation of long-run relationships. We take these in turn.

Unit Root Tests

The first step requires an analysis of the stationarity properties of the variables. Panel unit root tests have become a fast-growing area of research in econometrics with a view to improving the perceived low power of individual unit root tests – particularly in small samples. These tests are often grouped into two main categories: (i) first-generation tests, which assume cross-sectional independence – e.g. Levin et al (2002), Im et al (2003), Maddala and Wu (1999), and Choi (2001); and (ii) second-generation tests, which explicitly allow for some form of cross-sectional dependence – e.g. Pesaran (2007). As a starting point, consider the following autoregressive (AR) process for panel data:

$$y_{it} = \rho_i y_{i,t-1} + \delta_i Z_{it} + u_{it}$$

where ρ_i is the AR coefficient and the error term u_{it} is assumed to be independent and identically distributed (i.i.d.). Moreover, Z_{it} includes individual deterministic effects, such as constants ('fixed effects') and linear time trends, which capture cross-sectional heterogeneity.

Levin et al (2002)[12] propose a test (LLC) that can be seen as a panel extension of the augmented Dickey-Fuller (ADF) test:

[11] Moreover, the estimators for panel cointegrated models and related statistical tests are often found to have different asymptotic properties from their time series counterparts (Baltagi, 2008:298). An important contribution is Phillips and Moon (1999, 2000), who analyse the limiting distribution of double indexed integrated processes.
[12] Originally published in 1992 and one of the first panel unit root tests in the literature.

$$\Delta y_{it} = \alpha y_{i,t-1} + \sum_{j=1}^{p_i} \beta_{ij} \Delta y_{i,t-j} + \delta_i Z_{it} + u_{it}$$

Since the lag length of the differenced terms (p_i) is unknown, Levin et al (2002:5-7) suggest the following three-step procedure: (i) carry out separate ADF regressions for each individual and generate two orthogonalised residuals;[13] (ii) estimate the ratio of long-run to short-run innovation standard deviation for each individual; (iii) compute the pooled *t*-statistics, with the average number of observations per individual and average lag length. In this test, the associated AR coefficient is constrained to be homogenous across individuals (i.e. $\alpha_i = \alpha$ for all i). Hence, the null hypothesis assumes a common unit root (H_0: $\alpha = \rho - 1 = 0$) against the alternative hypothesis that each time series is stationary (H_1: $\alpha < 0$). The authors show that the pooled *t*-statistic has a limiting normal distribution under the null hypothesis. This test is often recommended for moderate sized panels, especially for N>10 and T>25.

Im et al (2003)[14] extend the LLC test by allowing heterogeneity on the AR coefficient. In practice, the test entails the estimation of individual ADF regressions, and then combining this information to perform a panel unit root test. This approach allows for different specifications of the coefficients (α_i for each cross-section), the residual variance and lag-length (Asteriou and Hall, 2007:368). The authors propose a *t*-bar statistic, based on the average of the individual unit root (ADF) test statistics. This statistic evaluates whether the coefficient α is non-stationary across all individuals (H_0: $\alpha_i = 0$ for all i), against the alternative hypothesis that at least a fraction of the series is stationary (H_1: $\alpha_i < 0$ for at least one i). Both LLC and IPS tests require N to be small enough relative to T, whilst the LLC test also requires a strongly balanced panel (Baltagi, 2008:280).

Breitung (2000) uses Monte Carlo experiments to show that the power of the LLC and IPS tests statistics is sensitive to the specification of the deterministic components, such as the inclusion of individual specific trends (Baltagi, 2008:280). He proposes a test statistic based on modifications to the LLC steps to overcome these difficulties. Breitung's test statistic

[13] Here, the lag order of the differenced terms (pi) is allowed to vary across individuals and is usually determined by a lag selection criterion (to correct for serial correlation).
[14] The IPS test was originally published in 1997.

assumes a common unit root process and is also shown to be asymptotically distributed as a standard normal. The test is often suggested for samples of around *N*=20 and *T*=30.

Maddala and Wu (1999:637) and Choi (2001) suggest the use of nonparametric Fisher tests. The main feature of these tests is that they combine the probability limit values (*p*-values) of unit root tests from each cross-section rather than average test statistics. Fisher tests are usually implemented using individual ADF or Phillips-Perron unit root tests, and their asymptotic distribution follows a chi-square (*P*-test).[15] Choi (2001) also proposes an alternative Fischer-type statistic that follows a standard normal distribution (*Z*-test). Both IPS and Fischer-type tests combine information of individual unit root tests, but simulation studies suggest that Fischer tests have better power properties than the IPS test. The disadvantage of Fischer-type tests relates to the need to derive *p*-values through Monte Carlo simulations.

Hadri (2000) proposes a residual-based Lagrange multiplier (LM) test, which is in fact a panel generalisation of the KPSS test (Baltagi, 2008:282). The test uses the residuals from individual OLS regressions of y_{it} on deterministic components (constant and trend) to compute the LM statistic. This test also differs from the previous in the sense that it is a stationarity test. The null hypothesis assumes no unit root in any of the time series (all panels stationary), against the alternative of non-stationarity for, at least, some cross-sections.

The main drawback of the first-generation tests described above relates to the assumption that the data is independent and identically distributed (i.i.d.) across individuals (cross-section independence). In practice, this means that the movements of a given variable through time are independent across countries. This restrictive assumption has often been challenged by empirical studies, and it should be evaluated on a case-by-case basis.[16] Some cross-sectional dependence tests include Pesaran (2004) and a Breusch-Pagan LM statistic (for $T>N$). Banerjee et al (2005) show that in the presence of cross-section dependence, first-generation tests tend to have serious size distortions and therefore perform poorly.

[15] Maddala and Wu (1999:645) also suggest a bootstrap procedure to account for cross-sectional dependence, but size distortions are only decreased rather than eliminated.

[16] Levin et al (2002) suggest 'demeaning' the data in order to attenuate the biases caused by the presence of cross-sectional dependence, which involves subtracting cross-sectional averages (for each time period) from the series before the use of unit root tests. Nonetheless, this procedure cannot ensure the successful elimination of the bias.

This often leads to the over-rejection of the null hypothesis (unit root) when the sources of non-stationarity are common across individuals.

These findings led to the development of unit root tests for panels with cross-sectional dependence (second-generation tests). Pesaran (2007) suggests a simple method to remove the influence of cross-sectional dependence, which involves augmenting standard ADF regressions with the cross-section averages of lagged levels and first-differences of the individual series. These individual cross-sectionally augmented Dickey-Fuller (CADF) statistics (or the corresponding *p*-values) can then be used to develop modified versions of standard panel unit root tests – such as IPS's *t*-bar, Maddala and Wu's *P*, or Choi's *Z*. The tests are applicable for both when $N>T$ and $T>N$, and are shown to have good size and power properties, even when *N* and *T* are relatively small (e.g. 10). However, the *t*-bar statistic (CIPS) can only be computed for balanced panels. For unbalanced panels, the modified *Z* test can be reported.

Table 7: Characteristics of Unit Root Tests

Test	Null	Alternative Hypothesis	Deterministic Components	Autocorrelation Correction	Cross-Section Dependence	Unbalanced Panel (Gaps)
LLC	UR	No UR	None, F, T	Lags	demean	No (–)
Breitung	UR	No UR	F, T	Lags	robust[1]	No (–)
IPS	UR	Some CS without UR	None, F, T	Lags	demean	Yes (No)
Fisher	UR	Some CS without UR	None, F, T	Lags/Kernel	demean	Yes (Yes)
Hadri	No UR	Some CS with UR	F, T	Kernel	robust[1]	No (–)
Pesaran	UR	Some CS without UR	F, T	Lags	robust	Yes (No)

Obs.: 'UR' unit root, 'CS' cross-sections, 'None' no exogenous variables, 'F' fixed effect, 'T' individual effect and individual trend. [1] Stata's 'xtunitroot' command computes robust versions that account for cross-sectional dependence. Source: Compiled from QMS (2007:110, corrected) and Stata's 'xtunitroot' command help.

Cointegration Tests

The panel unit root tests proposed above aim to assess the order of integration of the variables. If the main variables are found to be integrated of order one, then we should use panel cointegration tests to address the non-stationarity of the series. As before, some of these tests were developed as extensions of earlier tests for time series data.

Pedroni (1999, 2004:604) provides cointegration tests for heterogeneous panels based on the two-step cointegration approach of Engle and Granger (1987). Pedroni uses the residuals from the static (long-run) regression and constructs seven panel cointegration test statistics: four of them are based on pooling (within-dimension or 'panel statistics test'), which assumes homogeneity of the AR term, whilst the remaining are less restrictive (between-dimension or 'group statistics test') as they allow for heterogeneity of the AR term. The assumption has implications on the computation of the second step and the specification of the alternative hypothesis. The *v*-statistic is analogous to the long-run variance ratio statistic for time series, while the *rho*-statistic is equivalent to the semi-parametric 'rho' statistic of Phillips and Perron (1988). The other two are panel extensions of the (non-parametric) Phillips-Perron and (parametric) ADF *t*-statistics, respectively. These tests allow for heterogeneous slope coefficients, fixed effects and individual specific deterministic trends, but are only valid if the variables are I(1). Pedroni (1999) derived critical values for the null hypothesis of no cointegration.

Kao (1999) proposes residual-based DF and ADF tests similar to Pedroni's, but specifies the initial regression with individual intercepts ('fixed effects'), no deterministic trend and homogeneous regression coefficients. Kao's tests converge to a standard normal distribution by sequential limit theory (Baltagi, 2008:293). Both Kao and Pedroni tests assume the presence of a single cointegrating vector, although Pedroni's test allows it to be heterogeneous across individuals.

Maddala and Wu (1999) propose a Fisher cointegration test based on the multivariate framework of Johansen (1988). They suggest combining the *p*-values of individual (system-based) cointegration tests in order to obtain a panel test statistic. Moreover, Larsson et al (2001) suggest a likelihood ratio statistic (LR-bar) that averages individual rank trace statistics. However, the authors find that the test requires a large number of temporal observations. Both of these tests allow for multiple cointegrating vectors in each cross-section.

Westerlund (2007) suggests four cointegration tests that are an extension of Banerjee et al (1998). These tests are based on structural rather than residual dynamics and allow for a large degree of heterogeneity (e.g. individual specific short-run dynamics, intercepts, linear trends and slope parameters).[17] All variables are assumed to be I(1). Moreover, bootstrapping provides robust critical values in cases of cross-section dependence. The

[17] Westerlund (2007:710) argues that residual-based cointegration tests require the long-run cointegration vector in levels to equal the short-run adjustment process in differences – also known as 'common factor restrictions'. The trade-off is the assumption of weak exogeneity that ECM-based tests depend upon.

tests assess the null hypothesis that the error correction term in a conditional ECM is zero – i.e. no cointegration (Baltagi, 2008:306).

Banerjee et al (2004) argue that although these tests allow for cross-sectional dependence (via the effects of short-run dynamics), they do not consider long-run dependence, induced by cross-sectional cointegration. The authors demonstrate that in that case, panel cointegration tests may be significantly oversized (Baltagi, 2008:302-3). Moreover, most cointegration tests may be misleading in the presence of stationary data, as they require all data to be I(1).

Estimation of the Long-Run

A complementary issue relates to the efficient estimation of long-run economic relationships. In the presence of cointegrating non-stationary variables, one would like to be able to efficiently estimate and test the relevant cointegrating vectors. For that purpose, a number of panel estimators have been suggested in the literature. Once again, most of them are developed as extensions of well-known time series methods. An important difference is that the panel OLS estimator of the (long-run) static regression model, contrary to its time series counterpart, is inconsistent (Baltagi, 2008:299).

Kao and Chiang (2000) propose a panel dynamic OLS estimator (DOLS) which is a generalisation of the method originally proposed by Saikkonen (1991) and Stock and Watson (1993) for time series regressions. The regression equation is:

$$y_{it} = \alpha_i + \beta' X_{it} + \sum_{j=-q}^{q} c_{ij} \Delta X_{i,t+j} + \varepsilon_{it}$$

where X_{it} is a vector of explanatory variables, β the estimated long-run impact, q the number of leads and lags of the first-differenced data, and c_{ij} the associated parameters. The estimator assumes cross-sectional independence and is asymptotically normally distributed. The authors provide Monte Carlo results suggesting that the finite-sample properties of the DOLS estimator are superior to both fully-modified OLS (FMOLS)[18] and OLS estimators.

Pesaran et al (1999) suggest a (maximum-likelihood) pooled mean group (PMG) estimator for dynamic heterogeneous panels. The procedure fits an autoregressive distributed lag (ARDL) model to the data, which can be re-specified as an error correction equation to facilitate economic interpretation. Consider the following error correction representation of an ARDL(*p*, *q*, *q*,…, *q*) model:

$$\Delta y_{it} = \phi_i y_{i,t-1} + \beta_i' X_{i,t-1} + \sum_{j=1}^{p-1} \lambda_{ij} \Delta y_{i,t-j} + \sum_{j=0}^{q-1} \delta_{ij}' \Delta X$$

where X is a vector of explanatory variables, β_i contains information about the long-run impacts, ϕ_i is the error correction term (due to normalisation), and δ_{ij} incorporates short-run information. The PMG can be seen as an intermediate procedure, somewhere between the mean group (MG) estimator and the dynamic fixed-effects (DFE) approach.[19] The MG estimator is obtained by estimating N independent regressions and then averaging the (unweighted) coefficients, whilst the DFE requires pooling the data and assuming that the slope coefficients and error variances are identical. The PMG, however, restricts the long-run coefficients to be same (β=β_i for all i), but allows the short-run coefficients and error variances to vary across countries (Pesaran et al, 1999:621). This approach can be used whether the regressors are I(0) or I(1) (Pesaran et al, 1999:625).

4. Data

The data used in this paper was collected from the International Monetary Fund's (IMF) Balance of Payments Statistics (BoPS) and the World Bank's Africa Database. Complementary sources included the United Nations' National Accounts Main Aggregates Database, the IMF's World Economic Outlook (WEO), and the World Bank's World Development Indicators (WDI). There was a significant effort to construct a balanced panel for all 53 African countries covering the period 1970-2007. However, data for 1970-1979 is scarce for many countries, whereas data for 2006-2007 is usually based on

[18] The panel FMOLS estimator developed by Phillips and Moon (1999) and Pedroni (2000) is a generalisation of the estimator proposed by Phillips and Hansen (1990).
[19] A further estimation alternative would be Zellner's seemingly unrelated regression (SUR), but this procedure requires that N is significantly smaller than T, which unfortunately is not our case. Moreover, Pesaran et al (1999:626) argue that Swamy's static random coefficient model is asymptotically equivalent to the MG estimator.

estimates or projections. Moreover, data on aid flows for 2006 often contains outliers due to very large debt relief grants, which cannot be satisfactorily expunged. Hence, we have built a balanced panel for 1980-2005 for the macroeconomic variables, while for the fiscal variables we have a balanced panel for 1990-2005. It should be noted that our aid variables only include grants, due to the lack of data on concessional foreign loans. Nonetheless, there is a strong argument to separate these since aid grants and aid loans often have significantly different economic impacts.[20] Finally, seven countries had to be excluded from the initial sample. These countries either reached independence only in the 1990s (Eritrea and Namibia) or lack reliable data (Congo DR, Djibouti, Liberia, Somalia and Zimbabwe).

The list of variables includes:

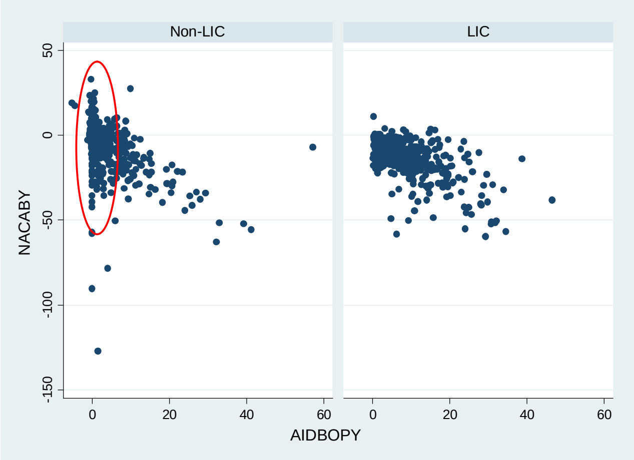
NACABY	Non-Aid Current Account Balance (% GDP)
AIDBOPY	Aid Grants (% GDP), as reported by the Balance of Payments Statistics
LTOT	Logarithm of the Terms of Trade
DRY	Change in International Reserves (% GDP)
NAGOBY	Non-Aid Government Overall Balance (% GDP)
AIDGOVY	Aid Grants (% GDP), as reported by the World Bank's Africa Database
INF	Inflation Rate (CPI, percentage change)
INVGY	Gross Public Fixed Capital Formation (% GDP)
BORY	Domestic Financing (% GDP)

The following graphs provide pair-wise plots of the main variables of interest. The full sample of African countries is utilised, as well as a sub-sample incorporating low-income countries (LICs) only.[21] The plots confirm the strong negative correlation between foreign aid and the macroeconomic and fiscal balances. This suggests that aid inflows are used, at least to a certain extent, to increase the (non-aid) current account and budget deficits. However, there is an important concern arising from the observation of these graphs. It appears that richer countries may potentially distort the analysis. This is because middle-income countries tend to be less aid-dependent, and therefore the relationship between aid inflows and other economic variables can be significantly weaker. The inclusion of these countries may thus affect the magnitude and significance of the estimated coefficients,

[20] In practice, we allow 'aid loans' to remain lumped with foreign non-concessional loans.
[21] As defined by the World Bank (July 2009).

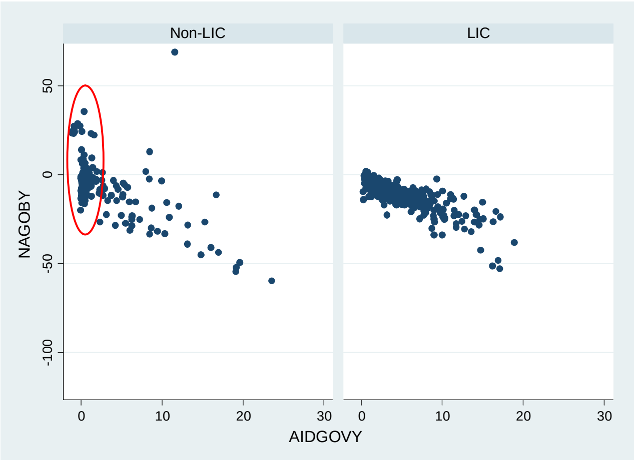
leading us to believe that aid absorption and spending is lower than desired. Further plots lead to similar conclusions for reserve accumulation and public investment. Finally, some of the richer countries are (at times) net 'donors', which further complicates the analysis.

Figure 1: Non-Aid Current Account Balances and Foreign Aid



Obs.: Excludes Lesotho (LSO)

Figure 2: Non-Aid Government Balances and Foreign Aid



Obs.: Excludes the Republic of Congo (COG)

The table below presents pair-wise correlations between the main variables of interest. The results corroborate the decision to exclude middle-income countries from the analysis, as for both macroeconomic and fiscal dimensions the (negative) correlations of the non-aid balances with foreign aid inflows are significantly stronger for low-income countries.

For the reasons presented above, this study will continue the analysis for the 25 African low-income countries in the sample. The following tables present basic statistics on the main variables.[22] As expected, both NACABY and NAGOBY have negative means, with fairly low maximums (surpluses). This highlights the importance of aid inflows in balancing these accounts. The average for AIDBOPY is higher than that for AIDGOVY, probably reflecting the presence of 'off-budgets' – i.e. aid flows not recorded in the budget, perhaps because they are implemented by the donor. BORY has a positive (but low) mean value.

Table 8: Correlations

	ALL		LIC	
1980-2005	NACABY	AIDBOPY	NACABY	AIDBOPY
NACABY	1.00		1.00	
AIDBOPY	–0.56	1.00	–0.63	1.00
1990-2005	NAGOBY	AIDGOVY	NAGOBY	AIDGOVY
NAGOBY	1.00		1.00	
AIDGOVY	–0.72	1.00	–0.83	1.00

Table 9: Basic Statistics for Macroeconomic Variables (1980-2005)

	Obs.	Mean	SD	Min	Max
NACABY	650	–12.2	9.6	–59.7	11.1
AIDBOPY	650	7.7	6.5	0.2	46.5
LTOT	650	4.7	0.4	2.7	5.8
DRY	650	–0.5	3.1	–16.0	34.9

Table 10: Basic Statistics for Fiscal Variables (1990-2005)

	Obs.	Mean	SD	Min	Max
NAGOBY	400	–11.6	7.4	–53.0	1.9
AIDGOVY	400	4.9	3.5	0.2	18.9
INF	400	13.4	20.5	–10.9	183.3
INVGY	400	7.6	3.8	1.4	32.2
BORY	400	0.8	2.5	–6.7	13.8

5. Empirical Results

This section undertakes a comprehensive econometric exercise to evaluate the uses of foreign aid in Africa's low-income countries. The sample for the macroeconomic specification (absorption) runs from 1980 to 2005, while the fiscal regressions (spending) cover the period 1990-2005. The previous section has demonstrated that the inclusion of middle-income countries – for whom foreign aid plays a much lesser role – can significantly distort the analysis. Hence, the sample in this section is restricted to the 25 African low-income countries in our sample.

[22] Not surprisingly, the full sample shows lower absolute averages and higher standard deviations for the aid variables.

Since we are dealing with macroeconomic and fiscal variables that are often found to be non-stationary, we first undertake panel unit root tests to evaluate their order of integration. The results provide evidence that at least some of the variables are non-stationary. We then apply panel cointegration tests to assess whether there are long-run relationships amongst the variables of interest. Finally, long-run relations are estimated through appropriate and efficient methods.

5.1 Panel Unit Roots

We start with the application of panel unit root tests. A detailed description of the specific characteristics of each test was provided in a previous section. All test specifications include a deterministic time trend. In the LLC, IPS and Fisher-type tests, cross-sectional means are subtracted to minimise problems arising from cross-sectional dependence. The Pesaran test and the versions of the Breitung and Hadri tests used here allow for cross-sectional dependence.[23] However, this version of the Breitung test requires *T*>*N*. In the LLC and IPS tests, the Bayesian (Schwarz) information criterion (BIC) is used to determine the country-specific lag length for the ADF regressions, with a maximum lag of 3. Moreover, the Bartlett kernel was used to estimate the long-run variance in the LLC test, with maximum lags determined by the Newey and West bandwidth selection algorithm. Finally, the Fisher-ADF and Pesaran's CADF tests include 2 lags.

Table 11: Panel Unit Root Tests

	LLC	IPS	Fisher		Breitung	Hadri	Pesaran	
	t*	W-t-bar	ADF-Pm	PP-Pm	λ	z	t-bar	z
NACABY	–1.20*	–2.56***	0.99**	7.33***	–0.09	16.77***	–1.80	2.76
AIDBOPY	–3.85***	–3.82***	1.49*	7.12***	–1.73**	17.40***	–1.86	2.43
LTOT	–1.09	–2.51***	1.72**	4.87***	–2.10**	19.45***	–1.75	3.03
DRY	–13.25***	–13.87***	4.89***	29.26***	–6.48***	1.68**	–2.98***	–3.58***
NAGOBY	–4.04***	–4.14***	0.88	7.77***	n/a	8.06***	–1.96	1.66
AIDGOVY	–5.44***	–4.19***	3.89***	7.93***	n/a	7.80***	–1.84	2.23
INF	–51.40***	–18.44***	1.65**	6.26***	n/a	6.29***	–0.91	6.85
INVGY	–5.21***	–5.40***	2.47***	6.85***	n/a	6.83***	–1.75	2.68
BORY	–8.53***	–6.90***	1.57*	15.16***	n/a	1.74**	–2.41	–0.60

Obs.: Test results generated by Stata. The asterisks represent significance at the 10 percent (*), 5 percent (**), and 1 percent (***) confidence levels.

The test results provide mixed evidence on the order of integration of the variables. The LLC test strongly rejects the null hypothesis of unit roots, except for LTOT and NACABY.

[23] The robust versions of the Breitung and Hadri tests are implemented by the new STATA command 'xtunitroot.'

The IPS test rejects the presence of unit roots for all variables. The results for the Fisher-type tests seem to depend on the underlying unit root test chosen. The Phillips-Perron option rejects the null hypothesis for all variables, whilst the ADF alternative presents significantly weaker evidence for some. For example, it cannot reject the presence of unit roots in NAGOBY, and has higher *p*-values for most variables. The last four columns show the tests that are robust to the presence of cross-sectional dependence. This variant of the Breitung test is only valid for the longer panel ($T>N$). The evidence it provides is mixed, with NACABY appearing to be non-stationary, while the other macroeconomic variables reject unit roots at 5 percent. The Hadri test has a different null hypothesis (stationarity) and provides strong evidence that (at least) some panels have unit roots. This test is an interesting alternative since it challenges the usually strong null hypothesis that all panels have unit roots. Finally, the Pesaran CADF test suggests that all variables have unit roots, except for DRY. The results from the CADF test are robust to the lag structure and specification of determinist components – with the exception of BORY, where a lower lag order (1) suggests that the variable is stationary.

Hence, while the IPS and Fisher-PP test results lead to the conclusion that all variables are stationary, the Hadri and Pesaran tests suggest the opposite (with the exception of DRY for the CADF test). The remaining tests (LLC, Fisher-ADF and Breitung) provide mixed evidence.[24] This observation may lead us to believe that there is some level of cross-sectional dependence affecting the results. Although the cross-sectional averages were subtracted from each series (de-meaning) prior to applying the LLC, IPS and Fisher-type tests,[25] there may still be some residual dependence left, which leads to the over-rejection of the null hypothesis of unit roots. However, we have also applied the original versions of the Hadri and Breitung tests, which are not robust to cross-sectional dependence, and we achieved fairly similar conclusions (no de-meaning applied either). Overall, it is fair to conclude that there is (at least) some non-stationarity that needs to be properly addressed.

5.2 Cointegration Tests

Despite the fact that (some of) the data is non-stationary, we may still be able to make valid inference if there is a meaningful relationship amongst the variables of interest. This will be the case if we find a linear combination that produces stationary error terms. The

[24] As noted before, the LLC and IPS tests require N to be relatively smaller than T, which is not the case here.

table below reports the results from several cointegration tests. The top row describes the variables included in the tentative cointegrating vectors. The Pedroni and Kao tests use the Bayesian information criterion (BIC) to automatically select the appropriate lag length (maximum set to 3). Moreover, spectral estimation is undertaken by the Bartlett kernel with the bandwidth selected by the Newey-West algorithm. Whilst the Pedroni and Kao tests are based on the residuals of the long-run static regression, the Westerlund test assesses the significance of the adjustment coefficient in the ECM specification. For the latter we specify the error correction equations with one lag and use a Bartlett kernel window of 3. Deterministic time trends are not included in the specifications since these are generally found to weaken cointegration results. This is later supported by their lack of statistical significance in the error correction models. All tests are derived under the null hypothesis of no cointegration.

Table 12: Cointegration Tests

	Statistic	NACABY AIDBOPY LTOT	DRY AIDBOPY LTOT	NAGOBY AIDGOVY INF	INVGY AIDGOVY INF	BORY AIDGOVY INF
Pedroni	Panel-*v*	0.05	–1.26	–1.04	–0.68	2.22
	Panel-*rho*	–3.35***	–9.18***	–2.56***	–0.11	–2.60***
	Panel-PP	–6.58***	–13.69***	–6.86***	–3.06***	–8.60***
	Panel-ADF	–7.12***	–14.02***	–6.89***	–3.55***	–8.05***
	Group-rho	–2.48***	–7.20***	–0.80	1.34	–1.13
	Group-PP	–8.55***	–15.29***	–8.41***	–3.80***	–9.86***
	Group-ADF	–7.86***	–15.42***	–8.42***	–4.37***	–7.90***
Kao	*t*	–2.71***	–2.16**	–2.23**	–1.18	–1.93**
Westerlund	G*t*	–3.55***	–5.91***	–0.65	0.78	0.96
	G*a*	–1.73**	–3.81**	3.97	4.69	3.86
	P*a*	–5.20***	–5.58***	0.64	2.13	3.40
	P*a*	–5.02***	–6.41***	2.18	2.87	2.86

Obs.: Test results generated by EViews and 'xtwest' Stata module. Panel tests tend to have higher power than Group tests, since pooling increases efficiency. Pedroni's Panel statistics are weighted, as well as (all of) Westerlund's. The asterisks represent significance at the 10 percent (*), 5 percent (**), and 1 percent (***) confidence levels.

The first column examines a vector of variables that includes the non-aid current account balance (NACABY), foreign aid inflows (AIDBOPY) and the logarithm of the terms of trade (LTOT). With the exception of Pedroni's Panel-*v* statistic, all tests reject the null hypothesis of 'no cointegration' among the variables. Hence, while unit root tests provided support for the presence of stochastic trends in the data, cointegration tests suggest that these trends have cancelled each other out – leading to stationary residuals. In practice, this means that these variables have a significant long-run relationship. The second column

[25] For each time period, the mean of the series (across panels) is calculated and then subtracted from the observations.

evaluates whether changes in international reserves (DRY), foreign aid inflows (AIDBOPY) and the terms of trade (LTOT) share a common stochastic trend. Once again, the results strongly suggest the presence of cointegration, but this can be a result of the fact that DRY is a stationary variable – as suggested by most unit root tests.

With regard to the third column, we test whether there is a relationship between the non-aid government balance (NAGOBY), foreign aid inflows (AIDGOVY), and inflation (INF). Here, the four Westerlund statistics and two Pedroni tests do not reject the null. Moreover, the fourth column – which investigates whether public investment (INVGY), aid inflows (AIDGOVY) and inflation (INF) are a cointegrating relation – provides similar results, and so does the last one. Since the fiscal sample is significantly shorter (and in fact $N>T$) it may be that some cointegration tests (especially Westerlund's) have poor power properties.[26] If we set the lag to zero and exclude INF from the fiscal vectors, the majority of Westerlund's tests reject the null, which may highlight the lack of power of the test.

We did not perform the Maddala and Wu Fisher tests because they can be quite onerous to implement and may provide unreliable results. Since these tests require fitting vector autoregression (VAR) models to each cross-sectional unit, the usual caveats of the time series literature apply. This means that the (individual) tests are only appropriate if the VAR model is correctly specified, which requires a significant amount of individual testing – for example, checking (residual) serial correlation. Moreover, because T is relatively short for a time series study, these tests may have poor size properties.

Overall, the results appear to suggest that the variables of interest are cointegrated, which means that we have uncovered meaningful long-run relationships. However, these tests have some limitations. In the presence of cross-sectional dependence/cointegration, the test results may be biased. Moreover, these tests are developed under the assumption that all variables are I(1). If some of the variables are truly stationary (e.g. DRY), inference might be invalid. Nonetheless, the next section may provide further evidence of cointegration if, as expected, the error correction terms are statistically significant.

[26] Low power means that the test is not able to reject the null hypothesis when the alternative is correct (Type II error).

5.3 Specification and Estimation (Long-Run)

We now use panel data estimation methods to investigate, amongst other things, the impact of foreign aid inflows on the non-aid current account balance and the non-aid government overall balance. Our empirical specifications are similar to Aiyar and Ruthbah (2008), but do not include the time-invariant country-specific control variables.[27] Hence we have:

$$y_{it} = \alpha_i + \beta_1 AIDY_{it} + \beta_2 x_{it} + \varepsilon_{it}$$

where y_{it} includes the non-aid current account balance (NACABY), accumulation of international reserves (DRY), non-aid government overall balance (NAGOBY), public investment (INVGY) and domestic financing (BORY) – all expressed as a share of GDP. $AIDY_{it}$ is the relevant foreign aid variable, whilst x_{it} is a control variable: the logarithm of the terms of trade (LTOT) in the macroeconomic specifications (firs two) and inflation (INF) in the fiscal specification (last three). Potential reverse causality between the fiscal variables and inflation is addressed in some of the empirical methodologies utilised. The estimates for β_1 contain information about the impact of aid on y_{it}.[28]

The panel data analysis is conducted for the 25 African low-income countries in our sample. The tables below report the results from a number of alternative estimation methods. The aim is to analyse the robustness of the results to different empirical strategies. We start by applying the popular system GMM (SYS-GMM) estimator in the context of a (fixed-effects) lagged dependent variable model. In comparison with the OLS (OLS-FE) and difference GMM (DIF-GMM) alternatives, this estimator is likely to minimise the bias and inconsistency associated with the presence of a lagged dependent variable. However, given the relatively large *T* in this study, we argue that a methodology based on the time series properties of the data may provide more efficient estimates of the coefficients of interest. Therefore, we complement the SYS-GMM results with the dynamic OLS (DOLS) approach and the maximum-likelihood estimates (MLE) for the error correction model. The DOLS methodology entails the estimation of the static long-

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[27] These variables are average income per capita and a measure of aid volatility. The methods used in this paper (except for system GMM) do not allow the inclusion of time-invariant variables, since these induce perfect multicollinearity. Moreover, the autocracy index is also excluded since it exhibits little variation through time. An alternative income per capita variable (with annual observations) would create significant distortions due to its interaction with the denominator of our variables (GDP).

[28] The PMG methodology, for example, requires that foreign aid is exogenous. This may not constitute a major concern since our aid variable only includes aid grants. Aid loans (e.g. IMF lending) tend to be more responsive to domestic conditions (e.g. balance of payments crisis and fiscal imbalances).

run relation augmented by leads and lags of the first-differenced explanatory variables. We chose to include two leads and two lags in the specification, and report robust standard errors. This strategy improves the efficiency of the long-run estimates, but does not provide much guidance on short-run behaviour. Therefore, we also use Pesaran's pooled mean group (PMG) estimator, which uses the panel extension of the single-equation autoregressive distributed lag (ARDL) model. It can be shown that the ARDL has an error correction representation, which is a particularly convenient feature for aiding economic interpretation. We are then able to efficiently estimate the long-run relationships whilst providing information about short-run behaviour (e.g. contemporaneous impacts and speed of adjustment to equilibrium). Another advantage is that while the long-run coefficients are assumed to be homogeneous (i.e. identical across panels), the short-run coefficients are allowed to be country-specific (heterogeneity). This methodology is appropriate for non-stationary panels where *N* and *T* are relatively large. For example, Pesaran et al (1999) apply their approach to two empirical examples with the following dimensions: (i) *T*=32 and *N*=24; and (ii) *T*=17 and *N*=10. We also estimate a mean group (MG) alternative, which allows the long-run parameters to vary, and then test the PMG's poolability assumption through a Hausman test. Finally, we also report the dynamic fixed-effects (DFE) estimator, which assumes short- and long-run parameter homogeneity.[29]

Table 13: Estimation Results for NACABY

	SYS-GMM	DOLS	DFE	PMG	MG
	NACABY	NACABY	D.NACABY	D.NACABY	D.NACABY
C	16.01	12.57	5.86	–3.11***	3.00
AIDBOPY	–0.43***	–0.86**			
LTOT	–3.66*	–3.80			
NACABY(–1)	0.62***		–0.31***	–0.40***	–0.64***
D.AIDBOPY			–0.63***	–0.63***	–0.76***
D.LTOT			0.32	1.14	–0.51
Cross	25	25	25	25	25
Time	25	21	25	25	25
Hausman					0.93
Long-run					
AIDBOPY	*–1.13****	–0.86**	–0.76***	–0.62***	–0.96**
LTOT	*–3.66**	–3.80	–5.28**	0.31	–2.88

Obs.: Robust standard errors. Coefficients in *italic* are calculated from the estimation output. SYS-GMM generates 327 instruments for 625 observations. The speed of adjustment for SYS-GMM equals one minus the coefficient on the lagged dependent variable (0.38). The asterisks represent significance at the 10 percent (*), 5 percent (**), and 1 percent (***) confidence levels.

[29] This will yield different results from the OLS-FE approach since it is based on the error correction specification rather than the lagged dependent variable model. The latter is, in fact, an ARDL(1,0,…,0).

We start by investigating the relationship between foreign aid inflows (AIDBOPY), the logarithm of the terms of trade (LTOT) and the non-aid current account balance (NACABY). In the SYS-GMM, the estimated coefficients of the explanatory variables are usually taken to represent short-term impacts, whilst long-run impacts are approximated by the short-term coefficient divided by 1 minus the coefficient of the lagged dependent variable. The results suggest that an increase by 1 percentage point in the aid-GDP ratio leads to an immediate deterioration of the non-aid current account balance by about 0.4 percentage points. Alternatively, we could say that about 40 percent of the aid inflow is being absorbed in the short-run (see Berg et al, 2007). In the long-run, its impact increases to around –1.1 percentage points (full absorption). The second column reports the dynamic OLS (DOLS) specification, which only provides information on the long-run. The coefficient is also significantly high (–0.86), suggesting almost full absorption. The last three columns provide the dynamic fixed-effects (DFE), pooled mean group (PMG) and mean group (MG) estimates. Whilst the PMG constrains the long-run coefficient to be identical across countries (homogeneity), the MG allows the long-run effects to be country-specific (and reports the averaged responses). The fact that the error correction term (coefficient on the lagged dependent variable) is statistically significant provides further evidence of the existence of a long-run relationship.[30] Moreover, its magnitude for the MG (–0.6) suggests that more than half of the equilibrium error is corrected in one year, whilst for the other methods adjustment towards equilibrium appears to be slower. The short-run aid impact estimate is –0.6 for the PMG and the DFE, and –0.8 for the MG, whilst the long-run impacts vary between –0.6 and –1.0. On average, these results suggest that around two-thirds of foreign aid is absorbed in the short-run, with a modest increase in the long-run. The SYS-GMM seems to underestimate the short-term impact of aid and overestimate its long-run effect.

To test the validity of the pooling assumption and decide on the preferred specification (PMG versus MG) we undertake a Hausman test. The test assesses whether the differences in long-run coefficients are not systematic (null hypothesis), and follows a chi-square distribution with two degrees of freedom. Given that the test does not reject the null (supporting long-run homogeneity), preference should be given to the PMG since it is

[30] This coincides with the coefficient on the lagged dependent variable due to normalisation.

more efficient (less parameters to estimate). Overall, the terms of trade do not appear to be statistically significant.

The table below reports results on a potential association between foreign aid inflows and the accumulation of international reserves (DRY). Overall, there is little support for a long-run relationship between the variables. In fact, the significance of the error correction term alone (in MG) suggests that DRY is self-correcting, hence stationary, corroborating the conclusions from unit root tests. However, there is some evidence of significant short-run effects. According to the PMG and MG estimates, an increase by 1 percentage point in the aid-GDP ratio will lead to an increase in the accumulation of international reserves of around 0.3 percentage points (a minus sign indicates increase) – i.e. 30 percent of aid is used to build up international reserves. Central banks may adopt this strategy to protect their economies from future external shocks or even to smooth the availability of foreign exchange in an environment of volatile and unpredictable aid inflows. The lack of significance in the short-run coefficient in the DFE equation is probably due to the invalidity of the pooling assumption.

Table 14: Estimation Results for DRY

	SYS-GMM	DOLS	DFE	PMG	MG
	DRY	DRY	D.DRY	D.DRY	D.DRY
C	–5.48	–2.91	–1.34	0.37***	–1.28
AIDBOPY	0.00	0.13			
LTOT	1.05	0.28			
DRY(–1)	0.08		–0.89***	–0.86***	–0.97***
D.AIDBOPY			–0.06	–0.27***	–0. 31***
D.LTOT			0.26	–0.64	–0.92
Cross	25	25	25	25	25
Time	25	21	25	25	25
Hausman					0.17
Long-Run					
AIDBOPY	*0.00*	0.13	0.01	–0.11***	–0.11
LTOT	*1.14*	0.28	0.18	–0.04	–0.39

Obs.: Robust standard errors. Coefficients in *italic* are calculated from the estimation output. The asterisks represent significance at the 10 percent (*), 5 percent (**), and 1 percent (***) confidence levels.

We now turn to the second main empirical question. In this case, we are trying to uncover the relationship between the foreign aid inflows (AIDGOVY), inflation (INF) and the non-aid government overall balance (NAGOBY). In the short-run, the SYS-GMM, DFE and PMG estimators show that an increase by 1 percentage point in the aid-GDP ratio leads to a proportional deterioration of the non-aid government balance (full spending). Moreover, inflation has a small negative impact on the government balance.[31] In terms of its long-run impact, aid inflows contribute to a relatively large (more than proportional) widening of the public deficit (around –1.5 percent). This may be due to a possible positive correlation between aid grants (AIDGOVY) and external loans to the government (either concessional or commercial). With regard to inflation, the long-run coefficients are around –0.1. Once again, the Hausman test favours the utilisation of the PMG approach over its less restrictive alternative. The error correction term is statistically significant and relatively large, suggesting a fast adjustment to long-run equilibrium.

Table 15: Estimation Results for NAGOBY

	SYS-GMM NAGOBY	DOLS NAGOBY	DFE D.NAGOBY	PMG D.NAGOBY	MG D.NAGOBY
C	2. 92***	1.60	–2.06***	–2.83***	–2.18***
AIDGOVY	–1.03***	–1.74***			
INF	–0.04***	–0.13***			
NAGOBY(–1)	0.35***		–0.63***	–0.61***	–0.81***
D.AIDGOVY			–1.04***	–1.03***	–1.31***
D.INF			–0.03**	–0.06**	–0.06**
Cross	25	25	25	25	25
Time	15	11	15	15	15
Hausman					0.92
Long-Run					
AIDGOVY	*–1.58****	–1.74***	–1.50***	–1.32***	–1.74***
INF	*–0.06****	–0.13***	–0.06***	–0.02*	–0.03

Obs.: Robust standard errors. Coefficients in *italic* are calculated from the estimation output. Dropping INF altogether makes the MG short-run aid coefficient fall to –1.2, and both PMG and MG long-run aid coefficients to converge around –1.55. The DFE, DOLS and SYS-GMM results are not significantly affected. The asterisks represent significance at the 10 percent (*), 5 percent (**), and 1 percent (***) confidence levels.

We now assess the impact of foreign aid inflows (AIDGOVY) on public investment (INVGY). In terms of the short-run impacts, the estimation methods indicate that an increase by 1 percentage point in the aid-GDP ratio leads to an increase of about 0.4 percentage points in the public investment ratio. This impact rises up to around 0.7 percentage points in the long-run. The MG procedure fails to find a robust association between the two variables, potentially due to the fact that when *T* is small the lagged dependent variable bias leads to the underestimation of their true values (Pesaran et al, 1999:627). The PMG performs better because this bias is reduced by the pooling assumption, which causes an upward bias (Pesaran et al, 1999:628). Since it requires the estimation of fewer parameter coefficients, it is less onerous on the degrees of freedom –

[31] There might be concerns of reverse causality (e.g. higher fiscal deficits causing higher inflation), since only the first two methodologies provide corrections for endogeneity. However, an increase in the non-aid fiscal deficit does not necessarily translate into an increase in money supply. It can be covered by the additional aid inflow, which appears to be the case. Moreover, the coefficients are almost identical to those from SYS-GMM.

MG requires the estimation of 48 extra parameters.[32] Pesaran et al (1999:629) also note that the MG can be quite sensitive to outliers. Their impact is more severe than on the PMG, probably due to the use of un-weighted averages. The extra column reports the results for the MG excluding the inflation variable, which is insignificant. The results are now in line with the other methodologies.

Table 16: Estimation Results for INVGY

	SYS-GMM INVGY	DOLS INVGY	DFE D.INVGY	PMG D.INVGY	MG D.INVGY	MG D.INVGY
C	2.12***	4.16***	1.75***	1.35***	3.10***	2.31***
AIDGOVY	0.35***	0.65***				
INF	0.01	0.03				
INVGY(–1)	0.47***		–0.39***	–0.39***	–0.57***	–0.51***
D.AIDGOVY			0.37***	0.35***	0.27***	0.36***
D.INF			0.01	0.01	0.02	
Cross	25	25	25	25	25	25
Time	15	11	15	15	15	15
Hausman					2.27	
Long-Run						
AIDGOVY	*0.66****	0.65***	0.58***	0.73***	0.17	0.60**
INF	*0.02*	0.03	0.01	0.04***	0.04	

Obs.: Robust standard errors. Coefficients in *italic* are calculated from the estimation output. Dropping INF altogether makes the PMG long-run aid coefficient increase to about 1. The results for DFE, DOLS and SYS-GMM are not significantly affected. The asterisks represent significance at the 10 percent (*), 5 percent (**), and 1 percent (***) confidence levels.

Finally, we look at the potential impact of foreign aid inflows on domestic financing (BORY). The results do not seem to support a long-run relationship between the variables, since the coefficient in the DFE is barely significant and not statistically significant for the remaining regressions. However, SYS-GMM and DFE estimates suggest a short-run impact of –0.15. This indicates that a small share of aid inflows may be used to reduce domestic public debt. However, this relation may be obfuscated (in the PMG and MG) by the time aggregation of the variable. If quarterly data were available, this relationship may have been stronger, as many countries use this strategy to mitigate the impact of unpredictable aid inflows. For example, when aid flows fall below the average, governments borrow to finance planned expenditures; when aid flows are above the average, government repay the loans. Nonetheless, the yearly data does not reveal a considerable impact.

[32] The two long-run coefficients of the explanatory variables are now allowed to vary, i.e. (25–1)*2 = 48.

Table 17: Estimation Results for BORY

	SYS-GMM	DOLS	DFE	PMG	MG
	BORY	BORY	D.BORY	D.BORY	D.BORY
C	1.56***	0.96	1.36***	0.90***	0.32
AIDGOVY	–0.15***	0.02			
INF	–0.01	–0.01			
BORY(–1)	0.13		–0.82***	–0.84***	–0.95***
D.AIDGOVY			–0.15**	–0.23	–0.09
D.INF			–0.01	0.03	0.04
Cross	25	25	25	25	25
Time	15	11	15	15	15
Hausman					0.70
Long-Run					
AIDGOVY	*–0.17*	0.02	–0.13*	–0.02	–0.17
INF	*0.01*	–0.01	–0.01	–0.01*	0.04

Obs.: Robust standard errors. Coefficients in *italic* are calculated from the estimation output. Dropping INF altogether does not significantly affect the results (even for DFE). The asterisks represent significance at the 10 percent (*), 5 percent (**), and 1 percent (***) confidence levels.

The table below provides a summary of the impacts of foreign aid inflows on the macroeconomic and fiscal sphere. Starting with absorption, the results suggest that foreign aid inflows have had significant short- and long-run impact on the non-aid current account balance (NACABY). The short-run results for the SYS-GMM are significantly lower than the other empirical methods, possibly due to a downward bias induced by the presence of the lagged dependent variable. Overall, it seems that around two-thirds of the aid flows are used to increase the (non-aid) current account deficit, most likely through making foreign exchange available to domestic importers of goods and services. In the long-run, the impact of aid is significantly higher for the SYS-GMM, which even suggests full absorption. The PMG coefficient is lower than that of the DFE and MG, but on the whole the evidence points to a high level of absorption. With regard to the accumulation of international reserves (DRY), the fixed-effects models do not reveal a significant short-run impact, while the heterogeneous alternatives suggest that about one-third of the foreign exchange provided by aid transfers is kept as central banks' foreign reserves. In the long-run, only the PMG appears to indicate a statistically significant effect, albeit lower than the short-run impact. In light of the PMG and MG results, and bearing in mind the macroeconomic identity below, there is only weak evidence that aid flows are 'exiting' through the capital account (capital outflows), as the sum of the (short-run) impacts on DRY and NACABY is approximately 1.[33]

$$AIDBOPY = \Delta RY - (NACABY + NAKABY)$$

The implication is that short-run aid absorption in African countries is higher than previously suggested by Berg et al (2007) and Aiyar and Ruthbah (2008). Moreover, aid resources are also found to be used (in the short-run) to build up international reserves, perhaps to strengthen the capacity to weather external shocks.

Table 18: The Impact of Aid Inflows

	SYS-GMM	DOLS	DFE	PMG	MG[1]
Short-run					
NACABY	–0.43***	n/a	–0.63***	–0.63***	–0.76***
DRY	0.08	n/a	–0.06	–0.27***	–0. 31***
NAGOBY	–1.03***	n/a	–1.04***	–1.03***	–1.31***
INVGY	0.47***	n/a	0.37***	0.35***	0.36***
BORY	–0.15***	n/a	–0.15**	–0.23	–0.09
Long-Run					
NACABY	–1.13***	–0.86**	–0.76***	–0.62***	–0.96**
DRY	0.00	0.13	0.01	–0.11***	–0.11
NAGOBY	–1.58***	–1.74***	–1.50***	–1.32***	–1.74***
INVGY	0.66***	0.65***	0.58***	0.73***	0.60***
BORY	–0.17	0.02	–0.13*	–0.02	–0.17

Obs.: [1] The MG results for INVGY exclude inflation. The asterisks represent significance at the 10 percent (*), 5 percent (**), and 1 percent (***) confidence levels.

Turning to spending, the empirical results imply that aid inflows have had large short- and long-run impacts on the non-aid government balance (NAGOBY). In fact, aid is fully spent in the short-run. This means that the full amount of aid is used to either (i) boost public expenditures; (ii) reduce taxes; or (iii) a mixture of both. Full spending is not compatible with the hypothesis that governments 'save' aid resources to pay government debt (either domestic or foreign). In the long-run, the impact on NAGOBY grows to about 1.5, a more than proportional impact. This finding is similar to that of Aiyar and Ruthbah (2008). This may either be a symptom of aid illusion, or the consequence of a positive correlation between aid grants (AIDGOVY) and foreign loans. With regard to government investment (INVGY), about a third of aid resources are used to finance public investment programmes (in the short-run), rising to two-thirds in the long-run. However, the SYS-GMM short-run coefficient is notably higher. Finally, only the fixed-effects models uncover significant short-run impacts on domestic borrowing (BORY), even though these are comparatively smaller than those for other variables. There is little evidence supporting a long-run relationship between aid and domestic financing. These results can be analysed with the support of the following fiscal identity (budget constraint),

[33] Note that an increase in DRY means a fall in international reserves.

$$AIDGOVY = (INVGY + CY - TY) - (BORY + LY)$$

where *CY* stands for public recurrent spending, *TY* for domestic revenue, and *LY* for external lending (including concessional loans). Bearing in mind the caveat of potential endogeneity (although addressed by GMM and DOLS estimators), we may argue that the short-run impact on public investment is somewhere between one-third and one-half of the aid inflow, leaving about two-thirds or one-half for either increasing recurrent expenditures or lowering domestic revenues (e.g. taxes). In fact, recurrent spending is the most obvious candidate, since it often includes several development-related activities (e.g. wages of nurses, textbooks, etc.). In the long-run, the impact of aid on public investment increases to two-thirds.

Further to these economic observations, the empirical results may also provide some information about the 'small sample' behaviour of the estimators. As the temporal dimension (*T*) increases, the downward bias induced by the lagged dependent variable tends to decline and even OLS-FE may become consistent. However, these performance gains are likely to be higher/faster for the ECM models. This may explain why, in the macroeconomic sample, the SYS-GMM short-run coefficients are significantly lower than in the other approaches.[34] However, the SYS-GMM is likely to outperform the ECM approach in shorter panels (small *T*), such as the fiscal sample. In fact, the short-run coefficients are now higher than those for the PMG and MG – with the exception of NAGOBY, which are similar. Hence, it appears that the downward bias is stronger in the SYS-GMM estimator in the macroeconomic sample (*T*=26), whilst the bias is larger for the ECM-type models in the fiscal sample (*T*=16). This implies a trade-off between these different methodologies.

On the whole, our preferred model is the PMG estimator for two main reasons. Firstly, it appears that its estimates remain robust in the shorter panel, as opposed to those from the MG. This robustness may be explained by the fact that imposing parameter homogeneity often causes an upward bias (in absolute terms) in the lagged dependent variable (Pesaran et al, 1999:628). Hence, the potential downward bias induced by small *T* may actually be reduced or even cancelled out. It can be seen that, in general, the absolute magnitude of the

[34] We have also estimated OLS-FE and DIF-GMM for the lagged dependent variable model, and the results indicate that these estimators tend to underestimate both short- and long-run impacts in relation to SYS-GMM.

estimated error correction coefficients follow the sequence MG>PMG>DFE. Moreover, the MG is also more sensitive to outliers. Secondly, the PMG assumptions are more appealing in economic terms. We allow heterogeneity in the short-run responses and the speed of adjustment to equilibrium, while constraining the long-run relationships to be the same. This is an appealing middle ground between the strong pooling assumptions of the DFE (and indeed GMM) estimator and the flexibility of the MG estimator.

However, we should bear in mind the weaknesses of the empirical analysis presented here. The results from our estimation strategies (including the system GMM) may be sensitive to the presence of cross-sectional error dependence. If T was significantly larger than N (which unfortunately is not our case) we could model and test the cross-correlation of the error terms through seemingly unrelated regressions (SUR). Nonetheless, we can test the assumption of cross-sectional independence with the Breusch-Pagan LM test statistic and Pesaran's (2004) CD statistic. The LM test follows a chi-square distribution with $N(N–1)/2$ degrees of freedom but requires $T>N$, whilst the Pesaran test is asymptotically normal. For both tests we use the DFE specification presented above. Although the results from the LM statistic strongly reject the hypothesis of cross-sectional independence, the CD statistic provides much weaker evidence of violations. We recall that the LM statistic relies on large T and small N and thus may not perform well when both dimensions are of similar magnitudes. In fact, the computations were just about possible for the macroeconomic sample, where T=26 and N=25. Thus, we may argue that there is only weak evidence that the assumption of cross-sectional dependence of the error structures is violated by the data, and thus the empirical estimates are not likely to be significantly biased. Furthermore, panel estimators that are robust to cross-sectional dependence are only at an embryonic stage – e.g. see recent literature on 'common correlated effects' estimator (Kapetanios et al, 2009).

Table19: Cross-Sectional Independence Tests

DFE model	NACABY AIDBOPY LTOT	DRY AIDBOPY LTOT	NAGOBY AIDGOV Y INF	INVGY AIDGOV Y INF	BORY AIDGOV Y INF
Breusch-Pagan LM statistic	395.88^{***}	366.76^{***}	n/a	n/a	n/a
Pesaran CD statistic	1.83^{*}	2.24^{**}	1.69^{*}	–0.89	–0.26

Obs.: Tests results generated by the Stata's 'xttest2' and 'xtcsd' modules. CD test results based on DOLS regressions do not reject independence, except for the INVGY equation at 10 percent, whilst the LM statistic cannot be computed (even for the macroeconomic sample). The asterisks represent significance at the 10 percent (*), 5 percent (**), and 1 percent (***) confidence levels.

Finally, the estimates only represent country averages. Policy responses may vary from country to country, and therefore this analysis does not preclude the use of other methodologies to unveil country-specific macroeconomic responses.

6. Conclusion

This paper revisits the issue of macroeconomic management of large aid disbursements. We have constructed a new panel dataset to investigate the level of aid 'absorption' and 'spending' in Africa's low-income countries. Our results suggest that, in the short-run, recipient countries have absorbed about two-thirds of the aid inflow, using them to increase the non-aid current account deficit. Moreover, around one-third of the foreign exchange provided by these inflows has been used to build up international reserves, perhaps to protect economies from future external shocks.[35] In the long-run, absorption of foreign exchange appears to increase further without reaching its maximum (full absorption). In terms of 'aid spending', recipient countries appear to have fully spent the amount of aid, using it to increase the non-aid government deficit. In particular, a substantial percentage of these inflows went to finance public investment expenditures. There is only weak evidence that some aid flows have been 'saved', i.e. used to substitute for domestic borrowing. Overall, these findings suggest that the macroeconomic management of aid inflows in Africa has been better than often suggested by comparable exercises.

These results challenge some of the conclusions from Aiyar and Ruthbah (2008), namely that short-run absorption is usually low, with aid exiting through the capital account. This may be due to the use of an inappropriate measure of aid flows (DAC's donor reported aid) or the application of a methodology that neglects the time series properties of the data. However, we corroborate the result that spending is higher than absorption, which represents an injection of domestic liquidity in the recipient country.

[35] Buffie et al (2004) suggest that a 'managed float' is the most attractive approach to manage shocks to aid inflows, therefore arguing that African central banks have been correct to intervene in the foreign exchange market.

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Appendix

In this Appendix, we compare our data with the country-specific estimates reported in IMF (2005) and Hussain et al (2009). For that purpose, we estimate country-level regressions for the following five African countries: Ethiopia, Ghana, Mozambique, Tanzania and Uganda. Since the samples for absorption and spending only include 26 and 16 time observations, respectively, these results should be interpreted with great caution. These estimates are far less robust than our panel analysis (especially individual DOLS), and should only be taken as indicative. Moreover, the heterogeneous short-run effects from the PMG estimator are also reported.

Table 20: Country-Specific Results (Impact of Aid)

		Absorption (NACABY)					Spending (NAGOBY)				
		IMF	PMG	ECM		DOLS	IMF	PMG	ECM		DOLS
			SR	SR	LR	LR		SR	SR	LR	LR
Ethiopia	ID19	-0.20	-0.47	-0.73	-2.50	**-0.73**	*0.14*	-0.55	-0.32	-0.68	3.76
Ghana	ID22	*1.82*	-0.03	0.12	-0.25	2.06	-0.07	**-0.70**	-0.31	-0.38	0.21
Mozambique	ID35	-0.66	**-1.38**	**-1.33**	**-1.60**	**-1.53**	*-1.08*	**-1.51**	**-1.77**	**-2.60**	**-4.70**
Tanzania	ID48	*1.05*	**-1.55**	**-1.82**	**-4.76**	**-3.57**	-0.92	**-1.76**	**-4.26**	**-2.71**	**-4.97**
Uganda	ID51	-0.28	**-0.79**	**-1.22**	**-1.77**	**-1.44**	-0.75	**-1.53**	**-1.79**	**-1.86**	**-2.22**

Obs.: The IMF values are recalculated and estimates in italic indicate that the original publication truncated them (i.e. bound them to the interval -1 to 0). The estimates in bold are statistically significant. DOLS regressions include only 1 lead and 1 lag to reduce estimated parameters.

The results appear to suggest that absorption and spending are quite high for Mozambique, Tanzania and Uganda. In fact, most estimates point to (more than) full absorption and spending in both the short- and long-run. The estimates for Ethiopia and Ghana exhibit higher standard errors, hence we are not able to accept them as statistically significant. Nonetheless, most of their values are higher than the IMF estimates. The table below reports the same results, in a more tractable format.

Table 21: Absorption and Spending

		Absorption (%)					Spending (%)				
		IMF	PMG	ECM		DOLS	IMF	PMG	ECM		DOLS
			SR	SR	LR	LR		SR	SR	LR	LR
Ethiopia	ID19	20%	47%	73%	100%	**73%**	0%	55%	32%	68%	0%
Ghana	ID22	0%	3%	0%	25%	0%	7%	**70%**	31%	38%	0%
Mozambique	ID35	66%	**100%**	**100%**	**100%**	**100%**	100%	**100%**	**100%**	**100%**	**100%**
Tanzania	ID48	0%	**100%**	**100%**	**100%**	**100%**	92%	**100%**	**100%**	**100%**	**100%**
Uganda	ID51	28%	**79%**	**100%**	**100%**	**100%**	75%	**100%**	**100%**	**100%**	**100%**

Obs.: Values are truncated.