Is Aid Volatility Harmful?*

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Abstract

This paper studies the causal effect of aid volatility on the economic performance of developing countries in 2000-2009 period. We construct a time-varying measure of aid volatility using autoregressive conditional heteroskedasticity (ARCH). We control for the endogeneity of aid flows by using as instruments for aid volatility three characteristics of donor counitres: (i) their budget deficits ; (ii) their electoral systems (majoritarian versus proportional), and (iii) their electoral cycles. Doubling aid volatility causes a fall in GDP growth of a typical beneficiary country by two-thirds. This effect mainly operates through the increase in violent conflict and displacement of the production in the economy towards less advanced sectors.

Keywords: foreign aid, aid effectiveness, time-varying volatility, political business cycles, political institutions.
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1 Introduction

The effectiveness of foreign aid is one of the key issues in development economics. The existing empirical evidence on the effectiveness of aid for development outcomes such as economic growth, health, and education, has been - at best - inconclusive. For instance, a recent state-of-the-art paper by Rajan and Subramanian (2008), after controlling for the potential reverse causality (i.e. that poorer countries might attract larger aid flows), fails to find a positive effect of aid flows on economic growth in developing countries. This finding holds regardless of the quality of policy or geographic environment in the beneficiary country. As Easterly puts it sharply, "[this and similar findings led to] a terrible disjunction: aid policy was based on the premise that aid raises growth, but [...] this premise was false" (Easterly 2006: 41).

The international aid community launched several large-scale initiatives to improve aid architecture. The most well-known of such efforts took the form of the so-called High-Level Forums (HLFs) on Aid Effectiveness. The Second High-Level Forum resulted in the famous Paris Declaration (2005), while the Third HLF (2008) led to the Accra Agenda for Action (AAA). These documents list a comprehensive set of measures that, if adopted by both donors and beneficiaries, is believed to result in a substantially higher effectiveness - in terms of improved well-being of beneficiary countries' citizens - of a given aid flow. A recent study commissioned by the European Commission estimates the benefits of fully implementing the Paris Declaration by the EU27 countries - in particular, better coordination and planning of aid flows - to be roughly € 5 bln per year (Bigsten et al. 2011).

One key element of these proposed reforms in international aid architecture is making aid flows more predictable and less volatile. The proponents of reducing aid volatility argue that this will increase the effectiveness of aid substantially, while keeping the total envelope of aid constant (Kharas 2008). However, there exist no plausible *causal* estimates of the effect of lower aid volatility on development outcomes. The main reasons for this are three. First, some parts of foreign aid are volatile by construction: for instance, humanitarian aid should ideally be volatile, because it reacts to humanitarian emergencies. Therefore, simply looking at the effect of volatility of total aid (ODA) on development outcomes is likely to underestimate the true negative effect of volatility.

Second, a researcher has to face the classical identification problem, because of potential omitted variables, in particular, unobservable time-varying beneficiary-country characteristics that could potentially have causal influence on both the behavior of donors (and thus affect aid flows) and the development performance of the beneficiary country. Consider a change in the quality of governance in the developing country (e.g. a coup that leads to the previously democratic country becoming autocratic). This can affect simultaneously the economic performance of the country and, if explicit or implicit conditionality of aid exists, imply a drastic reduction in aid flows (which shows up as an increase in aid volatility). To correctly identify the causal effect of volatility one needs, therefore, to find first a plausible exogenous variation in aid volatility.

Finally, we have no empirical knowledge about mechanisms through which aid volatility affects development outcomes. There exist several competing channels (discussed in the next section), but we know little about the relative importance of these mechanisms. Knowing more about these channels is a crucial issue from the policy perspective.

This paper tries to close this gap and to provide better answers to the following questions: Is aid volatility harmful for developing countries? If so, how badly? How would the effect of reduction of volatility by half compare to, say, the effect of doubling aid flows? What are the mechanisms through which this effect operates?

To do so, first of all, we construct a time-varying measure of volatility of the major component of aid flows - the Country Programmable Aid (CPA), as built by the OECD DAC - using the autoregressive conditional heteroskedasticity (ARCH) approach. Next, we propose a novel set of instruments for aid volatility, exploiting the fact that a beneficiary country typically has several bilateral donors. Our set of instruments includes the government budget balance in donor countries, political cycles in donor countries (i.e. the election and pre-election years), and the characteristics of the electoral system (majoritarian versus proportional) in donor countries. Using the instrumental-variables approach, we estimate the *causal* effect of higher aid volatility on development performance of beneficiary countries (as measured by GDP growth). We also shed light on the mechanisms through which this effect operates. In particular, we analyze whether higher aid volatility increases violent conflict, affects male and female employment, and increases reliance of the country on the minerals sector (as a fraction of GDP).

Our main findings are as follows. Higher unpredictable aid (CPA) volatility has a large and highly significant negative causal effect on the GDP growth of beneficiary countries. For a typical developing country, doubling of aid volatility would result in the loss of two-thirds of its average annual GDP growth. This effect comes almost entirely from the countries with high fractionalization of aid (in terms of the number of bilateral donors): the effect of higher aid volatility in countries with high fractionalization of aid is more than five times the effect in countries with low fractionalization of aid. Concerning mechanisms, we find that higher aid volatility increases violent conflict, depresses male (but not female) employment, and increases the reliance on the mineral sector. Overall, we find that instrumental-variables approach delivers results that radically differ from those obtained using a "naive" OLS specification with fixed effects.

The rest of the paper is organized as follows. Section 2 discusses the theoretical framework and lists the testable hypotheses. Section 3 discusses our identification strategy and presents the data. Section 4 presents and analyses the estimation results of the effect of aid volatility on GDP growth. Section 5 looks at the mechanisms behind this effect. Finally, section 6 discusses the general implications of our findings and concludes.

2 Theoretical framework and testable hypotheses

Why, in theory, foreign aid volatility could harm the development performance of a beneficiary country? The potential theoretical mechanisms can be divided into two broad classes: economic and institutional.

On the economic side, it is clear that the volatility of foreign aid affects the developing country essentially because of the limited access of the latter to the international capital markets. In the absence of such imperfections, the beneficiary country could fully smooth the shocks in foreign aid by borrowing/lending on the international capital market. Given this, the first key mechanism through which aid volatility hurts the long-run economic performance of a developing country operates via the displacement from investment to consumption, as argued by Arellano et al. (2009) and Celasun and Walliser (2008). Using a dynamic general equilibrium model, Arellano et al. (2009) show that higher aid volatility implies that households rationally reduce investment and increase consumption in their desire to smooth stronger variability in their incomes (given that aid inflow act as transfer of goods thus increasing household income). Similarly, Celasun and Walliser (2008) argue that developing country governments cannot rapidly adjust their investment spending upwards (e.g. construction of an additional road) in response to aid windfalls, whereas it might have severe difficulties in cutting government consumption (given that it is mainly composed of salaries of the public sector employees) in response to aid shortfalls. Therefore, higher aid volatility (i.e. an increase in the absolute size of shortfalls/windfalls) leads to higher government consumption at the expense of government investment.

A related argument is that higher aid volatility might generate a poverty trap in the developing country, by inducing it to under-invest into more advanced productive technologies Agenor and Aizenman (2010) present a simple two-period model in which production can me done either by a traditional technology or a modern technology. This latter has the 'time-to-build' character and thus requires (public) investment in both periods to be productive. In the absence of private physical capital and no access to international capital markets, such investment has to be financed through aid. Because of the diminishing marginal productivity of public investment, higher volatility of aid reduces the expected returns to public investment and thus induces the beneficiary country's agents to abstain from investing into the modern technology. Thus, the country remains captured in the low-output trap, if the aid volatility is sufficiently high.

The second class of mechanisms describes how aid volatility can negatively affect the institutions of a developing country, which, given the importance of institutions for development, maps into poorer economic performance over time. In most developing countries, disagreements over policies are mediated by non-democratic means, and thus often governments have to face rebels groups. Nielsen et al. (2011) discuss a channel through which aid shortfalls can lead to breakouts of violent conflict between rebels and the government. The government maintains peace by making transfers (side payments) to potential rebel groups and by investing into deterrence, using for both purposes, among other sources, foreign aid resources. An abrupt fall in aid shifts the balance of power in the favor of rebels, which then require larger transfers to maintain peace. However, the government cannot commit to such transfers, because if aid flows are restored to their pre-shortfall values, the newfound strength of the government will induce it to renege on this promise of higher transfers. The rebel groups might then find it more beneficial to launch a conflict. Therefore, a temporary negative shock to aid flows increases the likelihood of a violent conflict, which, of course is detrimental to economic and social development of the beneficiary country. Applying rare-event logit analysis to the data from 1981 to 2005, the authors then find a strong correlation between aid shortfalls and armed conflict onset.

Aid windfalls can also harm the beneficiary country's institutions, through a different channel. Svensson (2000) builds a dynamic game-theoretic model in which social or ethnic groups decide on engaging in rent-seeking activities (corruption, lobbying, fighting) to appropriate public funds (a part of which comes from aid). Such actions are strategic complements, i.e. higher rent-seeking by one group increases the incentives of the other groups to do the same. In one-stage interaction, this leads to a Prisoner's dilemma: all groups engage in sub-optimally high rent-seeking. The intertemporal nature of the game, however, allows for self-sustaining cooperative agreements between groups to abstain from rent-seeking. A temporary positive increase in aid (a windfall) increases the temptation to renege on this cooperative agreement, and thus can trigger socially costly rent-seeking wars and undermine the institutions of the country.

Taken together, these theories generate the following testable hypotheses:

1. An exogenous increase in aid volatility leads to a drop in GDP growth of a beneficiary country;

2. This effect results from: (i) re-allocation of economic activity away from the modern and towards less technology-intensive sectors; (ii) re-allocation away from the productive and towards socially unproductive activities (e.g. conflicts).

In the rest of the paper, we investigate empirically the validity of these theoretical hypotheses.

3 Identification strategy and data

This section describes the sources of the data that we use for our estimation, the construction of some of the key variables, discusses the empirical pitfalls of the 'naive' OLS approach, presents our identification strategy, and explains how we build our instrumental variables.

3.1 Dataset

For the measure of aid flows, we use the measure developed by the OECD DAC, the Country Programmable Aid, or CPA (See Benn et al. 2010 for details). It is defined as "the portion of aid on which recipient countries have a significant say and for which donors should be accountable for delivering 'as programmed'" (Benn et al. 2010: 1), and corresponds to a better estimate of aid flows that is really transferred to developing countries. Essentially, it is corresponds to the official development assistance (ODA) without humanitarian and food aid, debt relief, the portion of aid that entails no flows to the beneficiary country (administration, student costs, development awareness/research, refugee spending), aid to NGOs, and ODA equity investments. In 2008, CPA corresponded to 54% of gross bilateral ODA flows worldwide.

The CPA is still an imperfect measure: for instance, technical assistance is included (while corresponding only indirectly to real transfers of resources); similarly, the exclusion of food aid is debatable. Nevertheless, we believe that CPA is much better suited (as compared to ODA) for the purposes of our study, given that the theoretical framework discussed above analyzes the impact of volatility of real transfers that are made from developed to developing countries. If, for instance, most of the volatility in ODA comes from the volatility of humanitarian assistance, the effect of ODA volatility on growth in beneficiary countries would be clearly underestimated (even after controlling for reverse causality), given that humanitarian aid is inherently volatile. The downside of using CPA is having a shorter time span: the reliable data for the construction of CPA for most countries exists only starting 2000. The last year for which we have data currently is 2009; thus we have (at most) 10 observations for each beneficiary country.

All other economic variables, for both donors and beneficiaries (GDP, investment, public expenditures, human capital, trade openness, government budget deficit) comes from the World Bank Development Indicators dataset. For the political variables (quality of democracy, electoral system, electoral cycle), we use the Quality of Political Institutions dataset of the University of Gothenborg and the Database of Political Institutions of the World Bank.

The most basic measure of volatility is the time-invariant one, i.e. the coefficient of variation or the sample variance of aid flows to a beneficiary country over a given time period. However, as discussed by Desai and Kharas (2011), this has two potential serious shortcomings. First of all, for many countries, such measure would average out the years with high and low volatility. Given that aid volatility has been changing substantially over the years, such a measure would thus disregard this important source of variation in aid volatility, and therefore would only allow for between-country analyses, whereas policy makers are interested in knowing the within-country causal effect of reducing aid volatility. Secondly, such a measure can overstate the true measure of beneficiary-country uncertainty about future aid flows (if, e.g., there are predictable aid flow cycles).

We thus adopt the state-of-the-art approach to this issue, and follow Desai and Kharas by constructing a time-varying measure of conditional variance of CPA flows, using autoregressive conditional heteroskedasticity. Below we explain this in more detail.

Volatility is the conditional variance of a process. We do not observe this quantity directly (given that studying a process allows one to only have one observation at each time point), and therefore we have to estimate it.

Generally, consider a model of the type $y_t = X\beta + \varepsilon_t$ where ε_t denotes the error term (for example, this can be an $ARMA(p, q)$ process). The ε_t are modelled as being split into a stochastic piece z_t and a time-dependent standard deviation σ_t so that $\varepsilon_t = \sigma_t z_t$ with $z_t \sim N(0, 1)$.

In an ARCH(q) model, the series σ_t^2 are modelled as

$$\sigma_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2. \tag{1}$$

In our case, the model to be estimated for each recipient country is

$$AID_t = a_0 + a_1 AID_{t-1} + \varepsilon_t. \tag{2}$$

Time varying volatility in aid can be estimated through the following steps:

1. Estimate the coefficients a_0 and a_1, and then fit $\hat{\varepsilon}_t$using maximum likelihood (i.e. ARIMA).

2. Regress $\hat{\varepsilon}_t^2$ on $\hat{\varepsilon}_{t-1}^2$ using maximum likelihood.

3. Predict $\sigma_t^2 = E(\hat{\varepsilon}_t^2)$ from the model.

To analyze the robustness of our findings to alternative measurement of volatility, we also use the Kharas (2008) measure of deadweight loss of aid volatility. The advantage of this approach is that it allows to have a measure of the undesirability of volatility of aid (from the beneficiary country's point of view), in currency units.

The deadweight loss of volatility (DWL) is constructed using simple insights from finance theory. Consider a beneficiary country that with several donors. The flows of aid from each of these donors is volatile. Then, the partner country can be considered as holding a 'portfolio' of aid, similar to the portfolio of risky assets held by an investor. Given that higher volatility is considered as having negative consequences for the recipient country and thus undesirable, the recipient country would be willing to receive lower expected flows of aid in exchange for lower volatility of its aid portfolio. Taking this idea to the extreme, one can calculate the certainty equivalent of aid flows to any partner country: it is the lowest amount of aid that the country would agree on receiving if this aid were given to it with certainty. Finally, the difference between the expected aid flows of a recipient country (calculated using realized aid flows) and the certainty equivalent is interpreted as the deadweight loss, i.e. the amount of financial loss to donor countries that could have been avoided if the aid flows to the recipient country were certain.

In other words, it is assumed that any recipient country would agree on a cut in its (current and uncertain) aid flows in exchange for a fully guaranteed aid flow: the maximum amount of such cut (i.e. the one that would deliver the same benefits, by revealed preference) is the potential cost saving associated with making aid flows fully predictable.

Mathematically, the deadweight loss of aid flows to country j in year t is calculated as

$$DWL_{jt} = E(A_{jt}) - CE(A_{jt}) = E(A_{jt}) \left[\frac{S\sigma_{ajt}}{1 + r_t^f + S\sigma_{ajt}} \right], \tag{3}$$

where A_{jt} is the aid flow, $E(A_{jt})$ is its expected value, $CE(A_{jt})$ is the certainty equivalent of this uncertain flow, r_t^f is the risk-free rate (as Kharas (2008), we use the average annual value of the 6-month U.S. Treasury bills), S is the Sharpe ratio (the value of which is calculated from the U.S. stock exchange, i.e. $S = 0.388$), and σ_{ajt} is the volatility of aid.

3.2 Empirical strategy

The equation we want to estimate is of the type:

$$\ln(y_{it}) = \rho \ln(y_{it-1}) + \theta_1 Volatility_{it-1} + \theta_2 Aid_{it-1} + X_{t-1}\Theta + \varepsilon_{it}. \tag{4}$$

Here, $\ln(y_{it})$ is log GDP of beneficiary country i in year t, and the matrix of control variables contains: government consumption (as a percentage of GDP), investment (as % of GDP), schooling (measured by the secondary school enrollment rate), trade openness (exports plus imports as a % of GDP), year fixed effects. Individual (quasi-dyadic) fixed-effects are in the error term.

By taking the first difference of the equation above, we remove the individual country fixed effects, and the equation we want to estimate thus becomes:

$$\Delta \ln(y_{it}) = \rho \Delta \ln(y_{it-1}) + \theta_1 \Delta Volatility_{it-1} + \theta_1 \Delta Aid_{it-1} + \Delta X_{t-1}\Theta + \Delta\varepsilon_{it}. \tag{5}$$

Estimating this equation poses several endogeneity problem. First of all, $\Delta \ln (y_{it-1})$ is endogenous, by construction. Secondly, $\Delta Volatility_{it-1}$ and ΔAid_{it-1} might also be endogenous since they could be influenced by some unobservable time-varying beneficiary-country factors (which also influences $\Delta \ln (y_{it})$). We thus need valid instruments for all of these variables.

Given that we have to estimate a growth equation in panel data, we will use a system-GMM estimator. We basically estimate a system of equations using GMM

$$\left\{ \begin{array}{rcl} \ln (y_{it}) & = & \rho \ln (y_{it-1}) + \theta_1 Volatility_{it-1} + \theta_1 Aid_{it-1} + X_{t-1}\Theta + \varepsilon_{it} \\ \Delta \ln (y_{it}) & = & \rho \Delta \ln (y_{it-1}) + \theta_1 \Delta Volatility_{it-1} + \theta_1 \Delta Aid_{it-1} + \Delta X_{t-1}\Theta + \Delta \varepsilon_{it} \end{array} \right. . \tag{6}$$

We can thus use the following instruments: the past levels of log GDP ($\ln(y_{it-2}), ..., \ln(y_{it-T})$) to instrument $\Delta \ln (y_{it-1})$, the past growth rates of GDP ($\Delta \ln (y_{it-2})$) to instrument $\ln (y_{it-1})$, and past levels of aid (Aid_{it-2} ... Aid_{it-T}) to instrument ΔAid_{it-1}. We are thus left with the problem of finding valid instruments for aid volatility.

For this, we exploit two intuitive ideas. The first is that the decisions about foreign aid allocations by a donor country's government are fungible with respect to public spending for domestic programs. If a donor country's government is concerned with its public finances and is facing a more severe budget deficit, given the discretionary nature of most foreign aid programs, aid is likely to be among the first programs on which the government has to make a decision (whether to cut it or not) in order to balance its budget. From the point of view of the beneficiaries of this donor, therefore, more severe budget deficits of the donor imply less predictable aid flows.

The second idea is that given that budgetary decisions are made by elected representatives concerned with re-election incentives, we can exploit the fact that political incentives to adjust the aid allocation in response to a worsening budget deficit are not equal under different electoral systems and in various years of the electoral cycle. In particular, under the proportional electoral system, a government's survival typically depends on pleasing its' coalition partners (which is not the case under the winner-take-all majoritarian system). Therefore, when a government faces a more severe budget deficit under the proportional system, its incentives to use the fungibility between aid and domestic programs to avoid displeasing its coalition partners is stronger than under the majoritarian system. Similarly, such incentives are stronger during the election and pre-election years (under any system) than in other years.

Based on these ideas, we consider three excluded instruments for instrumenting volatility. All measures are considered in $t-2$. These instruments are:

1. The average budget deficit of the donors of the beneficiary country, weighted by the 2000-2009 mean of the weight of the donor in the aid flow of the beneficiary (denoted by Def);

2. Def interacted with a dummy variable taking value 1 if the electoral system of the donor is proportional

3. Def interacted with the numbers of years remaining in current term for the head of the executive of the donor country's government.

Our main identifying assumption is, therefore, that the budget deficits of donors and their electoral systems and their electoral calendars are not directly correlated with the economic performance of the beneficiary countries. This assumption can be invalid if there exist some factors that affect both the government finances of the donor countries and the development outcomes of their beneficiaries. The main culprit - the global economic cycle - can be taken care of by adding year dummies into the regression. However, if there are close links between the donor and the beneficiary other than foreign aid (e.g. via trade or remittances), then the validity of the above assumption is not warranted. We will discuss this below.

4 Estimation results

Figure 1 presents visually the simple correlation between the average aid volatility and the average annual growth rate of GDP in our sample. As one can see, the relationship in averages is negative: developing countries that have experienced higher average volatility of CPA in the period 2000-2009 have been growing on average more slowly. However, as discussed above, there are two key issues: the key part of this relationship might be hiding within-country and thus not revealed by the comparison between countries, and there might potentially be time-varying unobservable country-specific factors that drive both the variation in aid volatility and in the economic performance of the beneficiary countries.

One important distinction that one can make within the group of beneficiary countries is the degree of fractionalization (fragmentation) of its aid flows, i.e. the number of its donors. The standard measure of fractionalization is the Herfindahl index. Figure 2 shows the simple correlation between the donor fractionalization and the average aid volatility. There is a (small) positive correlation, i.e. countries whose aid flows are more fragmented also experience a somewhat higher volatility of aid. This indicates the well-known concern about the aid coordination problem.

Table 2 presents the results of the first stage of our two-stage estimation. For a typical beneficiary country, an improvement in the (weighted) average budget balance of its donors significantly reduces the volatility of aid flows that this country receives. Moreover, this is particularly stronger for beneficiary countries whose donors predominantly have proportional representation electoral systems, and in years when a larger fraction of its donors are having national elections. This supports our identification-strategy idea: in the politics of the donor countries, domestic political-economy issues (in particular, budget deficit issues) seems to dominate their international cooperation agendae. In particular, when donor countries are having larger budget deficits and their domestic politics configuration and electoral calendars are increasing the opportunity cost of sticking to their foreign aid plans, the predictability of the next-year aid flows decreases from the beneficiary country's point of view.

Table 3 shows our main results. Column 1 present the results of the "naive" OLS regression with dyad fixed effects, in which the dynamic relationship in the panel data is not taken into account. Standard errors are clustered at the dyad level. The coefficient on the volatility of aid in $t-1$ is positive and statistically indistinguishable from zero: the volatility of aid does not seem to have a negative effect on the GDP growth in beneficiary countries. Note that given the dyad fixed effects in our specification, these are within-country findings. Column 2 shows the results of the regression in which the aid volatility is instrumented as described above. We see that the coefficient on the volatility of aid in $t-1$ turns negative and is very large in absolute size. It remains, however, statistically indistinguishable from zero, although this has mainly to do with a much larger standard errors.

This specification, however, has an important shortcoming in that it treats each observation (for the same dyad) as independent draws from the same probability distribution. This assumption is clearly false, given that most variables in our analyses exhibit important intertemporal persistence. Column 3 thus presents the results of the specification that fully takes into account this dynamic structure of the data. We observe now that the coefficient on the volatility of aid in $t-1$ is negative and highly statistically significant. Column 4 shows that we obtain similar results when we use the deadweight loss of aid volatility as our main independent variable.

As mentioned above, the beneficiary countries differ strongly among themselves in terms of the fragmentation of their aid flows. We have therefore divided our sample into two: countries with above-median fractionalization of aid and those with below-median fractionalization. Columns 5 and 6 present our regression results with a specification identical to that in column 3, but for two sub-samples (above- and below-median fractionalization, respectively). While the coefficient on the volatility of aid in $t-1$ is negative in both columns, we see that almost all of the effect that we have identified in column 3 comes from the countries with high fractionalization of aid. The effect is more than five times bigger for this group (as compared to the countries with low fractionalization of aid flows).

This result of asymmetry in the strength of the effect between the high- and low-fractionalization beneficiaries is particularly comforting, given that the problem of the validity of our identifying assumption is much less present for high-fractionalization countries. Indeed, for the beneficiary countries that have relatively many donors the weight of the trade or remittance links with each individual donor country is quite small. Therefore, a variation in the budget deficit of any given donor is unlikely to have a direct effect on the development outcomes of the beneficiary country.

Table 4 provides some information about the quantitative importance of the effect. A typical beneficiary country in our sample has the annual GDP growth of about 3 percent. Doubling the volatility of its aid flows would reduce this GDP growth to about 1 percent; in other words, the economic performance of the beneficiary country would be cut by two-thirds. This indicates that the negative effect of aid volatility on economic growth is very large.

5 Uncovering the mechanisms

We can now turn to the analysis of mechanisms that drive the negative effect of aid volatility on growth. Following the theoretical framework in section 2, we will look at both the mechanisms that operate through economic channels and those that affect the beneficiary countries' institutions.

Concerning the economic channels, let's first of all note that the effect of volatility on growth that we find does not go through public consumption/public investment reallocation, given that these variables are included in the econometric specification of the growth equation. We cannot thus test for the theories described by Arellano et al. (2009) and Celasun and Walliser (2008). However, we can look at the effect of aid volatility on reallocation towards less investment-intensive sectors.

Column 4 of Table 5 reports the results of the regression similar to the one in Table 3, in which we substitute GDP growth with the share of mineral extraction sector (except oil, gas, and coal) in GDP. The coefficient on aid volatility is positive and highly significant. This indicates that higher volatility of aid flows induces the beneficiary country to change the structure of its production towards a less technologically advanced sector.

In columns 2 and 3 we report the results of the regression in which the dependent variable is male and female employment. Higher volatility of aid seems to hurt particularly strongly male employment. Intuitively, this can be explained by the fact that usually men are employed in sectors that rely on investment more that those in which women are typically employed.

Finally, we can study the causal effect of aid volatility on the institutions of beneficiary countries. To do so, we substitute the dependent variable with the number of battle deaths in violent conflict. The coefficient on aid volatility is positive and highly significant. This seems to confirm the story of Nielsen et al. (2011) and of Svensson (2000): higher aid volatility seems to cause outbreaks of violent conflict, thus undermining beneficiary countries' institutions.

6 Conclusion

In the paper, we have studied the effect of volatility in the country programmable aid on the development outcomes, using a large set of developing countries in the period 2000-2009. We have established a large, negative and statistically significant causal effect of aid volatility on economic growth in beneficiary countries. This average effect hides substantial heterogeneity across countries. In particular, the negative effect of volatility comes almost entirely from the countries with high fractionalization of aid.

We have also investigated the mechanisms behind this effect. The harm that aid volatility generates seems to operate both through economic and institutional channels: higher volatility increases the reliance of the developing economy on the mineral sector and depresses male employment more than it affects female employment. Moreover, higher volatility of aid leads to outbreaks of violent conflict as attested by a higher number of battle deaths. Taken together, these findings seem to support the testable predictions coming from the theoretical models (Arellano et al. 2009, Agenor and Aizenman 2010, Svensson 2000, and Nielsen et al. 2011).

There are several important caveats to our results. First of all, the time-series dimension in our data is quite short, to exploit fully the potential of the ARCH approach. Unfortunately, data limitations do not allow to construct longer series of CPA, whereas using a more standard measure of aid (ODA) would risk to potentially incorrect conclusions. We have opted for a solution that gives a less precise but also potentially less biased estimation. Secondly, we are unable to study the reallocation from public investment to public consumption, which has been highlighted as a key mechanism behind the harmful effect of aid volatility. Finally, although we find evidence for several mechanisms, we do not conduct a horserace comparison of their relative importance.

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Table1: Relative importance of selected donors and recipient

Country	Canada	France	Germany	Japan	USA
Albania	0.67%	1.38%	16.88%	3.31%	19.3%
Bolivia	3.49%	3.85%	12.04%	8.51%	25.36%
Mali	11.50%	22.78%	9.20%	4.96%	14.17%
Thailand	0.73%	4.60%	3.89%	81.13%	4.01%

Table 2: First-stage results

Variable	Obs	Mean	Std. Dev.	Min	Max
def	24650	-1.431725	4.801103	-15.59378	19.08717
cvalldonarch	23693	.2261469	.1319357	.0118139	.85065

```
Fixed-effects (within) regression               Number of obs      =     23693
Group variable: idint                           Number of groups   =      2465

R-sq:  within  = 0.0006                         Obs per group: min =         8
       between = 0.0000                                        avg =       9.6
       overall = 0.0000                                        max =        10
```

cvalldonarch	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
def	-.0002867	.0000831	-3.45	0.001	-.0004496	-.0001237
_cons	.225741	.0002579	875.31	0.000	.2252355	.2262465

cvalldonarch	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
inst	-.0003816	.0001309	-2.91	0.004	-.0006382	-.000125
_cons	.2256573	.0002844	793.48	0.000	.2250999	.2262147

Table 3: Main results (second-stage)

	FE	IV-FE	Dynamic	Dynamic	Dynamic	Dynamic
log(GDP$_{t-1}$)	-0.133***	-0.141***	-0.011***	-0.016***	-0.021***	0.006***
	(0.015)	(0.032)	(0.004)	(0.004)	(0.004)	(0.002)
Investment$_{t-1}$	0.032	0.005	0.098***	0.128***	0.073**	0.101***
	(0.020)	(0.033)	(0.020)	(0.027)	(0.030)	(0.023)
Public Expenditure$_{t-1}$	-0.008	-0.041	-0.077***	-0.081***	0.026	-0.125***
	(0.056)	(0.075)	(0.015)	(0.017)	(0.031)	(0.013)
Human Capital$_{t-1}$	-0.022	-0.022	0.080***	0.082***	0.107***	0.032***
	(0.030)	(0.037)	(0.011)	(0.010)	(0.011)	(0.009)
Democracy$_{t-1}$	-0.002*	-0.002	-0.002***	-0.002***	-0.000	-0.004***
	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Openness$_{t-1}$	0.049***	0.065**	0.003	0.004*	0.003	0.003
	(0.011)	(0.026)	(0.002)	(0.002)	(0.004)	(0.003)
Total Aid$_{t-1}$	0.379***	0.473	0.180***	0.064	0.074	0.229***
	(0.041)	(0.628)	(0.048)	(0.053)	(0.088)	(0.036)
Volatility$_{t-1}$	0.014	-0.602	-0.108***	-0.300***	-0.083***	-0.016
	(0.013)	(0.404)	(0.024)	(0.075)	(0.025)	(0.020)
Sample	Complete	Complete	Complete	DW	High_frac	Low_frac
R-squared	0,34	0,15	0,23	0,23	0,24	0,19
Number of Observations	11017	9686	11339	11837	5228	6111
Number of Dyads	1503	1477	1825	1825	1183	1316

Clustered standard errors in parentheses

Table 4: Size of the effect

	FE	IV-FE	Dynamic	Dynamic	Dynamic	Dynamic
log(GDP_{t-1})	-0.133***	-0.141***	-0.011***	-0.016***	-0.021***	0.006***
	(0.015)	(0.032)	(0.004)	(0.004)	(0.004)	(0.002)
Total Aid_{t-1}	0.379***	0.473	0.180***	0.064	0.074	0.229***
	(0.041)	(0.628)	(0.048)	(0.053)	(0.088)	(0.036)
$Volatility_{t-1}$	0.014	-0.602	-0.108***	-0.300***	-0.083***	-0.016
	(0.013)	(0.404)	(0.024)	(0.075)	(0.025)	(0.020)
Marginal effect (dy/ex) - g=0.03	-	-	-0.02	-0.02	-0.02	-0.00
Sample	Complete	Complete	Complete	DW	High_frac	Low_frac
R-squared	0,34	0,15	0,23	0,23	0,24	0,19
Weak Identification CD	-	9,280	9,280	9,280	9,280	9,280
		(bias =6%)	(bias =6%)	(bias =6%)	(bias =6%)	(bias =6%)
Overidentification J	-	0,980	248,690	263,620	106,570	161,900
		(p=0.613)	(p=0.336)	(p=0.237)	(p=1.000)	(p=0.679)
Number of Observations	11017	9686	11339	11837	5228	6111
Number of Dyads	1503	1477	1825	1825	1183	1316

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Mechanisms

VARIABLES	Battle deaths	Female employment	Male employment	Mineral/GDP
AR(1)	0.920***	0.994***	0.983***	0.988***
	(0.088)	(0.004)	(0.008)	(0.010)
log(GDP_{t-1})	127.992**	-0.086	-0.173**	0.093***
	(50.013)	(0.054)	(0.070)	(0.033)
$Investment_{t-1}$	-493.450*	-0.586	-2.788**	1.145**
	(267.567)	(1.082)	(1.090)	(0.451)
Public $Expenditure_{t-1}$	-610.725***	-0.292	-0.246	-0.532**
	(189.523)	(0.395)	(0.432)	(0.229)
Human $Capital_{t-1}$	-601.661***	1.149***	1.461***	-0.179*
	(165.939)	(0.249)	(0.277)	(0.098)
$Democracy_{t-1}$	3.335	0.029**	0.006	-0.002
	(5.483)	(0.012)	(0.019)	(0.012)
$Openness_{t-1}$	-46.983	-0.166***	-0.158*	-0.092**
	(33.193)	(0.064)	(0.086)	(0.037)
Total Aid_{t-1}	-712.348	1.497	0.278	0.965*
	(457.239)	(0.932)	(1.108)	(0.587)
$Volatility_{t-1}$	1,668.236***	-0.507	-0.942**	0.796**
	(439.219)	(0.366)	(0.417)	(0.324)
R-squared	0,02	0,001	0,02	0,02
Observations	10176	10249	10249	10866
Number of idint	1801	1808	1808	1804

Clustered standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Figure 1: Aid volatility and GDP growth

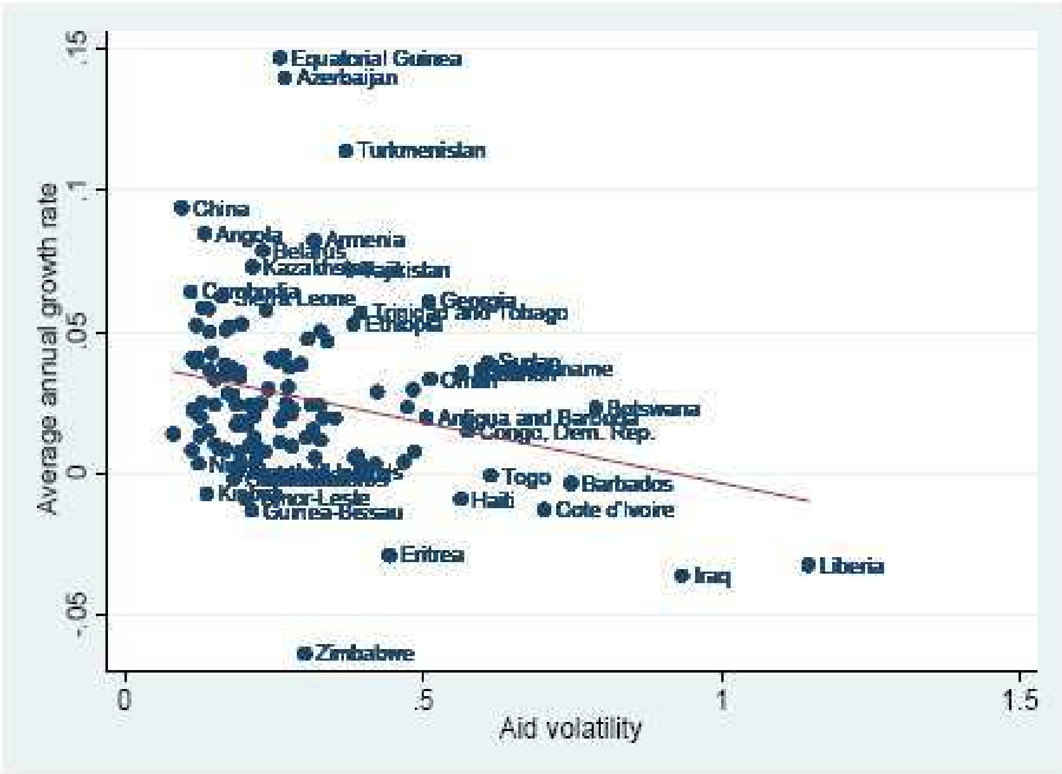

Figure 2: Aid fractionalisation and volatility