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Volatility of Development Aid: An Update

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The positive impact of foreign aid is limited by the erratic behavior of aid flows. The introduction in 1999 of various initiatives anchored in IMF Poverty Reduction Strategy Papers aimed at strengthening coordination among donors, improving the design of financial support programs, and improving domestic records of policy implementation should have led to an improvement in the time series properties of aid flows. We find no evidence of any fundamental changes in the way aid has been delivered during 2000–03. If anything, aid volatility has worsened somewhat and the information value of long-term lending commitments has declined. We take these results to mean that the main causes of the volatility and unpredictability of aid, and the broader issue of macroeconomic instability in low-income countries, may not have been addressed in a systematic manner by the donor community. [JEL F35, 019]
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I. Volatility and Predictability of Aid: What Exactly Is the Issue?

This paper updates our previous work on aggregate aid volatility and predictability (Bulíř and Hamann, 2003). Specifically, we ask whether aid during 2000–03—that is, following the introduction of the Poverty Reduction Strategy Papers (PRSPs) and related donor initiatives—became more stable and predictable than in previous periods.[1] In our 2003 paper we found that aid was (1) highly volatile and (2) mildly procyclical (that is, aid on average tends to be disbursed in periods when output or domestic revenue are high and held back when domestic economic activity is contracting), and that (3) aid disbursements are difficult to predict on the basis of donor commitments. In this paper we do not test directly how the various initiatives introduced since the late 1990s under the umbrella of the PRSPs and aimed at improving donor practices, domestic policy processes, program design, and so on have fared. We simply do not have a counterfactual model of how aid would develop in the absence of these changes. But we find no evidence of a change in the way aid is delivered. This result is robust to changes in the way in which aid is measured or in de-trending methods.

II. Data and Measurement Issues

Compared with Bulíř and Hamann (2003), we extended the sample, added a few countries, filled some gaps in the coverage of domestic fiscal revenue, and tested the robustness of our results using alternative aid definitions and smoothing techniques. Our database contains data for 76 countries from 1975 to 2003, with both gross and net aid series and domestic revenue series (including both tax and nontax). Given that not all the revenue series are available from 1975, we have an unbalanced panel of observations (see Appendix Table A1 for data availability).

Choices, Choices

The specific definition of aid seems to matter surprisingly little from an empirical viewpoint: our key results are robust to every definition of aid we employed. One choice is between gross aid (disbursements) and net aid (disbursements net of repayments). However, net aid measures may be misleading if the recipient country is in arrears or in the process of rescheduling, because accrual-based debt service does not necessarily reflect actual repayments. Another choice is between a narrow, reasonably well-measured definition (grants and loans, excluding food and emergency aid and debt relief) and broader definitions that include these inflows.[2] Whereas we

[1]See Appendix I in Bulíř and Hamann (2006) for a brief survey of these initiatives.

[2]See Appendix II in Bulíř and Hamann (2006) for a detailed description of all series and their transformations.

focus on narrow definitions of gross aid, our results remain broadly unchanged when net aid or broadly defined gross aid are used.

The choice of a common denominator matters more for the statistical measures of relative volatility than the definition of aid. Typically, aid is denominated in U.S. dollars whereas domestic revenue is denominated in local currency units. Comparisons require first expressing both variables in the same currency. As a result, statistical measures of relative volatility are affected by the relative volatility of the exchange rate, whose impact can be very large. To account for this fact, we follow Bulíř and Hamann (2003) and compute aid and revenue in two different ways: as percentages of nominal gross domestic product (GDP) and in constant U.S. dollars in per capita terms.[3] Arguably, denominating aid and revenue in per capita U.S. dollars is preferable if both were to be spent on tradable goods, whose prices tend to be fixed in U.S. dollars (Bulíř and Lane, 2004). 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 aid-to-GDP ratio is a better indicator.

Data Transformations

All transformed aid and revenue series are converted into natural logarithms and de-trended using the Hodrick-Prescott filter ($\lambda = 7$). A measure of relative aid volatility, Φ, is then calculated as the ratio of the variances of the filtered series of aid and revenue.[4] We note that Φ is a ratio of variances estimated with a common number of observations in both the numerator and denominator for a given country. Thus, the statistical significance of sample averages can be assessed using an *F*-test. Additional robustness checks, such as comparisons of sample averages and medians of Φ across countries and various groups of countries, were also carried out. Finally, we calculate the correlation coefficient of de-trended aid and revenue, which amounts to a test of aid procyclicality because revenues are a strongly procyclical variable.

III. Measuring the Variability of Aid: Two Approaches

In this section we reexamine the evidence on volatility and predictability of aid since our previous study. As stated earlier, the year 1999 provides a natural breaking point for the analysis because it marks the introduction of

[3]To circumvent the exchange rate problem, Hudson and Mosley (forthcoming) demean aid and revenue series, finding fairly similar patterns of relative aid volatility as in this paper.

[4]The logs eliminate the scale effect in the series, which would otherwise bias the estimates of Φ downward (because revenues tend to be larger than aid in most cases). In Bulíř and Hamann (2003), Φs are computed on the basis of the raw data (not in logs) and, thus, the estimates of Φ are affected by the relative scale of the aid and revenue series. To the extent that the focus of that paper is mainly the budgetary impact of aid instability, the use of absolute values is the correct approach. Given our main interest in this paper, namely, to see whether the relative volatility of aid has changed in recent years, estimating Φs in logs would seem the appropriate choice. The estimates in non-log data are not, however, substantially different.

the PRSP initiative, a cornerstone of many initiatives introduced simultaneously (or shortly thereafter) and aimed at addressing key issues such as insufficient donor coordination or a lack of ownership by aid recipient countries (OECD, 2003; and Birdsall, 2004). We hasten to say that this study does not present a counterfactual model of donor behavior in the absence of these initiatives; it could well be that without them aid would have been even more volatile and less predictable. However, we have not been able to identify an a priori factor, or set of factors, that could have produced this result. Thus, by contrasting the pre-1999 and post-1999 periods, we try to answer two questions. First, does aid continue to be, for the most part, more volatile than domestic revenue? Second, has aid become more predictable (that is, are aid disbursements more closely related to donor commitments)?

Aid Volatility and Procyclicality

We find, first, that the volatility of aid is much higher than that of revenue and, second, that the relative volatility of aid increased on average in the early 2000s as compared with the late 1990s (see Table 1 and Figure 1 for unbalanced and balanced samples, respectively). These results are statistically significant and invariant to alternative definitions of aid and de-trending methods.

The average volatility of aid relative to revenue (Φ) is about 14 when variables are expressed in percent of GDP and 5½ when they are expressed in constant U.S. dollars per capita. Using medians, which are arguably better statistics in the presence of large outliers, the estimates of the relative volatility of aid are 6 in percent of GDP and 2½ in constant U.S. dollars per capita. The small differences between these results and those in Bulíř and Hamann (2003) are due to the fact that we use logs in this study and employ a slightly larger sample with updated and revised historic data.

Instances in which aid is less volatile than revenue ($\Phi < 1$) are rare—between 1 in 25 and 1 in 5, respectively. We find only three instances in the GDP-based series (Bolivia, Chad, and Comoros) and 16 in the U.S. dollar per capita series (Angola, Bolivia, Burkina Faso, Chad, Comoros, Ecuador, Guinea-Bissau, Lao P.D.R., Lebanon, Lesotho, Mongolia, Nigeria, Papua New Guinea, Sudan, Uganda, and Vietnam). The results in these countries seem to be mostly driven by relatively unstable revenue rather than relatively stable aid: while the absolute volatility of their revenue series was typically a multiple of the sample median, the absolute volatility of their aid series was comparable to the sample median.

On average, aid has been delivered in a mildly procyclical fashion—the average of individual-country correlation coefficients between aid and revenue is positive, albeit statistically insignificant. In other words, declines in de-trended aid tend to be associated with declines in de-trended revenue, and vice versa. Thus, aid is not only unstable; it tends to fall when it may be needed the most.

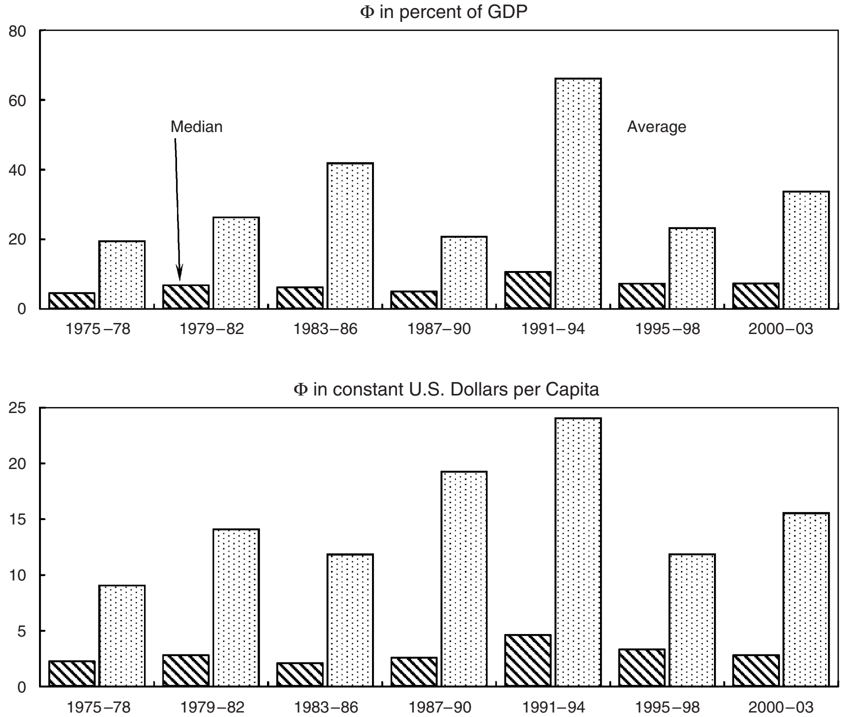
Table 1. Aid Remains More Volatile Than Revenue and Procyclical, 1975–2003

	Full Sample	Sample 1 ($A/R<25\%$)	Sample 2 ($25\%<A/R<50\%$)	Sample 3 ($A/R>50\%$)
	In percent of GDP			
Average Φ	14.2*	21.9*	6.8*	4.8*
Median Φ	6.2*	12.8*	4.6*	3.9*
Frequency indicators of Φ				
Sample size	76	40	16	20
Number of countries where $\Phi>1$	73	40	15	18
Procyclicality of aid (correlation of aid and revenue)	0.04	0.04	0.08	0.02
Number of countries where corr > 0	38	20	8	10
Aid-to-revenue ratio (in percent)	32.1	11.1	37.5	72.2
	In constant U.S. dollars per capita			
Average Φ	5.4*	7.9*	2.6*	1.8*
Median Φ	2.5*	3.6*	2.5*	1.4*
Frequency indicators of Φ				
Sample size	76	42	21	13
Number of countries where $\Phi>1$	60	34	17	9
Procyclicality of aid (correlation of aid and revenue)	0.12*	0.03	0.20	0.30*
Number of countries where corr > 0	49	23	15	11
Aid-to-revenue ratio (in percent)	29.3	11.2	38.6	75.1

Sources: Fiscal revenue—IMF, World Economic Trends in Africa (WETA) database; aid—Organization for Economic Cooperation and Development (OECD), Development Assistance Committee (DAC) database; exchange rate, GDP, population, and U.S. consumer price index (CPI)—IMF, World Economic Outlook (WEO) database; for country-specific data availability see Appendix Table A1 and for series details see Bulíř and Hamann (2006).

Note: This table reports the average and median ratios of variances of aid and domestic fiscal revenue (Φ), the correlation coefficient of aid and revenue, and frequency indicators of these measures for an unbalanced panel of 76 countries. Aid and revenue are converted into natural logarithms, expressed in percent of GDP and in constant U.S. dollars per capita, and de-trended using the Hodrick-Prescott filter with $\lambda=7$. Sample variances are calculated for each country. A measure of relative aid volatility, Φ, is calculated as the ratio of the variances of the Hodrick-Prescott filtered series of aid and revenue and averaged for various samples (full, countries with an aid-to-revenue (A/R) ratio equal to less than 25, 25–50, and more than 50 percent, respectively). If Φ is larger than one, volatility of aid is higher than that of fiscal revenue and the statistical significance thereof can be assessed using an F-test, with a null hypothesis of $\Phi\leq 1$. The Pearson correlation coefficient of de-trended aid and revenue measures aid procyclicality, with a null hypothesis of corr(A; R) = 0). *Denotes significance at the 5 percent level.

Figure 1. Relative Aid Volatility (Φ) Worsened in the Post-PRSP Period



Sources: Fiscal revenue—IMF, World Economic Trends in Africa (WETA) database; aid—Organization for Economic Cooperation and Development, *Development Assistance Committee* database; exchange rate, GDP, population, and U.S. consumer price index—IMF, *World Economic Outlook* database; for country-specific data availability see Appendix Table A1, and for series details see Bulíř and Hamann (2006).

Note: This figure reports the four-year average and median ratio of variances of aid and domestic fiscal revenue (Φ) for a balanced sample of 50 countries with the complete 1975–2003 series. The 1999 observation—the year of the introduction of the PRSP initiative—is dropped from the calculation.

The initiatives started in the late 1990s do not seem to have lowered the relative volatility of aid. On the contrary, average aid volatility (Φ) increased in the 2000s after a decline in the late 1990s (Figure 1).[5] The median measure of (Φ) remained broadly unchanged in the 2000s as compared to the late 1990s. In other words, while aid volatility changed little for the median country, it increased substantially in a few others.

In which countries did aid volatility increase during 2000–03? One would have expected the poorest countries to benefit the most from the PRSP-related initiatives. In reality, declines in the relative volatility of aid have been

[5]Figure 1 is based on a balanced sample of 50 countries with complete 1975–2003 series and plotting four-year average and median estimates of Φ's. These results are not materially different from the 76-country unbalanced sample presented in Table 1.

Table 2. Aid Volatility Is Higher in HIPC Countries Than in Non-HIPC Countries

	1995–98		2000–03	
	HIPC $N=41$	Non-HIPC $N=35$	HIPC $N=41$	Non-HIPC $N=35$
	In percent of GDP			
Average Φ	25.0	27.0	62.0	35.8
Median Φ	5.8	7.6	9.3	9.5
	In constant U.S. dollars per capita			
Average Φ	16.8	12.2	22.7	22.0
Median Φ	2.8	3.4	4.6	4.5

Sources: Fiscal revenue—IMF, WETA database; aid—OECD, DAC database; exchange rate, GDP, population, and U.S. CPI—IMF, WEO database; for HIPC eligibility, see Appendix Table A1 and for series details see Bulíř and Hamann (2006).

Note: The full sample of 76 countries is divided into countries that qualify for the Highly Indebted Poor Countries (HIPC) Initiative and those that do not, and the average and median ratio of variances of aid and domestic fiscal revenue (Φ) is calculated for two four-year periods: 1995–98 and 2000–03. Aid and revenue are converted into natural logarithms, expressed in percent of GDP and in constant U.S. dollars per capita, and de-trended using the Hodrick-Prescott filter with $\lambda = 7$. Sample variances are calculated for each country. A measure of relative aid volatility, Φ, is calculated as the ratio of the variances of the Hodrick-Prescott filtered series of aid and revenue and averaged for the various samples.

both rare and comparatively small in the poorest countries (Haiti or Togo). In contrast, the increases in relative volatility were frequent and large in several sub-Saharan African countries, such as Benin, Lesotho, and Uganda, but also in Western Hemisphere countries, such as Bolivia and El Salvador. Breaking down our sample into countries that qualified for debt relief under the Heavily Indebted Poor Countries (HIPC) Initiative and those who did not, we find no significant differences in relative volatility in 2000–03 compared with 1995–98 (Table 2). The average Φs almost doubled during the last four-year period in both groups, median Φs also almost doubled in HIPC countries, whereas median Φs increased only by about one-third in non-HIPC countries. In levels, aid volatility in HIPC countries remained higher than in non-HIPC countries. We thus find it difficult to argue that the poorest countries benefited from the PRSP initiative in terms of more stable aid flows.

We tested the robustness of our results to changes in aid definitions (various measures of gross versus net aid) and the de-trending methodology, and found our results robust to all proposed alternatives.[6] First, the estimates

[6]See Crowards and Adam (2005) for a critique of our 2003 paper.

of Φ for all three definitions of aid are quite similar—see Table 3, section I, summarizing the calculations for series in percent of GDP. Second, we reset the parameter λ in the Hodrick-Prescott filter from 7 to 100, applied first differences to the series instead of using a smoothing technique for de-trending, and corrected for the end-sample bias in the Hodrick-Prescott filter (Cogley and Nason, 1995). Regarding the possibility that the Hodrick-Prescott filter may create spurious serial correlation in de-trended data, we note that series de-trended with the first-difference filter yield practically identical results as those de-trended with the Hodrick-Prescott filter (lines II.C and II.A–B, respectively). Regarding the possibility that end-period observations have larger mean square errors than observations in the middle of the sample, we dropped the first two (1975–76) and last two (2002–03) observations from the calculation of aid and revenue variances and recalculated the average and median Φs (line II.D). The average Φs declined only marginally compared to the full sample (line II.A). The impact on end-period Φs—that is, in the post-PRSP period—remained equally negligible: the average and median Φs in percent of GDP increased marginally from 33.7 and 7.3 in the original 2000–03 sample to 34.7 and 9.1 in the shortened 2000–02 sample, respectively.

Table 3. Aid Is Volatile: Never Mind the Definitions and Smoothing Techniques

	All Countries	Countries with Aid Equivalent to at Least 50 Percent of Revenue
I. Aid definitions (Hodrick-Prescott filter, λ = 7)		
A. Φ for gross aid, narrow definition (loans and grants)	14.2	6.8
B. Φ for gross aid, broad definition (loans, grants, emergency and food aid)	12.2	6.2
C. Φ for net aid, *World Development Indicators* definition	13.5	7.7
II. Smoothing techniques (Φ for gross aid; loans and grants)		
A. Hodrick-Prescott filter, λ = 7	14.2	6.8
B. Hodrick-Prescott filter, λ = 100	11.5	5.5
C. First difference	11.2	6.3
D. Hodrick-Prescott filter, λ = 7; end-sample bias correction	13.1	4.5

Sources: Fiscal revenue—IMF, WETA database; aid—OECD, DAC database; exchange rate, GDP, population, and U.S. CPI—IMF, WEO database; for series details see Bulíř and Hamann (2006).

Note: In the first line of this table we replicate the first line of Table 1 (average Φs) and then recalculate the Φs for a broader measure of gross aid and a measure of net aid (Part I). Next, we reset the parameter λ in the Hodrick-Prescott method to 100, drop two observations from the beginning and from the end of the sample, and apply first differences to the series (Part II).

Predictability

It could be argued that aid volatility would be less of a problem if such volatility were predictable. However, fully anticipated volatile aid would still be problematic because most aid-dependent countries face serious liquidity constraints. We find, as in Bulíř and Hamann (2003), that long-term commitments by official lenders remain unreliable and that the predictive power of commitments is particularly low in the poorest countries in the sample.

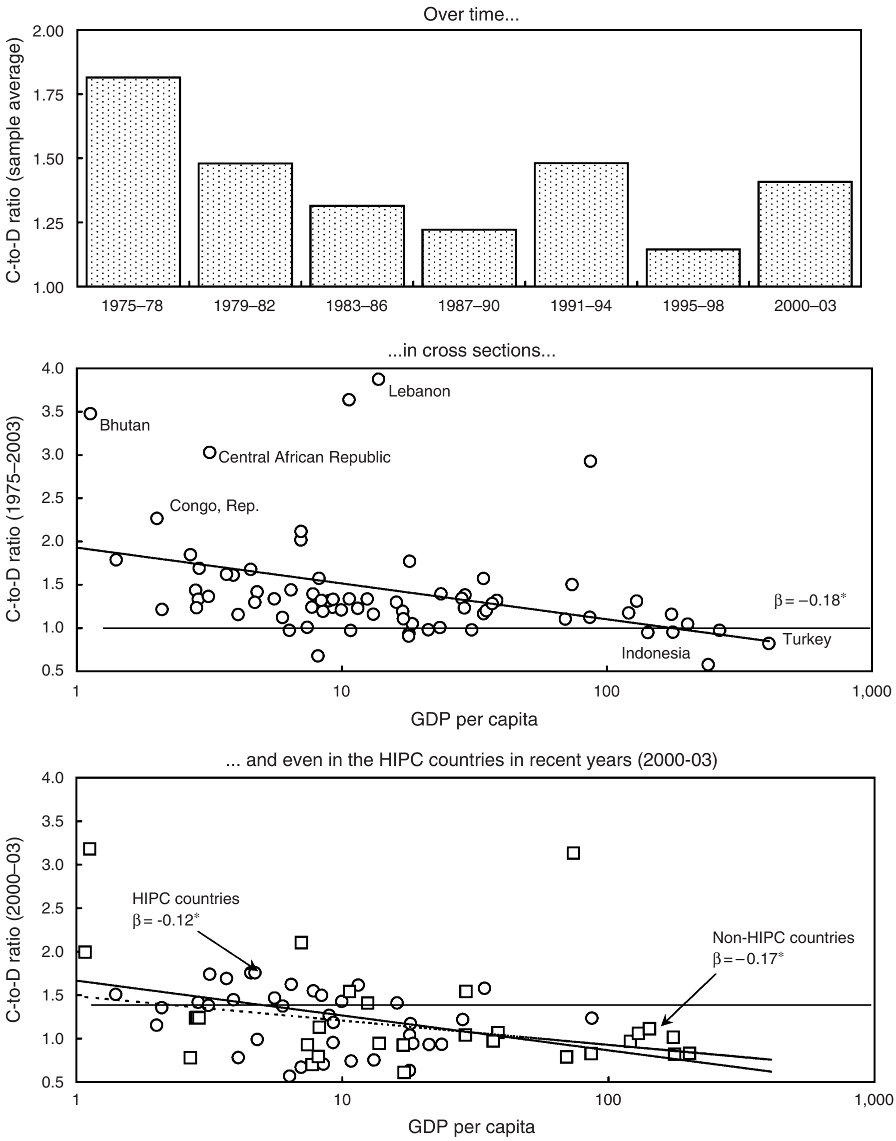
Unfortunately, no comprehensive database with broadly defined aid commitments and disbursements has been compiled. Thus, we rely on commitments and disbursements of long-term loans compiled in the World Bank's Global Development Finance (GDF) database. The GDF data produce a reasonable, albeit imperfect, approximation, because (1) most aid-dependent countries cannot borrow on nonconcessional terms and (2) disbursements in the GDF database are positively correlated with official development assistance (ODA) loans for most countries in the Organization for Economic Cooperation and Development database—the average and median of Pearson correlation coefficients for aid and long-term loans is 0.4 in percent of GDP.

In 2000–03, disbursements fell short of commitments by about one-third (Figure 2, top panel). In other words, during 2000–03 lenders promised, on average, two-fifths more than they actually disbursed. Incidentally, this is also the average for the full sample period of 1975–2003. Moreover, the last-period increase in the ratio was driven jointly by larger commitments and lower disbursements: during 2000–03 average commitments grew by about 4 percent, relative to 1995–98, whereas average disbursements fell by some 5 percent during the same period.

Even more disturbing is the finding that this measure of unpredictability has been negatively correlated with the level of development (measured by purchasing power parity (PPP) GDP per capita; Figure 2, middle panel). An increase in constant PPP GDP by US$100 is associated with a reduction of almost 0.2 in the C-to-D (commitments-to-disbursements) ratio, that is, better reliability of commitments during the full-sample period of 1975–2003. Countries at the upper end of the income scale appear to have received almost as much loan aid as was committed, whereas countries at the lower end of the income scale have received on average only about one-half of commitments: the C-to-D ratios for the 10th and 90th percentiles of the C-to-D series ordered by GDP per capita were 2.0 and 1.0, respectively. The difference in aid predictability remains sizable even if we compare the 25th and 75th percentiles.

We looked also at whether HIPC countries benefited from the recent initiatives in terms of lending predictability, and we failed to find any statistically significant impact. Breaking down our sample into HIPC and non-HIPC countries and focusing on the 2000–03 period, we find that the negative relationship is similar in both groups of countries (Figure 2, bottom

Figure 2. Loan Commitments Are Poor Predictors of Disbursements



Sources: Long-term loans—World Bank, *Global Development Finance*; GDP per capita in U.S. dollars and purchasing power parity exchange rate—IMF, *World Economic Outlook*; for series details see Bulíř and Hamann (2006).

Note: Commitments and disbursements of long-term loans, excluding IMF lending; the C-to-D ratio compares commitments and disbursements for a given year. Heavily Indebted Poor Countries (HIPCs) are shown as circles, with a dotted trend line; non-HIPC countries are shown as squares, with a solid trend line. We exclude the 2001 C-to-D observation for the Central African Republic that was drastically changing the slope of the HIPC-country trend line.

panel). The regression slopes are comparable to those in the post-PRSP period (2000–03) but also to the single slope estimated for the full sample period (1975–2003). These results suggest that long-term lending predictability may have been unaffected by the initiatives of the late 1990s and that their impact on predictability in the poorest countries was barely noticeable.

IV. Conclusions and Policy Implications

In this paper we reexamined some of the issues taken up in Bulíř and Hamann (2003) on the volatility, predictability, and cyclicality of aid. The availability of six new years' worth of data allowed us to look closely at whether the way in which aid is disbursed has improved since the late 1990s, when various initiatives, anchored in PRSPs, were introduced. These initiatives were expected to lead to better compliance with IMF conditionality and a more predictable and less erratic stream of aid flows into low-income countries. Better compliance with conditionality, along with improved donor practices, should have also have led to aid being less procyclical.

The results of our study, however, are not encouraging. The analysis shows that aid remained more volatile than domestic fiscal revenues by a wide margin. We also find little evidence that absolute aid volatility has decreased recently. Aid commitments continue to be poor predictors of disbursements, a problem that is particularly serious among countries with the lowest per capita incomes. The results are equally disappointing for the cyclical behavior of aid: we found that disbursements remain slightly procyclical on average.

APPENDIX I

Table A.1. List of Countries and Sample Periods[1]

Country	Years	Country	Years
Albania	1992–2003	*Kyrgyz Republic*	1993–2003
Algeria	1975–2003	*Lao People's Dem. Rep.*	1975–2003
Angola	1981–2003	Lebanon	1975–2003
Armenia	1994–2003	Lesotho	1975–2003
Bangladesh	1975–2003	*Madagascar*	1978–2003
Benin	1975–2003	*Malawi*	1975–2003
Bhutan	1981–2003	*Mali*	1975–2003
Bolivia	1975–2003	*Mauritania*	1975–2003
Burkina Faso	1975–2003	Mongolia	1975–2003
Burundi	1980–2003	Morocco	1992–2003
Cambodia	1987–2003	*Mozambique*	1975–2003
Cameroon	1980–2003	*Nepal*	1980–2003

Table A.1 *(concluded)*

Country	Years	Country	Years
Central African Rep.	1980–2003	*Nicaragua*	1975–2003
Chad	1980–2003	*Niger*	1975–2003
Colombia	1975–2003	Nigeria	1980–2003
Comoros	1980–2003	Pakistan	1975–2003
Congo, Dem. Rep. of	1980–2003	Papua New Guinea	1975–2003
Congo, Republic of	1980–2003	Paraguay	1975–2003
Côte d'Ivoire	1980–2003	Peru	1975–2003
Djibouti	1980–2003	Philippines	1975–2003
Dominican Republic	1975–2003	*Rwanda*	1975–2003
Ecuador	1975–2003	*Senegal*	1975–2003
Egypt	1975–2003	*Sierra Leone*	1975–2003
El Salvador	1975–2003	Sri Lanka	1975–2003
Ethiopia	1980–2003	*Sudan*	1975–2003
Fiji	1975–2003	Swaziland	1975–2003
Gambia, The	1975–2003	Syrian Arab Republic	1975–2003
Ghana	1975–2003	Tajikistan	1992–2003
Guatemala	1975–2003	*Tanzania*	1975–2003
Guinea	1980–2003	Thailand	1975–2003
Guinea-Bissau	1980–2003	*Togo*	1975–2003
Guyana	1975–2003	Tunisia	1975–2003
Haiti	1975–2003	Turkey	1975–2003
Honduras	1975–2003	*Uganda*	1975–2003
Indonesia	1975–2003	*Vietnam*	1981–2003
Jamaica	1975–2003	*Yemen, Republic of*	1975–2003
Jordan	1975–2003	*Zambia*	1975–2003
Kenya	1975–2003	Zimbabwe	1978–2003

[1]Countries in italics are eligible for debt relief under the HIPC Initiative. For a list of HIPC-eligible countries see http://www.imf.org/external/np/exr/facts/hipc.htm.

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