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Aid Volatility: An Empirical Assessment

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This article examines empirical evidence on the volatility and uncertainty of aid flows and their main policy implications. Aid is found to be more volatile than fiscal revenues—particularly in highly aid-dependent countries—and shortfalls in aid and domestic revenue tend to coincide. The article also finds that uncertainty about aid disbursements is large and that the information content of commitments made by donors is either very small or statistically insignificant. Specific policies and broader international efforts to cope with these features of aid are briefly discussed. [JEL F35, O19]

This article documents key cyclical properties of external aid flows from the point of view of the recipient country: their degree of volatility and predictability, and the way in which they covary with domestic economic activity. Why the focus on the cyclical properties of aid? First, available estimates of the welfare cost of business fluctuations in developing countries suggest that they are significantly larger than those in industrial economies.[1] Developing countries tend

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[1]Pallage and Robe (2001b) estimate that, on average, the welfare cost of output volatility in sub-Saharan Africa could be as much as 15–20 times higher than that in the United States.

to be subject to more frequent and stronger external shocks and are less able to cope with them owing to pervasive liquidity constraints and the lack of effective countercyclical policy tools. A direct implication of this result is that advice to developing countries should pay more attention to reducing volatility (Caballero, 2000). Second, these countries are also likely to be recipients of large aid flows, which have been found to be very volatile (see the discussion of this issue later on). This feature of aid can indirectly offset some of its direct beneficial effects by, for example, complicating the conduct of fiscal and monetary policy or exacerbating exchange rate variability (Edwards and van Wijnbergen, 1989). In particular, the negative aspects of the volatility of aid flows will be larger, the higher the covariance between fluctuations in aid and output, or domestic fiscal revenue.[2]

In principle, dealing with aid volatility could be more challenging than dealing with commodity price volatility. Only a few recent empirical studies have focused on the magnitude and consequences of aid volatility (and on best practices to deal with them) in contrast with the case of export price instability, where the main issues have been dealt with extensively in the economic literature.[3] Lensink and Morrissey (2000) find that the effect of aid on growth is insignificant unless some measure of aid uncertainty is included in the cross-country regressions and that uncertainty about aid is detrimental to growth. Gemmell and McGillivray (1998), using a sample of 48 developing countries, find that shortfalls in aid are followed most frequently by reductions in government spending, sometimes by increases in taxes, and sometimes by both. In other words, the typical aid-receiving country is unable to offset an unexpected nondisbursement of aid by borrowing and has to resort to costly, swift, and possibly inefficient fiscal adjustment.[4] They also find that aid is significantly more volatile than revenue and that, on average, aid tends to be procyclical. (That is, countries tend to receive more aid in years when economic activity is on the rise; this, in turn, may imply a positive correlation between aid and fiscal revenues.) These results are corroborated by Pallage and Robe (2001a) for a sample of African countries. To the best of our knowledge, Collier (1999) is the only study that finds aid (to sub-Saharan Africa) to be less volatile than tax revenues and countercyclical.[5]

[2]Assuming that government spending is financed only with tax revenues and foreign aid, it is possible to show that the loss function of a risk-averse policymaker interested in minimizing deviations of public spending from planned levels is a positive function of the covariance between aid disbursements and actual revenues. This, however, is a point about the cyclical movement of aid, not its level. Throughout this article, we abstract from the issue of aid effectiveness or even from the effect of aid volatility on growth. For a recent survey of those issues, see, for example, Hansen and Tarp (2000 and 2001).

[3]Varangis and Larson (1996) provide a clear explanation of the problems posed by commodity price uncertainty and clarify the differences among the main instruments to deal with price variability, unpredictability, and expenditure smoothing. Engel and Meller (1993) contain a set of case studies analyzing best policies to neutralize external shocks in developing countries: stabilization funds and the use of financial instruments. In practice, however, donors would not accept aid funds going into a reserve fund and aid-dependent countries lack access to the necessary financial instruments.

[4]Of course, incomplete adjustment to the shortfall in aid is likely to crowd out private investment and/or create inflationary pressures (Hadjimichael and others, 1995).

[5]Collier (1999) is also the only study based on nondetrended data. He takes his results to imply that "a budget with a large component of aid would be more reliable than one with a low component of aid" (p. 542) and that all committed aid should be included in the budget.

In this article, we reexamine these issues using a broader database than those used in the studies cited above (including both publicly available time-series data and a cross section of detailed data provided by IMF desk officers for countries receiving aid) and examine the extent to which the results vary with aid dependency. In line with the studies of Gemmell and McGillivray (1998) and Pallage and Robe (2001a), we find, first, that aid is substantially more volatile than fiscal revenue and that this relative volatility increases with the degree of aid dependency as measured by the aid-to-revenue ratio. We also find some evidence that aid and domestic revenue tend to move in the same direction and that countries suffering from relatively high revenue volatility also exhibit higher volatility in aid receipts.

Second, time-series data show that commitments by donors consistently exceed disbursements and that aid cannot be predicted reliably on the basis of donors' commitments alone. Cross-sectional data from IMF-supported country programs reveal that commitment-based projections tend to overestimate project and, to a much higher degree, program aid. In addition, intra-year disbursements of program aid differ significantly from projections. Despite their poor track record as a predictor of disbursements, commitments continue to be used in budgetary exercises in aid-receiving countries, mainly as a result of pressures from donor countries and/or agencies. This deficiency continues to hamper fiscal and monetary projections in aid-dependent countries.

Since the economic effects of aid are largely determined by the recipient country's budgetary practices, we stress the need to account properly for aid volatility when designing adjustment programs in aid-receiving countries—particularly when it comes to planning for the possibility of delays and/or shortfalls in aid disbursements vis-à-vis commitments. Finally, we discuss briefly measures that can be taken by both donors and aid recipients—mainly regarding compliance with program objectives, program design, coordination among donors, and improved disbursement procedures in donor countries—in order to reduce the volatility and unpredictability of aid and, thus, enhance its overall effects.

The article is organized as follows. Section I discusses briefly our data sources, as well as some problems posed by the need to select a common unit of measurement for several variables and the limitations of using aggregate data on aid. Section II looks at various measures of the relative instability of foreign aid and fiscal revenues. Section III deals with the issue of predictability of aid flows and the information content of commitments made by donors. This section also looks at the accuracy of predictions of aid made at various stages of a program supported by the donor community. Section IV concludes with a discussion of the main policy implications of our findings.

I. Data Sources and Measurement Issues

In this section, we discuss the origin and scope of our data, as well as some problems associated with their measurement. These problems relate to the limitations of any empirical analysis based on aggregate aid estimates, problems linked to the selection of a common unit of measurement (denominator) for aid and domestic revenues, and problems posed by the nonstationarity of the aid and revenue time series.

The Dataset

Our database covers 72 countries from 1975 to 1997. The data on aid were taken from the World Bank's *World Development Indicators* (*WDI*), which, in turn, are based on the Organization for Economic Cooperation and Development (OECD) data on official development assistance (ODA). Fiscal data used in this study—total domestic revenue in local currency—were drawn from two sources. For 60 countries, the series were available from the IMF's *International Financial Statistics* (*IFS*). For the remaining 12 countries, all of which are in sub-Saharan Africa and Asia, we used data provided by IMF country desk officers. Even with these additions, complete revenue series for the period 1975–97 are available for only 47 countries (see Table A1 in Appendix I). Data on GDP in local currency units, average exchange rates, and population were also drawn from *WDI*.

In principle, aid data are available for more than 100 countries; however, not all aid recipients represent relevant cases for this study. For example, some former aid recipients became donors, and several former communist countries joined the pool of aid recipients, in the early 1990s. Thus, to compile a consistent database, we considered only countries that remained aid recipients throughout the whole period and met the following selection criteria: (i) at least eight annual observations were available; (ii) at least one IMF-supported program was in effect during the sample period; and (iii) the country had a population of at least 400,000. The second criterion was intended to capture the mobilizing impact of IMF programs on aid flows and their composition. The third criterion was intended to eliminate the small-country bias (World Bank, 2000). Use of these three criteria narrowed the potential sample to 72 countries.

Augmented Dickey-Fuller tests (not reported here but available from the authors upon request) indicate that both aid and revenue series are nonstationary (or, in a few cases, stationary around a deterministic trend). As a result, we detrended our aid and revenue series using the Hodrick-Prescott filter (HP) and only then computed conventional measures of volatility.[6] To test the robustness of our results, we recalculated the measures of volatility using first-differenced data. These results (not reported here but available from the authors upon request) differed only marginally from those based on the HP filter.

The Composition of Aid

ODA comprises balance of payments support, investment projects, food aid, debt and emergency relief, peacemaking efforts, technical assistance, concessional funding to multilateral development funds, and other small categories of aid. However, more than 90 percent of aid falls in the first two categories.[7] Of course, certain

[6]Following Pesaran and Pesaran (1997), we set λ at 7. Changing the value of λ does not seem to affect our results materially.

[7]Of this, project aid accounts for more than one-half.

categories of aid are bound to be more volatile than others: for example, food aid is disbursed only during disaster periods.[8] In fact, aggregate volatility of aid may be high (low), even though the volatility of aid components may be low (high) when the covariance between the components is positive (negative) and large.[9]

But there is an additional dimension to the aid heterogeneity problem: different forms of aid have different conditionality. For example, some forms of aid are disbursed if an IMF-supported program is considered to be "on track"; others may have sector-specific conditionality; and in other cases, disbursements may depend on historic donor-recipient relations (Alesina and Dollar, 2000). Unfortunately, the literature offers little evidence on the empirical relevance of these points for aid volatility.[10] Hence, we use the aggregate ODA definition of aid in Section II and the first subsection of Section III and investigate aid predictability separately for project and program aid in the second subsection of Section III.

Common Denominator for Aid and Fiscal Revenue

The choice of a common denominator matters for the statistical measures of relative volatility. Aid and revenue are denominated in U.S. dollars and domestic currency units, respectively, and their comparisons require first expressing both variables in the same currency. Hence, statistical measures of relative volatility are affected by the exchange rate. The impact of exchange rate volatility can be very large: on average, the volatility of the exchange rate (measured by the coefficient of variation) in trended, raw data is almost forty times higher than that of aid.

We use two common measures: percentages of GDP and current U.S. dollars in per capita terms.[11] On the one hand, when expressing aid and revenue in U.S. dollars per capita, the volatility of domestic revenue becomes a composite measure of revenue volatility in local currency terms and exchange rate volatility. On the other hand, when expressing the variables as percentages of GDP, the volatility of aid becomes a composite measure of aid volatility in U.S. dollars, exchange rate volatility, and the impact of those variables on GDP. Owing to the lack of a preferred denominator for aid and revenue, we use both transformations and keep in mind the biases that each of them are likely to introduce when interpreting our results.

[8]Although it is often stated that fungibility of its various components makes foreign aid homogeneous, this statement is not always correct. For example, aid is not fungible when the preferences of donors and aid recipients differ (Lancaster, 1999; and Bulíř and Lane, 2002).

[9]Bulíř and Hamann (2001) illustrate this point in the case of Malawi.

[10]The few small-scale studies that have tried to decompose aid into various subcategories have either rejected parameter constancy across regions (White, 1992; and Mosley, Hudson, and Horrell, 1987 and 1992) or found the impact of aid to be insignificant in a cross-country setup (Mosley, Hudson, and Horrell, 1992). Individual country studies are also inconclusive (Pack and Pack, 1990 and 1993).

[11]Arguably, measuring aid and revenue in U.S. dollars per capita is preferable if they both were to be spent on tradable goods, whose prices tend to be fixed in U.S. dollars (Bulíř and Lane, 2002). In reality, a significant portion of aid proceeds is spent on nontradable goods. More generally, if the objective is to assess the macroeconomic impact of aid, the relevant denominator is the aid-to-GDP ratio.

II. Measuring the Relative Variability of Aid and Revenue

This section reviews our findings on the relative volatility of aid and domestic fiscal revenue. We detrend aid and revenue series and calculate the variances of these series, θ^A and θ^R, respectively. A measure of relative volatility is then defined as the ratio of these variances, $\Phi = \theta^A/\theta^R$.

In the rest of this section we examine the properties of the measure of relative volatility, Φ. In particular, we (i) calculate Φ for each country; (ii) look at the frequency distribution of individual country Φs and test the significance of averages and medians across countries;[12] (iii) test the relationship of Φs vis-à-vis other variables, such as the correlation coefficients between (detrended) aid and revenue and the ratio of (not detrended) aid to revenue (that is, aid dependency); and (iv) in order to check the robustness of our results, arrange countries into two subgroups according to their degree of aid dependency and compare the results for the full sample with those obtained for the smaller samples. Thus, we carry out our calculations not only for the full sample of 72 countries but also for a subsample of countries with aid-to-revenue ratios of 10 percent or more (57 countries and 55 countries, respectively, when measured in percent of GDP and U.S. dollars per capita) and also for a subsample of countries with aid-to-revenue ratios of 50 percent or more (33 countries and 29 countries, respectively, when measured in percent of GDP and U.S. dollars per capita). The first cutoff point eliminates the more developed Latin American and Asian countries from the sample, while the second cutoff point defines a group of highly aid-dependent countries, mostly from sub-Saharan Africa. The results are presented in Table 1.

Our first finding is that aid is more volatile than revenue, particularly in countries with a high aid-to-revenue ratio. On the one hand, when variables are expressed as percentages of GDP, aid is, on average, more volatile than revenue in all samples, and this result is statistically significant. (The F-test fails to reject the null hypothesis that the average Φs are larger than one at the 1 percent level of significance in every case.)[13] Furthermore, the relative volatility of aid grows with aid dependence: the average value of Φ increases from 3.94 to 7.42 as the sample is narrowed down to the most aid-dependent countries. (The results for the median values of Φ follow a similar pattern.) On the other hand, when the variables are expressed in U.S. dollars per capita, the average Φ is also bigger than one in all samples, but in the full sample, the difference from one is statistically significant at only the 10 percent level. These results confirm that the choice of the scale variable matters. In the other two subsamples, aid is, on average, relatively more volatile than revenue and the results are statistically significant at the 5 percent level or better. Again, the average value of Φ increases with aid dependency (from $1\frac{1}{3}$ to 3). The estimated medians also grow as the sample is restricted to more aid-dependent countries, but they are not significantly different from one, except for Subsample 2.

[12] Given that Φ is a ratio of variances, estimated with a common number of observations per country, we checked the statistical significance of sample averages using an F-test. The significance of sample medians was checked using a "runs test" (SPSS, Inc., 1999).

[13] See Table A1 in Appendix I for country-specific estimates of the absolute volatility of aid and revenue.

Table 1. Relative Volatility of Aid and Revenue (Φ)

	Full Sample	Subsample 1 *(Aid-to-revenue ratio larger than 10 percent)*	Subsample 2 *(Aid-to-revenue ratio larger than 50 percent)*
Variables expressed in percent of GDP[1]			
Average	3.94***	4.96***	7.42***
Median	1.10	2.19***	4.91***
Frequency indicators			
Sample size	72	57	33
Number of countries where $\Phi > 1$	37	37	28
Number of countries where $\Phi < 1$	35	20	5
Aid-to-revenue ratio *(in percent)*	70.4	85.9	129.9
Variables expressed in U.S. dollars per capita[1]			
Average	1.33*	1.73**	3.00***
Median	0.36	0.80	2.25*
Frequency indicators			
Sample size	72	55	29
Number of countries where $\Phi > 1$	23	23	21
Number of countries where $\Phi < 1$	49	32	8
Aid-to-revenue ratio *(in percent)*	64.5	83.1	132.6

Source: Appendix I, Table A1.

[1]The null hypotheses that $\Phi > 1$ is tested for averages with an *F*-test and for medians with a "runs test"; the symbols *, **, and *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent level, respectively.

We also found that countries where aid is more volatile than revenue, $\Phi > 1$, outnumber those with higher relative revenue volatility, particularly in the subsample of the most aid-dependent countries. When variables are expressed as percentages of GDP, the share of countries with more volatile aid grows from about half in the full sample to about 2/3 in the middle sample and to well over 4/5 in the sample of the most aid-dependent countries. For variables denominated in dollars per capita, there are more cases of aid being less variable than revenues in the full and middle samples. In contrast, in the last subsample, countries with higher relative aid volatility outnumber those with higher revenue volatility by a margin of 5 to 2.

Second, we find that the relationship between the relative volatility of aid and aid dependency is robust.[14] The first column of Table 2 shows the correlation coefficients between Φ and aid dependency in each of the three samples. The measure used makes little difference in this case: the simple correlation coefficients between Φ and the aid-to-revenue ratio are of the order of 0.5–0.6 in the full sample, 0.5 in

[14]This result is not driven by lower absolute revenue volatility in aid-dependent countries. For example, narrowing the sample to countries with aid-to-revenue ratios of more than 50 percent leads to increases in average absolute aid volatility of 90 percent and 80 percent when variables are expressed in percent of GDP and in dollars per capita, respectively. By comparison, revenue volatility increases by 80 percent and declines by 97 percent, respectively. See Table A1 in Bulíř and Hamann (2001).

Table 2. Relationship Between Aid and Revenue Flows
(aid and revenue measured as differences from its Hodrick-Prescott filter)

	Correlation Coefficient		
	Relative volatility and aid-to-revenue ratio[1]	Aid and revenue[2]	Volatilities of aid and revenue[3]
Variables expressed in percent of GDP			
All countries *(sample size=72)*			
Simple correlation coefficient *(Pearson)*	0.53***	0.07*	0.29**
Rank correlation coefficient *(Spearman's ρ)*	0.85***		0.40***
Subsample 1 *(aid-to-revenue ratio larger than 10 percent; sample size=57)*			
Simple correlation coefficient *(Pearson)*	0.45***	0.08*	0.28**
Rank correlation coefficient *(Spearman's ρ)*	0.72***		0.52***
Subsample 2 *(aid-to-revenue ratio larger than 50 percent; sample size=33)*			
Simple correlation coefficient *(Pearson)*	0.34*	0.05	0.34*
Rank correlation coefficient *(Spearman's ρ)*	0.49***		0.55***
Variables expressed in U.S. dollars per capita			
All countries *(sample size=72)*			
Simple correlation coefficient *(Pearson)*	0.56***	0.10**	0.08
Rank correlation coefficient *(Spearman's ρ)*	0.89***		0.19
Subsample 1 *(aid-to-revenue ratio larger than 10 percent; sample size=55)*			
Simple correlation coefficient *(Pearson)*	0.49**	0.09**	0.10
Rank correlation coefficient *(Spearman's ρ)*	0.78**		0.56**
Subsample 2 *(aid-to-revenue ratio larger than 50 percent; sample size=29)*			
Simple correlation coefficient *(Pearson)*	0.17	0.11*	0.92***
Rank correlation coefficient *(Spearman's ρ)*	0.18		0.76***

Sources: IMF, *International Financial Statistics;* World Bank, *World Development Indicators;* and authors' calculations.

Note: The symbols *, **, and *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent level, respectively.

[1]Correlation coefficient between each country's Φ and its aid-to-revenue ratio.

[2]Average of individual countries' correlation coefficients between detrended aid and revenue.

[3]Correlation coefficient of each country's aid and revenue variances (θ).

Subsample 1, and a much lower 0.2–0.3 in Subsample 2. The rank correlation coefficients (Spearman's ρ) are about 0.7–0.9 in the full and middle samples and about 0.2–0.5 in the most aid-dependent group. The positive correlation between the relative volatility of aid and aid dependency is statistically significant in all cases but one (Subsample 2, when variables are expressed in U.S. dollars per capita). The weaker results in the smallest subsample may reflect the fact that by eliminating countries with a low aid-to-revenue ratio, we substantially lower the variance of the aid-to-revenue ratio series. In any case, we would stress that the average Φ is about 20 times higher in the 10 most aid-dependent countries than in the 10 least aid-dependent countries.

Third, we find that deviations of aid and revenue from their respective trends are positively correlated (see the second column of Table 2). The averages of individual correlation coefficients of detrended aid and revenue are always positive and of similar size in all samples, although the degrees of statistical significance are somewhat lower than in the case of relative volatility. A look at the distribution of correlation coefficients (Figure 1) reveals that they are concentrated to the right of zero and that only a small number of countries exhibit large negative correlations. Furthermore, the share of countries with a correlation coefficient smaller than –0.3 falls between 5 percent and 10 percent, whereas the share of countries with a correlation coefficient larger than 0.3 is 35–40 percent, depending on whether the variables are expressed as percentages of GDP or in U.S. dollars per capita. Thus, the results provide some support for the view that shortfalls in aid tend to coincide with shortfalls in domestic revenue, a result that we interpret as an indirect measure of the procyclicality of aid.

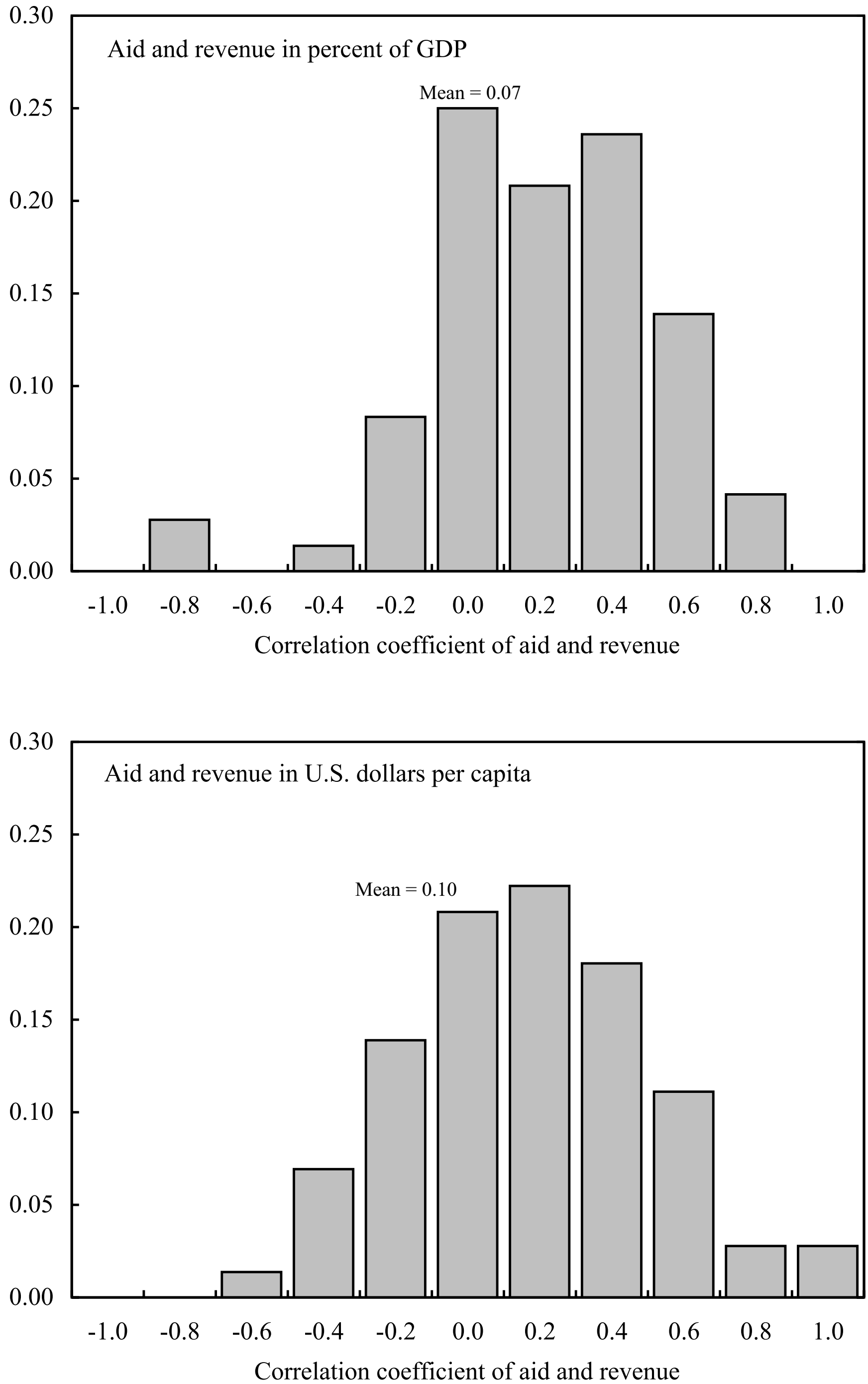
Finally, we find that shocks to domestic revenue are correlated with those to foreign aid (last column of Table 2). The correlation coefficients between the variances of detrended aid (θ^A) and detrended revenue (θ^R) are stable at about $^1/_3$ for the variables in percent of GDP and grow from 0.1 to 0.9 for the variables in dollars per capita. While the sign of the correlation coefficient might have been expected, the size of the correlation coefficients and their stability across different samples are surprising.

We summarize our main results graphically in Figure 2, where the top panel corresponds to variables expressed in percent of GDP and the bottom panel to variables denominated in dollars per capita. Each panel captures three dimensions: on the horizontal axis, we plot the relative volatility of aid, Φ; on the vertical axis, the correlation coefficient of aid and revenue; and each observation is represented by a bubble whose size indicates the country's aid-to-revenue ratio. First, we observe that aid is more volatile than revenue in countries with high aid dependency, since most of the "larger" bubbles are to the right of the vertical line $\Phi = 1$. Second, the majority of bubbles are in positive territory (that is, above the horizontal line corresponding to a zero correlation between aid and revenue). Moreover, in only a few aid-dependent countries—that is, those with "larger" bubbles—the correlation between detrended aid and revenue is negative. This pattern is more pronounced in the bottom panel, where aid and revenue are measured in dollars per capita.

III. Predictability of Aid

In this section, we establish some stylized facts regarding the predictability of aid both in general and in the context of IMF-supported programs. To this end, we carry out two separate exercises. The first one is based on time-series data on aid disbursements and commitments measured in current U.S. dollars and seeks to assess the information content of commitments in the context of a simple autoregressive model for aid disbursements. Available time series were typically longer in this case, since there was no need to compute them as percentages of GDP or to constrain them to be of equal length as revenue series. The second exercise is based on responses to a questionnaire completed by IMF country desk economists. The results of this

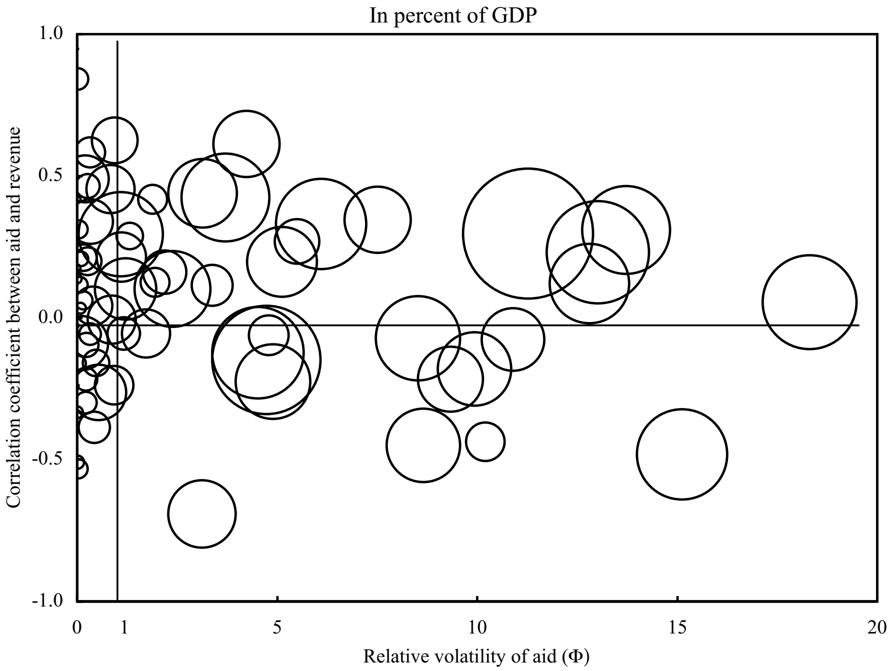
Figure 1. Frequency Distribution of the Cyclical Character of Aid
(relative frequency)

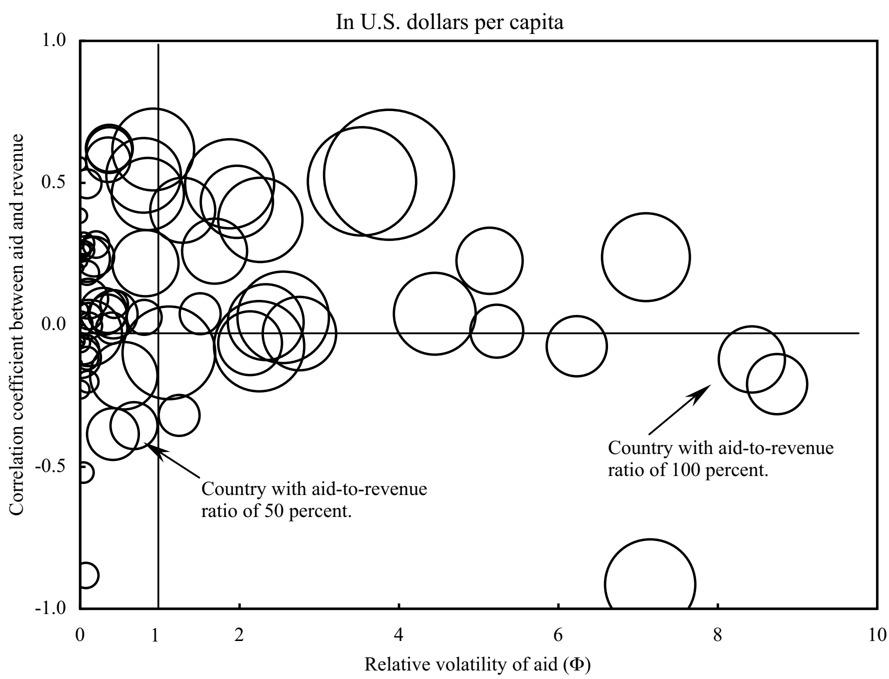


Source: Table A1 in Appendix I.

Figure 2. Characteristics of Aid: Volatility, Cyclicality, and Dependency

(size of bubble indicates aid-to-revenue ratio)





Source: Table A1 in Appendix I.

questionnaire allow us to test whether there are systematic differences among commitments made by donors, projections prepared in the context of IMF-supported programs, and actual disbursements.

The Time-Series Evidence

Our main objective in this section is not to develop an elaborate forecasting model for disbursements based on all available information but, instead, to test the significance of commitments in the context of a parsimonious model. The reason for focusing on commitments is that they are commonly used by recipient countries, largely as a result of the complex politics that surround budgetary processes in these countries. Here we examine whether this politically sensitive variable is also a good predictor of disbursements.

Before turning to the estimation of the marginal contribution of commitments, C, to the prediction of disbursements, D, we would like to provide some basic information on these two variables measured in current U.S. dollars for our sample of 72 countries. A simple look at individual-country plots of their C and D series (available from the authors upon request) reveals two salient features: several episodes of spikes in commitments that, generally, were not followed by increased disbursements; and a systematic tendency for commitments to exceed disbursements.

The first point reflects a propensity for donors to react, in terms of large increases in commitments but not necessarily in disbursements, to positive changes in recipient countries, such as occurred in the Central African Republic following the end of Bokassa's regime in the early 1990s or the end of the civil war in Mozambique in the mid-1990s. The exceptions to the second point are mainly (but not exclusively) a relatively small number of instances within our sample in which a country has received some form of financial help following an unforeseen balance of payments crisis. These cases, however, are concentrated among countries with higher levels of income per capita and capital mobility and low aid dependency. For the other countries in our sample, the C-to-D ratio was larger than one (that is, commitments exceeded disbursements), with the implicit average overprediction of disbursements reaching up to 20 percent.[15]

Although the simple calculations discussed above reveal that commitments tend to overestimate disbursements by a relatively wide margin, they do not reveal much about the information value of a commitment figure for predicting aid for the budget. In order to assess the marginal value of aid commitments in predicting aid disbursements in the context of a simple autoregressive model, we estimated the following equation for the same sample of countries as in the previous section:

$$\Delta D_t = \beta_0 + \sum_{i=1}^{K} \beta_i \Delta D_{t-i} + \gamma \Delta C_t + \varepsilon_t. \tag{1}$$

[15]Of the 71 countries in the sample (Cambodia had to be excluded from this exercise owing to the small number of observations available), only 18 received on average more aid than was committed. Of these, half have very low aid-to-revenue ratios and are among the best-known cases of balance of payments crisis-related financial assistance (Argentina, Brazil, Ecuador, Indonesia, Mexico, the Philippines, Thailand, Turkey, and Venezuela).

The equation was estimated in first differences because of the nonstationarity of both commitments and disbursements (with K representing the lag length). The ability of commitments to help predict the future course of disbursements is tested through the statistical significance of γ. We would expect that γ should be not only statistically significant but also positive and close to one if commitments contained high marginal information value. Of course, there are no simple a priori interpretations for the possible failure of γ to be significantly different from zero. Potential reasons for the failure of commitments to materialize include, inter alia, noncompliance by the receiving country with conditions attached to committed aid, delays associated with administrative problems in donor countries, or simply changes in underlying economic and/or political developments. Whatever the case, though, we think that it is important to document the predictive power of a variable that is widely used in fiscal-programming exercises, mainly in response to pressure from donors.

The estimation process was carried out in two steps. In the first step, two alternative values of K were selected from a version of equation (1) that did not include ΔC_t: those that minimized the Akaike Information Criterion (AIC) and the Schwartz-Bayes Information Criterion (SBIC). The value of γ was then estimated by adding ΔC_t as a regressor in the resulting equations. The results obtained using the AIC are summarized in Table 3; there are no substantial differences between the results obtained under the AIC and those obtained under the SBIC.

In general, the estimated γs are not statistically significant, especially in countries with higher aid-dependency ratios. When all countries are considered, γ is significant at the 5 percent level in about one-third of the regressions.[16] In these cases, the average value of γ is about 0.4; however, the median value is smaller (about one-third), reflecting the fact that the estimated value of γ was quite large for only a few countries: γ was higher than 0.7 in 5 higher-income countries with very low aid-to-revenue ratios (Argentina, Mexico, Panama, Turkey, and Venezuela).[17] The estimated values of γ decreased (and the difference between their average and median values narrowed significantly) when the sample of countries was reduced to cases in which aid represents at least 10 percent of revenues. The estimated value of γ did not change further when the sample was reduced to countries where aid represents at least 50 percent of revenues, but the share of regressions with γs significant at the 5 percent level fell from about $^1/_3$ in the full sample to about $^1/_5$. When the level of statistical significance was lowered to 10 percent, none of the conclusions described above changed significantly.

Two main conclusions can be drawn from Table 3.[18] First, the marginal predictive power of commitments made by donors is statistically significant in only a relatively small fraction of the countries in our sample, and this fraction falls as the sample is reduced to include only countries where aid is relatively important. Second, even among countries where commitments contain statistically significant information about future disbursements, the results suggest that commitments should not necessarily be taken at face value.

[16]In one case, Thailand, γ is negative and statistically significant.

[17]The estimated value of γ was between 0.9 and 1.0 in Argentina, Turkey, and Venezuela.

[18]See Bulíř and Hamann (2001) for individual estimates of γ.

Table 3. Commitments Are Poor Predictors of Actual Disbursements
(estimated values of γ in italics)

	Equations Based on Akaike Information Criterion		
	All countries	Subsample 1[1]	Subsample 2[2]
All regressions			
Number of countries	71	56	32
percentage of total sample	100	100	100
Average value of γ	*0.21*	*0.13*	*0.09*
Median value of γ	*0.15*	*0.12*	*0.07*
Regressions where γ was significant at 5 percent			
Number of countries	24	15	6
percentage of total sample	34	27	19
Average value of γ	*0.43*	*0.32*	*0.33*
Median value of γ	*0.33*	*0.29*	*0.31*
Regressions where γ was significant at 10 percent			
Number of countries	30	20	9
percentage of total sample	42	36	28
Average value of γ	*0.42*	*0.31*	*0.30*
Median value of γ	*0.33*	*0.28*	*0.29*

Source: Authors' estimates.
[1]Countries where aid represents more than 10 percent of government revenues.
[2]Countries where aid represents more than 50 percent of government revenues.

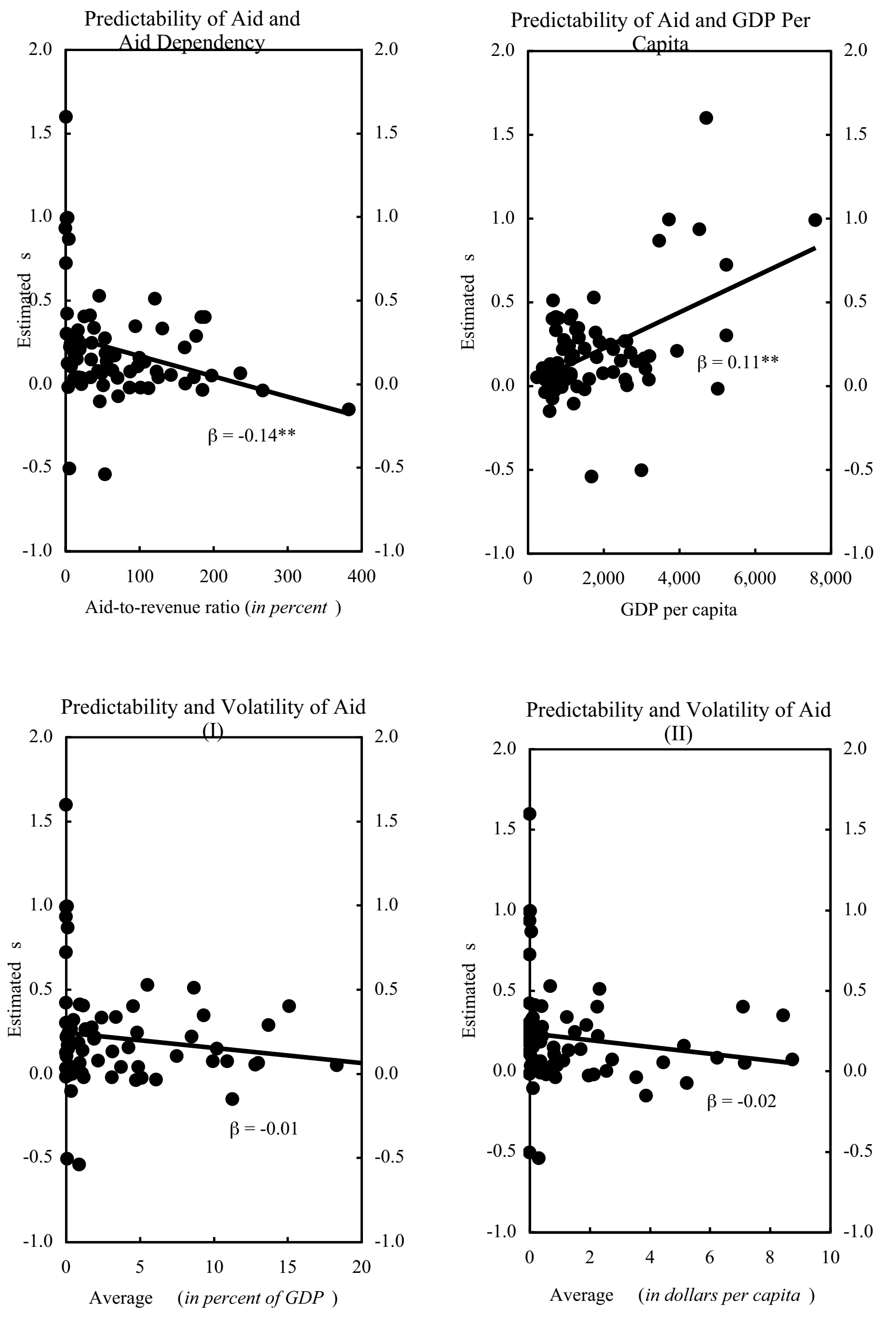
Finally, in line with the results of Section II, we explored the relationship between predictability of aid, as measured by γ, and a few other variables. The top two panels of Figure 3 plot the estimated values of γ against the aid-to-revenue ratio and GDP per capita, respectively (the panels also show a fitted regression line and the estimated regression coefficient). The relationship is negative in the first case, positive in the second case, and the estimated regression coefficients are statistically significant at the 1 percent level. These results show quite clearly that the predictive power of donors' commitments tends to be lower in poorer and in more aid-dependent countries. The bottom two panels of Figure 3 plot the estimated γs against the two measures of relative aid volatility (Φ). In both cases, the relationship is negative, albeit not statistically significant, indicating only a weak correlation between volatility and unpredictability.

How Good Are Aid Projections in IMF-Supported Programs?

The survey

The results in this subsection are based on responses by 37 IMF desk economists to a questionnaire we sent them in late 1999. (See Appendix II, Table A2 for a list of the countries.) Although the definition of aid employed in this questionnaire was intended to be as close as possible to that based on the OECD's ODA definition, in most cases the IMF estimates of aid inflows are smaller. This discrepancy reflects the asymmetric nature of information on aid between donors and recipients: data on

Figure 3. Aid-Dependent, Poor Countries and Countries with Volatile Aid Also Have Less Predictable Aid



Source: Authors' estimates.

Notes: The slope of the regression line is denoted by β. The symbol ** indicates statistical significance at the 5 percent level.

Table 4. Categorization of Aid Projections

	Original Projection	IMF Program Projection	Budget Projection	Disbursement (*actual data*)
Timing				
Project aid	One year ahead	Normally at the start of the year	Early in the year	Available immediately
Program aid	One year ahead	Normally at the start of the year	Normally at the start of the year	Following year, with some reporting lags
Estimates reflect inputs from				
Project aid	IMF staff, authorities, donors, and World Bank	IMF staff, authorities, donors, and World Bank	Authorities, donors, and World Bank	Authorities, donors, and World Bank
Program aid	IMF staff, authorities, donors, and World Bank	IMF staff, authorities, donors, and World Bank	IMF staff, authorities, donors, and World Bank	Authorities, donors, and World Bank
Basis for projections				
Project aid	Heavily discounted preliminary commitments and history of disbursements	Commitments with 5–10 percent discount	Updated donor commitments	—
Program aid	Heavily discounted preliminary commitments and history of disbursements	Updated donor commitments	Same as IMF-program projection	—
Number of observations				
Project aid	27	32	24	32
Program aid	23	28	...	28

Source: Authors' estimates.

such components as technical assistance; peacemaking efforts; and other, smaller categories of aid are often not reported to the recipient country and, hence, are not recorded in the countries' fiscal and balance of payments accounts on which the responses to our questionnaires were based.

We divided aid projections into the following four different categories related to the life of IMF-supported programs: "original projections," "budget projections," "IMF program projections," and "disbursements." See Table 4 for an overview of the projection categories and Bulíř and Hamann (2001) for a detailed description of the results of the questionnaire.

Project aid

Table 5 shows the results of the survey expressed as percentages of the IMF program projection. This is an intuitive normalization—for example, the figure of 94.9 in the last column of the first row indicates that the average aid disbursement was

Table 5. How Good Are Short-Term Aid Projections?
(percent of IMF program projections, sample averages)

	Original Projections *(one-year-ahead IMF projections)*	Budget Projections *(authorities' commitment-based projections)*	Disbursements *(as provided by the authorities)*
Project aid[1]			
All countries	102.6	109.5	94.9
Of which:			
Without program interruptions	106.3	109.1	95.9
With program interruptions[2]	86.2	111.6	89.7
Program aid *(annual data)*[3]			
All countries	100.9	. . .	68.5
Of which:			
Without program interruptions	106.2	. . .	76.0
With program interruptions[2]	65.5	. . .	30.8
Of which:[4]			
Grants			
All countries	98.3	. . .	87.3
Of which:			
Without program interruptions	104.0	. . .	92.3
With program interruptions[5]	. . .	. . .	. . .
Loans			
All countries	91.7	. . .	61.6
Of which:			
Without program interruptions	100.2	. . .	74.7
With program interruptions	49.1	. . .	3.9
Program aid (quarterly data)[6]			
All countries	. . .	. . .	49.3
Of which:			
Without program interruptions	. . .	. . .	44.3
With program interruptions[2]	. . .	. . .	82.9

Source: Authors' estimates.

[1]Data for 27 countries for original projections, 24 countries for budget projections, and 31 countries for actual outturns.

[2]Data for 4 countries. In one country, no program aid was committed and none was disbursed.

[3]Data for 23 countries for original projections and 26 countries for actual outturns.

[4]The sum of grants and loans does not equal total program aid, because it reflects data from a subset of countries for which the breakdown was available. Grant and loan data are available for 19 and 24 countries, respectively.

[5]Averages are not reported, because only one observation was available.

[6]Average deviation from the quarterly IMF program projection.

lower than the IMF projection by 5.1 percent. The average disbursement of project aid falls short of all types of projections and the ranking of errors is unambiguous: budget projections are the worst, with an average error of 15 percent; IMF program projections are the most accurate, with an average error of 5 percent; while original projections fall in the middle, with an average error of almost 8 percent.[19] Interruptions in IMF programs appear to have limited impact on disbursements. The fact that budget projections fare the worst even though they are prepared relatively

[19]One percentage point of prediction error amounts to about 0.1 percent of GDP.

late in the process—and with updated donor commitments—presumably reflects the pressure exerted by donors for aid recipient countries not to discount their commitments. Although all projections overestimated disbursements on average, disbursements were also frequently underestimated (see Figure 4, top panel).

Program aid

Program aid shortfalls vis-à-vis IMF projections are larger than those of project aid. Both original and IMF program projections overestimated disbursements by, on average, more than 30 percent.[20] Out of the 28 countries, only 4 recorded disbursements in excess of IMF program projections (see Figure 4, middle panel). Program aid not only falls significantly short of the programmed level, but its quarterly distribution also differs substantially from the programmed path (see Figure 4, bottom panel). On average, quarterly outturns deviate by about 50 percent from the quarterly path estimated at the beginning of the program period.

The intuitive explanation for the much larger prediction errors in program aid projections as compared with project aid lies in the different nature of the conditionality associated with the two types of aid. Unlike project aid, which flows gradually according to multiple-year disbursement schedules and entails direct monitoring by donors of some large projects, program aid is generally disbursed only if the IMF-supported macroeconomic program is on track (it is held back if the program is off track). The difference in type of conditionality, however, does not fully explain the excessively optimistic projections. Although countries with program interruptions received, on average, only about one-third of program aid commitments, countries with successful, uninterrupted programs received only three-quarters of program aid commitments.[21]

What could explain the substantial shortfall vis-à-vis program projections in programs that remained officially on track? We suggest three possible explanations: (i) program-aid shortfalls originated in donor countries and were not related to recipient countries' performance; (ii) aid recipient countries breached donor conditionality but not that associated with the IMF-supported program; or (iii) the overestimation reflects strategic behavior by the IMF, given its unique role as arbiter of external assistance. Unfortunately, we do not have the information needed to assess the relative importance of these hypotheses.

Another way of dissecting our results is to compare prediction errors for program loans and program grants separately. The results show that bilateral aid in the form of program grants (about one-third of total program aid) has a much smaller prediction error than program loans (see the bottom part of Table 5).[22]

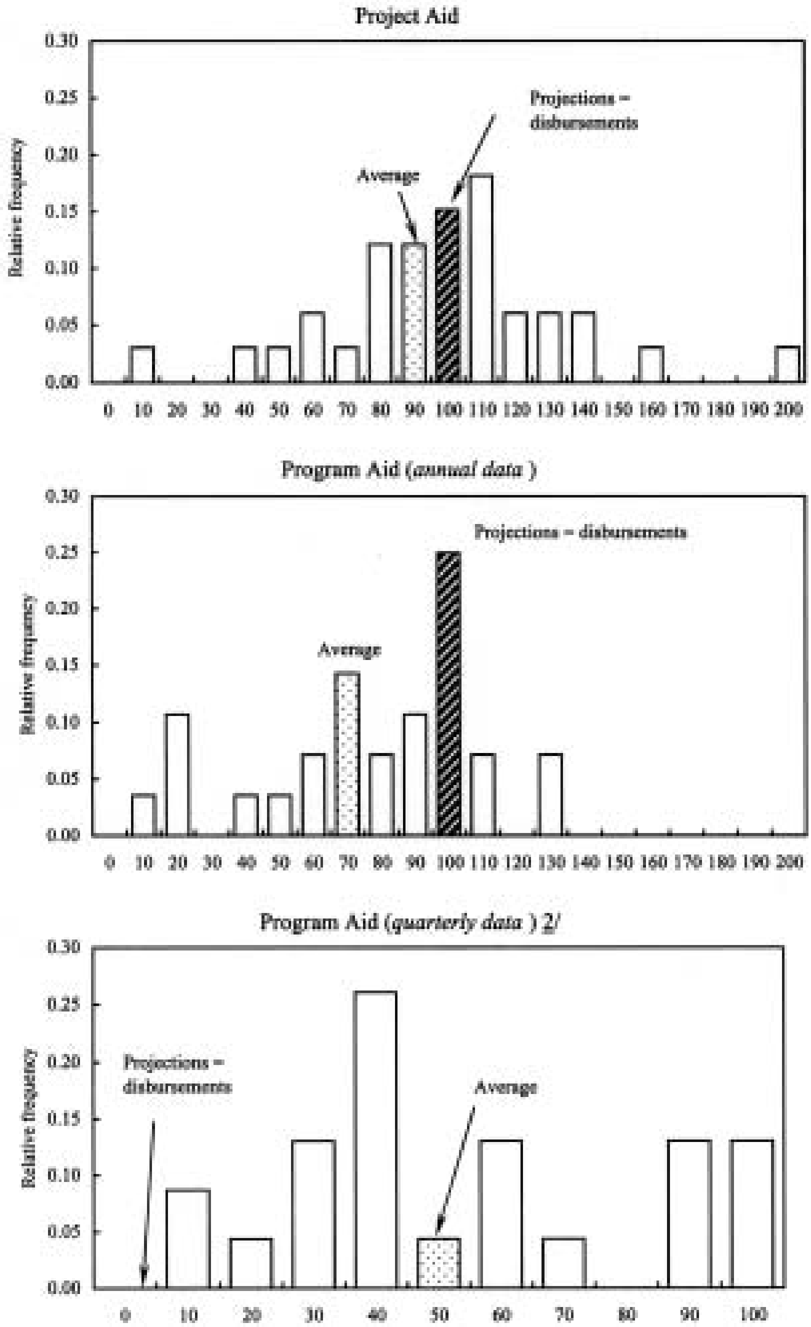
[20] One percentage point of prediction error amounts to about 0.05 percent of GDP.

[21] Interestingly, in the group of interrupted programs, the original, one-year-ahead projections were some 35 percent smaller than the IMF-program projections, perhaps reflecting initial IMF staff skepticism about the prospects of the country adhering to an IMF-supported program.

[22] This analysis allows us to compare prediction errors vis-à-vis bilateral and multilateral donors, respectively. The differentiation in our data is not perfect, however. On the one hand, grants are disbursed only by bilateral donors. On the other hand, loans are disbursed both by bilateral and multilateral donors. Moreover, the sample size is smaller than in previous cases (19 and 24 countries for grants and loans, respectively), primarily because breakdowns of program aid are not available for some countries.

Figure 4. Frequency Distribution of Aid Disbursements[1]

(In percent of program projections)



Sources: IMF questionnaire; authors' calculations.

[1]The samples contain 33, 28, and 23 countries, respectively. Countries with no disbursements and countries with program interruptions are excluded.

[2]Average deviation from the quarterly projection.

While grant disbursements are almost 13 percent lower than program projections, the corresponding estimate for loan disbursements is almost 40 percent.

IV. Conclusions and Policy Recommendations

In this article, we assess empirically various aspects of the cyclical behavior of aid flows. Although the overall economic implications of highly volatile and unpredictable aid flows can be substantial—especially in countries that receive large volumes of aid—the issue has not received enough attention in the literature. We hope that this article will stimulate further research, particularly in assessing the robustness of our results to changes in detrending methods, the specific definition of aid flows, or even the units of measurement. We also hope that the paper will help in focusing the attention of policymakers on policies aimed at reducing economic instability in poor countries.

We find that aid is substantially more volatile than domestic revenues; this relative volatility grows with the degree of aid dependency; and these results are quite robust. We also find that shortfalls in aid tend to coincide with shortfalls in domestic revenue (an indirect measure of the procyclicality of aid) and that countries that suffer from revenue volatility also exhibit higher volatility in aid receipts, perhaps because both revenue and aid fluctuations are driven by domestic policy instability.

Given the relatively high volatility of aid, we find the positive correlation of deviations of aid and revenue from their trends particularly worrisome, since the two results combined could imply that aid is being disbursed in a less than ideal manner. While our results in this regard apply to total aid, similar findings for separate components of aid have been obtained in other studies. Grants and technical assistance have been found to be procyclical, particularly in sub-Saharan Africa (Pallage and Robe, 2001a). Furthermore, U.S. food aid (provided under Public Law (PL) 480)—one category of aid that one would expect to be highly countercyclical—has also been found to be mildly procyclical (Barrett, 2001). The procyclicality of aid is likely to reflect a variety of factors. At the theoretical level, Svensson (2000) shows that when donors are unable to monitor the recipient country's reform effort, a second-best outcome arises in which aid disbursements are tied to economic performance, thus rendering aid procyclical. In practice, compliance with conditionality from multilateral agencies and, thus, timely disbursements of aid are less likely when countries are hit by unforeseen adverse shocks.

We also show that aid cannot be predicted reliably on the basis of donors' commitments. There seems to be a tendency for all parties involved (donors, the local authorities, and the IMF) to systematically overestimate aid disbursements in aid-receiving countries with IMF-supported programs. Given the economic inefficiencies and financing difficulties associated with implementing swift fiscal measures to compensate for large unexpected shortfalls in aid, our findings suggest that fiscal programming in aid-receiving countries should rely on cautious assumptions about the availability of committed funds and that projections of aid disbursements should be based on past experience rather than on promises made by donors. Of course, budgets can be designed to accommodate aid disbursements in excess of the conservative baseline, but this should be done in a way that ensures that domestic currency funds are released to spending agencies only after the equivalent foreign currency-denominated aid has been deposited at the central bank.

There is no presumption that our findings of aid volatility, predictability, and procyclicality must be taken as given. In fact, significant room seems to exist for both aid recipients and donors to improve the pattern of aid disbursements. For example, a higher degree of compliance with conditions attached to aid is likely to lead to a smoother path of aid disbursements. There are also factors, however, that lead to disruptions in aid disbursements over which the recipient country has less control. A country hit by an external shock may have its aid flows temporarily suspended because it has delayed the necessary adjustment, owing, for example, to domestic politics. Adjustment may eventually be undertaken, perhaps at a more opportune time, but disbursements would be missed and their macroeconomic impact felt long afterward. This is essentially an avoidable problem that can be addressed through improved program design.[23] Furthermore, as explained by Barrett (2001) for U.S. food aid, the procyclicality of aid can be corrected through the development of reliable early-warning systems to anticipate emergencies and allow donors to disburse aid when it is needed most or through improved budgetary practices in the donor country. The recent emergence of poverty reduction strategy papers (PRSPs) is a positive development in this regard.[24] The PRSPs are expected to not only lead to better design and stronger ownership of the programs supported by multilateral agencies—and, thus, to higher compliance—but also to play an important role in coordinating the actions of other donors.

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[23]There is some evidence that donors may be insufficiently flexible in certain situations and tend to become increasingly prescriptive with reformers once good policies are in place (Branson and Hanna, 2000).

[24]For an explanation of the PRSP and its connection with the IMF's Poverty Reduction and Growth Facility, see International Monetary Fund (2000).

Table A1. Volatility of Aid and Revenue: Country Data

	Years	Volatility (θ)		Relative Volatility (Φ)	Correlation Coefficient of Aid and Revenue	Aid/Revenue Ratio (*in percent*)	Volatility (θ)		Relative Volatility (Φ)	Correlation Coefficient of Aid and Revenue	Aid/Revenue Ratio (*in percent*)
		Aid	Revenue				Aid	Revenue			
		In percent of GDP					In U.S. dollars per capita				
Argentina	1979–96	0.00	1.33	0.00	0.17	1.54	0.55	7,391.79	0.00	–0.07	1.34
Bangladesh	1975–89	0.68	0.61	1.11	0.21	56.15	3.25	1.92	1.69	0.26	93.33
Belize	1977–89	4.26	0.42	10.22	–0.44	34.85	375.71	465.93	0.81	0.03	27.14
Benin	1985–97	2.26	0.72	3.13	–0.69	101.94	24.44	44.59	0.55	–0.18	101.39
Bolivia	1993–97	0.84	0.39	2.19	0.16	43.84	18.33	201.17	0.09	0.23	47.07
Brazil	1975–94	0.00	7.86	0.00	–0.03	0.46	0.41	9,535.42	0.00	0.23	0.20
Burkina Faso	1992–97	2.23	0.45	4.91	–0.23	125.42	9.27	11.56	0.80	0.53	123.95
Cambodia	1991–97	5.18	1.14	4.53	–0.12	188.33	67.71	9.53	7.10	0.24	168.46
Cameroon	1975–97	1.64	3.72	0.44	–0.39	21.98	26.74	486.23	0.05	–0.09	20.01
Cape Verde	1986–97	2.98	2.71	1.10	0.29	162.05	622.41	244.29	2.55	0.02	184.69
Central African Rep.	1986–97	5.32	0.62	8.52	–0.07	160.90	53.84	23.76	2.27	0.37	157.48
Chad	1986–97	2.69	0.57	4.74	–0.15	266.37	20.59	5.81	3.54	0.50	254.77
China	1979–97	0.00	0.73	0.00	0.14	2.52	0.04	19.72	0.00	–0.06	2.38
Congo, Dem. Rep. of	1975–97	1.12	1.34	0.84	0.45	54.31	7.33	20.73	0.35	0.58	44.99
Congo, Republic of	1975–97	9.46	8.04	1.18	–0.06	25.30	747.96	1,856.89	0.40	–0.01	22.63
Costa Rica	1975–97	0.70	0.37	1.90	0.42	19.01	130.06	648.67	0.20	0.28	16.31
Côte d’Ivoire	1988–97	12.91	3.82	3.38	0.11	38.84	317.94	255.12	1.25	–0.32	37.16
Djibouti	1985–97	38.47	3.53	10.90	–0.08	87.56	3,174.30	363.05	8.74	–0.21	78.63
Dominican Republic	1975–97	0.28	1.28	0.22	–0.30	10.47	19.15	393.50	0.05	–0.52	9.72
Ecuador	1975–97	0.04	1.21	0.03	–0.53	8.85	5.75	737.76	0.01	–0.06	8.28
Egypt	1975–97	3.27	6.73	0.49	–0.16	16.94	167.50	2,317.52	0.07	–0.88	14.39
Equatorial Guinea	1986–97	18.24	4.92	3.71	0.42	173.97	358.69	390.90	0.92	0.62	149.14
Ethiopia	1981–97	4.19	7.63	0.55	–0.26	70.45	3.29	7.99	0.41	–0.39	58.83
Fiji	1975–97	0.20	0.83	0.24	–0.10	13.66	49.63	562.84	0.09	–0.12	12.56
Gabon	1979–85	0.04	3.10	0.01	–0.51	3.98	125.34	52,537.78	0.00	0.38	4.82
Gambia, The	1975–97	34.20	3.44	9.93	–0.18	123.61	187.36	67.98	2.76	–0.03	119.37
Ghana	1975–97	1.09	3.11	0.35	0.34	46.62	21.39	195.63	0.11	0.09	35.29
Guatemala	1975–97	0.10	0.60	0.17	0.21	15.87	7.26	64.20	0.11	0.03	16.57
Guinea	1986–97	1.68	1.38	1.21	0.10	86.78	39.31	18.42	2.13	–0.07	90.12
Guinea–Bissau	1983–92	70.87	6.28	11.28	0.30	382.58	150.41	38.78	3.88	0.53	372.47
Guyana	1975–97	39.48	8.23	4.80	–0.06	36.00	1,252.43	829.67	1.51	0.04	36.56
Haiti	1975–97	21.91	2.35	9.34	–0.22	94.45	187.03	22.18	8.43	–0.12	97.21
Honduras	1975–97	2.52	0.46	5.51	0.27	45.89	68.10	99.85	0.68	–0.36	48.04
India	1975–97	0.03	0.21	0.17	0.06	7.28	0.15	4.37	0.04	0.27	5.84
Indonesia	1975–97	0.03	0.94	0.03	–0.16	6.23	0.65	82.96	0.01	0.05	5.75
Jamaica	1975–97	0.55	2.08	0.27	0.46	13.73	4.59	1,272.84	0.00	0.00	14.56
Jordan	1975–97	28.46	1.13	25.08	–0.24	63.95	5,952.98	954.75	6.24	–0.08	81.21

Table A1. (*concluded*)

	Years	Volatility (θ) Aid	Volatility (θ) Revenue	Relative Volatility (Φ)	Correlation Coefficient of Aid and Revenue	Aid/Revenue Ratio (*in percent*)	Volatility (θ) Aid	Volatility (θ) Revenue	Relative Volatility (Φ)	Correlation Coefficient of Aid and Revenue	Aid/Revenue Ratio (*in percent*)
		In percent of GDP					In U.S. dollars per capita				
Kenya	1975–97	1.53	1.64	0.93	–0.24	33.59	12.73	70.94	0.18	0.24	34.62
Lao People’s Dem. Rep.	1988–97	16.94	1.23	13.72	0.31	176.40	20.94	11.13	1.88	0.50	174.10
Lesotho	1982–97	3.60	17.01	0.21	0.49	51.00	25.91	70.16	0.37	0.62	46.19
Madagascar	1988–96	5.99	0.69	8.66	–0.45	120.90	28.23	12.10	2.33	0.01	128.11
Malawi	1975–97	12.27	1.63	7.51	0.35	97.98	14.51	17.57	0.83	0.22	97.33
Mali	1975–88	11.00	0.86	12.82	0.12	142.79	25.95	5.82	4.46	0.04	145.89
Mauritania	1990–96	29.00	6.84	4.24	0.61	99.70	307.39	59.81	5.14	0.22	96.87
Mexico	1975–97	0.00	0.46	0.00	–0.24	0.50	0.32	5,883.07	0.00	–0.13	0.50
Mozambique	1980–97	79.78	6.12	13.03	0.23	236.20	34.05	30.38	1.12	–0.10	186.43
Nepal	1975–96	0.62	0.12	5.13	0.20	112.19	2.06	1.05	1.97	0.43	113.73
Nicaragua	1975–96	50.74	516.93	0.10	–0.09	66.71	912.92	113,647.89	0.01	–0.12	36.37
Niger	1985–97	9.63	0.64	15.13	–0.48	183.43	19.20	8.54	2.25	–0.08	176.77
Nigeria	1975–97	0.03	4.63	0.01	–0.33	3.23	0.14	668.24	0.00	0.20	1.40
Pakistan	1975–97	0.48	0.25	1.95	0.12	19.03	3.84	9.01	0.43	0.07	17.42
Panama	1975–96	0.14	1.36	0.10	0.21	4.79	96.52	1,716.84	0.06	0.26	4.51
Papua New Guinea	1975–94	1.67	1.91	0.88	–0.01	53.58	86.51	292.00	0.30	0.05	49.93
Paraguay	1975–93	0.07	0.27	0.26	0.20	17.56	18.76	200.14	0.09	0.18	12.57
Peru	1975–97	0.06	1.37	0.05	0.31	7.55	5.98	581.48	0.01	–0.23	7.23
Philippines	1975–97	0.12	0.36	0.33	–0.06	10.73	4.91	51.13	0.10	–0.20	10.32
Rwanda	1975–85	58.56	3.20	18.32	0.05	197.97	212.25	29.67	7.15	–0.92	177.61
Senegal	1975–84	3.94	2.27	1.73	–0.06	53.28	67.41	160.82	0.42	0.04	52.70
Sierra Leone	1975–97	5.63	1.80	3.14	0.44	107.24	33.70	26.14	1.29	0.40	94.09
Sri Lanka	1975–97	1.34	3.29	0.41	0.04	33.89	8.85	25.39	0.35	0.04	33.55
Swaziland	1975–97	2.34	7.15	0.33	0.58	21.77	96.71	1,057.13	0.09	0.49	19.43
Tanzania	1988–97	8.15	1.33	6.11	0.33	185.18	17.80	20.94	0.85	0.46	113.14
Thailand	1975–97	0.01	0.18	0.07	0.12	5.49	1.60	521.20	0.00	0.57	4.31
Togo	1975–97	4.78	5.07	0.94	0.62	48.98	69.90	189.92	0.37	0.62	47.77
Tunisia	1975–96	0.16	0.72	0.23	–0.22	12.10	28.22	396.03	0.07	0.26	7.82
Turkey	1975–96	0.06	0.62	0.09	0.03	2.90	27.97	1,094.49	0.03	0.22	2.80
Uganda	1975–97	6.72	2.81	2.39	0.10	131.10	7.94	70.82	0.11	–0.03	95.47
Uruguay	1975–97	0.01	1.38	0.01	0.42	1.33	10.78	12,209.22	0.00	0.28	1.29
Venezuela	1975–97	0.00	5.56	0.00	0.95	0.19	0.37	12,922.44	0.00	0.32	0.16
Yemen, Republic of	1990–97	0.75	39.25	0.02	0.84	11.43	20.14	472.71	0.04	0.29	10.31
Zambia	1975–96	58.93	1.92	30.69	0.12	70.98	801.79	153.36	5.23	–0.02	61.14
Zimbabwe	1975–97	1.48	1.11	1.33	0.29	16.74	54.36	472.86	0.11	0.00	16.00

Source: Authors’ estimates.

APPENDIX II

Table A2. List of Countries Used in the Survey

Country	Period	Type of IMF Arrangement
Albania	January 1998–December 1998	ESAF
Algeria	July 1998–June 1999	EFF
Azerbaijan	January 1998–December 1998	ESAF
Bolivia	January 1998–December 1998	ESAF
Burkina Faso	January 1998–December 1998	ESAF
Cambodia	January 1998–December 1998	ESAF
Cameroon	July 1998–June 1999	ESAF
Cape Verde	January 1998–December 1998	Stand-By
Central African Republic*	January 1998–December 1998	ESAF
Congo, Republic of*	December 1997–December 1998	ESAF
Côte d'Ivoire	January 1998–December 1998	ESAF
Djibouti	January 1998–December 1998	ESAF
Dominican Republic	January 1998–December 1998	None
Ecuador	January 1998–December 1998	None
Egypt	June 1998–June 1999	Stand-By
El Salvador	December 1997–December 1998	Stand-By
Gabon	January 1998–December 1998	EFF
Ghana	January 1998–December 1998	ESAF
Guyana	January 1998–December 1998	ESAF
Indonesia	April 1998–March 1999	Stand-By/EFF
Jordan	January 1998–December 1998	EFF
Kyrgyz Republic	January 1998–December 1998	ESAF
Lao People's Dem. Rep.	October 1997–September 1998	None
Macedonia, FYR of	January 1998–December 1998	ESAF
Madagascar	January 1998–December 1998	ESAF
Mauritania	January 1998–December 1998	ESAF
Mongolia	January 1998–December 1999	ESAF
Mozambique	December 1997–December 1998	ESAF
Nepal	July 16, 1998–July 15, 1999	None
Nigeria	January 1998–December 1998	None
Panama	January 1998–December 1998	EFF
Papua New Guinea*	January 1998–December 1998	None
Sierra Leone	January 1998–December 1998	ESAF
Tajikistan	July 1998–June 1999	ESAF
Yemen	January 1998–December 1998	ESAF
Zambia*	January 1998–December 1998	ESAF
Zimbabwe*	January 1998–December 1998	Stand-By

Notes: The symbol * denotes an interruption in the Fund program; ESAF denotes Enhanced Structural Adjustment Facility; EFF denotes Extended Fund Facility; and Stand-By denotes Stand-By Arrangement.

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