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Who gives aid to whom and *when*? Aid accelerations, shocks and policies

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Abstract

We address the pitfalls of averaging by exploiting the longitudinal variation in aid to identify sudden and sharp increases in aid flows. Focusing on specific events, we test if aid accelerations correspond to policies and shocks in the recipient country. For a large sample of 145 recipient countries and 33 donors from 1960-2007, we find that positive regime changes and wars are significant predictors of aid accelerations. Disaggregating aid flows by donors, we find indicative evidence for competing allocation rules, particularly among European donors. We argue that drivers of aid accelerations differ from drivers of average aid flows - a distinction that can reconcile some of the ambiguous empirical results in the aid literature.

Keywords: ODA, growth accelerations, policies

JEL codes: O1, F35, F50

1 Introduction

This paper uses an event study approach to understand some under-researched aspects of aid allocation. While the current literature on aid allocation largely neglects aid volatility by averaging out fluctuations, we exploit the longitudinal variation in aid by identifying sudden and sharp increases in aid flows for a recipient country. By focusing on these episodes of *aid accelerations*, we explicitly test if shifting aid flows correspond to events in the recipient country. This allows us to explore several policy questions: Do donors reallocate aid following civil conflicts and wars? Do donors support developing countries that democratize or pursue economic reforms? And, perhaps most importantly, are aid flows coordinated or do donors pursue competing interests?

Using a large sample of 145 recipient countries and 33 donors covering the period 1960 to 2007, we find evidence for a significant positive relationship between domestic events

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and subsequent aid accelerations. Positive regime changes and wars, in particular, are significant predictors of aid flows: International wars are not only associated with aid accelerations in the recipient country but also predict increasing aid flows in neighboring countries. Internal conflicts, in contrast, do not exhibit a systematic association with aid accelerations. Disaggregating the aid flows by donor countries, we find indicative evidence for competing allocation rules, particularly among European countries. Our main result is robust to changes in measures and the definition of an aid acceleration.

This paper contributes to three areas of research: First, the paper contributes to the methodology in the aid literature by employing an empirical strategy hitherto only used in the growth and business cycle literature (Hausmann et al., 2005). Second, we touch upon the fragility of aid regressions by arguing that drivers of aid accelerations differ from drivers of average aid flows - a distinction that can reconcile a range of contradicting and ambiguous results (Roodman, 2007). Finally, we add value to the emerging field of security economics by examining spill-overs in conflict and aid, thereby testing for the "securitization of aid" (Murdoch and Sandler, 2002; Woods, 2005).

The remaining sections are organized as follows: Section II reviews the literature on aid allocation and aid volatility, arguing that most work on aid allocation has not explicitly looked at the dynamics of aid allocation by averaging out most of the large annual fluctuations. Section III first provides some stylized evidence to characterize country-specific aid volatility and then proposes a filter to identify aid accelerations. Section IV uses a probit model to study the predictors of aid accelerations. Section V concludes.

2 Literature

2.1 Determinants of (average) aid allocation

The main criteria of aid allocation can be divided into economic and political factors[3]. Aid, according to economic factors, should flow to the poorest countries, either to meet financing gaps (Easterly, 1997) or to yield its highest marginal return (Collier and Dollar, 2002a). Along political factors, on the other hand, aid should flow to low income countries with "good" institutions to prevent rent-seeking and capture by corrupt regimes (Azam and Laffont, 2003). Political factors can also subsume interests of the donor coun-

[3]This paper focuses on aid allocation and does not discuss the vast aid effectiveness literature. For a review of latter field, refer e.g. to Doucouliagos and Paldam (2010)

try, where aid is allocated along historical path dependencies, ideologies, trade interests or even domestic security concerns (Azam and Delacroix, 2006).

The evidence in the empirical literature, however, is mixed: Alesina and Dollar (2000) test for both economic and political criteria in aid allocation using a panel of 128 recipient countries and 20 donors. In addition to economic factors proxied by GDP per capita and country size, the authors find significant evidence for political and strategic considerations, such as historical colonial ties and political alliances. In contrast using a similar empirical strategy, Burnside and Dollar (2004) and Alesina and Weder (2002) find no evidence that their proxies for policies and governance possess statistically significant explanatory power for aid allocation.

The empirical strategy for most existing contributions, however, follows the specification of growth regressions, relying on regressing period averages on averaged explanatory variables. Yet, aid growth is conceptually very different from conventional GDP growth: This is well illustrated in Balla and Reinhardt (2008), where a Heckman model is used to capture the two stage nature of aid allocation. The donor first decides whether to allocate aid at all and only then decides how much aid is allocated. Estimating the determinants of aid in two stages, the authors find a significant association between aid and conflict, as well as evidence for aid spill-overs from conflicts in nearby countries.

Our strategy is not concerned with these time-invariant or slowly changing drivers that drive average aid flows; instead, we examine the association between specific economic, political and social events in the recipient country and the decision of the donor to increase aid flows. By doing so, we contribute to a clearer distinction between long-run drivers of average aid flows and short-run drivers of sudden changes in aid flows.

2.2 Aid volatility and the pitfalls of averaging

While there is a large body of literature examining the low persistence of economic growth, only few studies have explicitly dealt with the volatile nature of aid flows. For economic growth, Easterly et al. (1993) first prominently contrasted the high persistence of policies against the large cross-decade volatility of economic growth: Some countries like Singapore, Mauritius or Chile would experience sudden upward shifts in growth rates, while other countries like Afghanistan, Nicaragua or Zimbabwe would suffer sudden growth collapses. Periods of spectacular growth would follow periods of sudden collapses, generating country-specific growth patterns (Pritchett, 2000).

These crucial structural breaks, however, were ignored by conventional growth empirics where growth rates were commonly averaged over longer periods (Johnson et al., 2004). While the averaging procedure removed measurement errors, it came at the cost of introducing serial correlation and losing annual variations that were possibly key to understanding the drivers of growth (Acemoglu et al., 2008). Departing from this shortcoming, Hausmann et al. (2005) and Hausmann et al. (2006) employed an innovative turning point approach. By identifying sudden growth spurts and collapses and examining correlates around these turning points, it was hoped to find possible drivers of shifts in growth trajectory beyond average-based regressions. Since publication of this seminal article, the methodology has been widely applied to study patterns of growth (Dovern and Nunnenkamp, 2007; Jones and Olken, 2008; Jong-A-Pin and Haan, 2011).

The role of longitudinal variation, however, is even more important for the case of aid flows: On the one hand, the sum of aid disbursed is likely to be procyclical and correlated with the business cycles of the donor countries[4]. On the other hand, a large fraction of aid is often allocated following events in the recipient country, for example food aid or peacekeeping support following prolonged droughts or conflicts, respectively. Anecdotal evidence includes substantial aid inflows following the Iraq and Afghanistan wars, as well as sudden cuts of aid flows in the aftermath of a negative regime change.

Consider the case of Afghanistan: Figure 1 plots the growth rates of total net bilateral aid flows between 1960 and 2005 using different averaging periods. In contrast to the annual growth rates, period averages exhibit much lower standard deviations: While the standard deviation for annual growth rates is 0.67%, it is 0.22% for five year periods and only 0.03% for ten year periods. While smoothing short-run volatility is theoretically justified when examining long-run trend changes in output growth (Hodrick and Prescott, 1997), averaging removes crucial turning points for aid: In contrast to the stark aid collapse coinciding with the Soviet invasion 1979, seven and ten year averages would even suggest a slight increase in aid growth. Similarly, variations coinciding with the Soviet exit 1987, the end of the Cold War and the US Invasion 2001 are not captured. Along the period averages, aid flows would have roughly remained constant throughout the period. If the determinants of aid flows are of main concern, it is not surprising that estimations using smoothed data often prove fragile (Meyer and Winker, 2005).

[4]Paragraph 42 of the 2002 Monterrey Consensus, for example, explicitly states "we urge developed countries that have not done so to make concrete efforts towards the target of 0.7 percent of gross national product (GNP) as ODA to developing countries." (UN Report of the International Conference on Financing for Development 2002, A/CONF.198/11.)

Indeed, a growing body of literature stresses the volatile nature of aid. Among a number of similar studies (Fielding and Mavrotas, 2005; Hudson and Mosley, 2008a), Bulir and Hamann (2008) for example find that aid flows are not only procyclical in the recipient country, but exhibit higher variances vis-à-vis revenue, particularly for aid-dependent countries. In addition, there is often a large discrepancy in the amount of aid commited and actually disbursed, rendering aid flows unpredictable. This volatility, combined with a procyclical allocation, does not only render aid less effective but also intransparent, allowing corrupt officials to extract rents (Hudson and Mosley, 2008b; Cage, 2009).

Surprisingly, the related literature on the determinants of aid flows has not yet acknowledged the important role of aid volatility, resorting to the same averaging process done in growth regressions: Out of the nine major contributions examined in Roodman (2007), for example, eight rely on four year periods and one on twelve year periods. But if aid is indeed volatile, with aid inflows timed along high frequency events, current findings on aid allocation might have averaged out most of the story.

3 Identifying aid accelerations

3.1 Evidence for aid volatility

Before proceeding with the empirical strategy, we establish a few stylized facts underlining the significance of aid volatility. In line with Pritchett (1998), we employ simple measures to characterize annual aid flows. The data for net disbursed aid (constant 2009 USD) is obtained from OECD Development Assistance Committee (DAC), the most commonly used dataset in the aid literature. The DAC data defines ODA as flows to countries which are provided by official agencies (states and local governments) and aimed at promoting economic development and welfare in developing countries. Most importantly for the purposes of examining aid and security, ODA along the DAC definition does not include military aid or peacekeeping aid[5]. Table 1 reports measures of aid volatility for the total aid flows and a breakdown by selected donor countries.

For total aid flows, the median aid growth of all recipient countries is 5.7%, with a median standard deviation of 67.7%. The median variation coefficient is accordingly high, implying very large within fluctuations relative to the mean aid growth rate. The variation is highest for United States and lowest for Germany. The volatility becomes

[5] For a detailed explanation of this definition, see http://www.oecd.org/dataoecd/21/21/34086975.pdf

even more apparent when fitting a single linear trend for $log(1 + aid)$ for each country: The median standard deviation of the deviation from trend (residual) is about 0.65% for the total aid flows and increases even more once disaggregated by single donors. The median R^2 of the single trend model is low: The linear trend explains only 1.4% of the variation in total aid flows. Once disaggregated, the median R^2 is nearly zero.

Figure 2 complements the summary statistics by presenting exemplary time-series for total aid flows to illustrate the aggregate volatility. Following the metaphors in Pritchett (1998), the volatile aid flow for a given country can be characterized using distinct patterns. There are, for example, periods of steady declines ("valleys") such as in Afghanistan 1980-85, Egypt 1965-70 or Israel 1965-70. These periods are followed by sudden increases in aid ("steep hills") that either stagnate at a high level (for example the "plateau" in Afghanistan 1990-2000) or gradually decline (the "mountain" pattern in Egypt). The volatility is further increased by "spikes", large and one-off inflow or outflow of aid like in Israel 1995 or Afghanistan 1991. These patterns are often associated with events such as treaties or wars but are averaged out in panel regressions.

In addition to the within country variations, there are also large variations in how aid is allocated *across* recipient countries: One way to capture this is to interpret the allocation as the outcome of developing countries competing for shares of aid (Epstein and Gang, 2009). Following this intuition, the Herfindahl index - originally applied to measure industrial concentration - can be used to capture how concentrated or dispersed a donor allocates aid (Hirschman, 1964). We compute normalized Herfindahl indices over time for total aid flows and a breakdown by the largest donors.

Figure 3 plots the time-series from 1980 to 2009. While there does not appear to be a clear trend, there are obvious level differences across countries. In comparison to other large donors, US aid flows are most concentrated on average, with an average Herfindahl of 0.09. German aid flows, on the other hand, tend to be more dispersed, with a Herfindahl of 0.03. Like the within volatility, the between volatility in allocation is large: The US Herfindahl, for example, exhibits large sudden "spikes" that are associated with specific events: While Israel received 8% of all bilateral aid disbursed by the US in 1995, the share jumped to 44% in 1996, the year when Operation Grapes of Wrath was launched against Lebanon. The second spike coincides with the aftermath of the Iraq war. While pre-2003 Iraq received nearly zero aid from US, bilateral aid to Iraq had increased up to 55% of all US aid disbursed in 2005. Even if these examples comprise

the extreme cases, the annual volatility in the share of aid allocated is substantial.

3.2 Constructing the filter

In order to systematically identify sudden spurts of aid inflow, we adjust the original criteria found in Hausmann et al. (2005) for the case of aid. Let $y_{i,t,t+4}$ denote the least squares average annual growth rate[6] of the aid flow from t to $t+4$. By definition, an aid acceleration has occurred in country i if and only if:

$$y_{i,t,t+4} \geq d(y_i) \text{ (Increase in aid is large)} \quad (1)$$

$$\Delta y_{i,t,t+4} \geq d(\Delta y_i) \text{ (Increase in aid is accelerating)} \quad (2)$$

where $d(\cdot)$ returns the 9th decile cut-off for the y_i and Δy_i of country i. We depart from the original filter in Hausmann et al. (2005) in three aspects:

First, while Hausmann et al. (2005) set cut-off points for all countries at $y_{i,t,t+7} \geq 3.5\%$ and $\Delta y_{i,t,t+7} \geq 2\%$, we aim to account for country specific volatility by setting the threshold at each country's highest decile, thereby allowing each country to have its own cut-off. While common cut-offs for GDP growth rates can be justified on the basis of "stylized facts" (e.g. steady-state GDP per capita growth is 2% p.a.), aid volatility is largely country specific. Second, while the original filter was aimed at capturing long-run trend shifts using 8 year periods, we examine 5 year periods[7]. Again, the reason here is the high volatility of aid where single year blips ("spikes") are averaged out using long periods. Third, we drop the last condition of the original filter that excluded periods of convergence growth ($y_{i,t,t+7} \geq \max(y_i) \forall i \leq t$). While an ever rising GDP is deemed favourable, it does not hold for aid flows. Since the concept of convergence growth is not transferable to the growth of aid flows, we simplify the filter by removing this rule. Finally, we follow Hausmann et al. (2005) and employ a structural break test to determine the onset when several subsequent years qualify as an aid acceleration. In line with Xu (2011), we interpret the original test as a Chow test and date the onset to the year where the test statistic is highest among the subsequent years.

[6] The least squares growth rate of aid from t to $t+n$ is the coefficient obtained by an OLS regression of $\log(y_{i,t+j}) = a + g_{i,t,t+n}t$, $j = 0 \ldots n$

[7] Since we are running a structural break test (see below), we need at least 4 year periods in order to estimate the parameters. To ensure the results are not driven by our definition, we also experimented with different periods but the results do not change substantially.

3.3 Aid accelerations

We find a large number of aid accelerations (Figure 4): Based on the filter employed, we identify 215 aid accelerations for the total flow of all aid allocated between 1960 and 2007 (Table 2)[8]. For the sample of 145 countries, this translates into 1.5 accelerations per country on average. Examining the list, it is encouraging to see that the modified filter roughly identifies most of the well-known accelerations often associated with specific events (e.g. Egypt 1968, Somalia 1991, Afghanistan 2000, Iraq 2002). But like the case of growth accelerations, there are also a large number of episodes that do not appear to be associated with any large and observable changes. The question how far events such as regime changes, international wars or civil conflict *consistently* correlate with these accelerations will be examined below using a probit regression.

The unconditional probability of an aid acceleration is calculated by dividing the number of accelerations by the total number of country-years. Dividing the 215 accelerations by the 5308 country-years yields an unconditional probability for an acceleration of about 4% for a given country-year. This probability does not vary substantially across decades: The probability of an acceleration is 4% for the 60s, 5% for the 70s and about 3.5% for the 80s and 90s. The region[9] with the highest probability is 4.7% in Middle East and North Africa and lowest in Eastern Europe and Central Asia with 2.8%. The unconditional probability does not change substantially when separately applying the filter to each donor: The unconditional probability is highest for USA (4.5%) and United Kingdom (4.4%) and lowest for Sweden (2.8%) and Spain (3.4%).

Aid accelerations do not only occur frequently, but their magnitudes are very large: On average, the least squares growth rate $\bar{g}_{t,t+4}$ of an aid acceleration over 5 periods is 92.75% p.a., with a considerable acceleration vis-à-vis the previous period of 118.91% ($\Delta\bar{g}_{t,t+4}$). Since these changes in aid allocation are sudden and substantial, they are likely to correspond to policy changes or other events in the recipient country.

The volatility of aid becomes once more apparent when dividing accelerations into unsustained and sustained accelerations. By definition, an aid acceleration is sustained if its least squares average growth rate in $[t+5, t+9]$ is positive and unsustained otherwise. Applying this rule, 66 of the 215 episodes are flagged as unsustained accelerations with a $\bar{g}_{t+5,t+9} = -19.1\%$, implying that almost a third of the large increases in aid are

[8] Refer to the Webappendix for a complete list of aid accelerations

[9] We follow Hausmann et al. (2005) by using their regional definitions.

partially reversed. While the majority of accelerations are sustained, the subsequent average growth rate is 63.65% lower than during the acceleration.

4 Predicting aid accelerations

4.1 Estimation and approach

We fit a probit model to gauge the association between a range of explanatory variables and the onset of aid accelerations. In brief, we estimate:

$$y_{it} \quad = \quad \Phi(x_{it}\beta + d_t\gamma + z_i\delta + \epsilon_{it}) \tag{3}$$

where $y_{it} = y_{it+1} = y_{it+2} = 1$ if an acceleration occured in country i at year t. We code the two periods following an acceleration as 1 to account for imperfections of the filter in identifying the exact turning point. Since the empirical strategy compares countries with aid accelerations in a given year to countries without, we drop all data pertaining to the periods $t + 2...t + 5$. We regress the onset of an aid acceleration y_{it} on the $1 \times k$ vector x_{it} that captures changes in a set of k explanatory variables. d_t is a $1 \times T$ vector of dummies that varies over the T years and controls for time-variant confounds all recipient countries are equally subject to. z_i is a $1 \times R$ vector controlling for time invariant effects of the R regions the countries are grouped into. β, γ and δ are the vector of coefficients, where the main interest lies on the estimated β. ϵ_{it} is the disturbance term and Φ is the cdf of a standard normal distribution.

4.2 Explanatory variables

Conflict: The main conflict variables are derived from the UCDP/PRIO Armed Conflict Dataset v4-2009 (Gleditsch et al. 2002), documenting conflicts over the period 1946-2008. The dataset enables a distinction between international wars and internal wars[10]. $prio\_inter1_{it}$ is a dummy indicating the outbreak of an interstate conflict or internationalized internal armed conflict. Analogously, the dummy $prio\_intra1_{it}$ captures an internal armed conflict in i at t. We combine the conflict dataset with a distance matrix from CEPII (Mayer and Zignano 2006) to construct measures for spill-over effects.

[10]Since the main focus is on abrupt and large changes, we restrict the analysis to conflicts with at least 1.000 battle-related deaths in a given year.

$prio\_inter3x_{it}$ is a dummy for international conflicts beginning in t that are located in countries bordering country i. Similarly, $prio\_intra3x_{it}$ is a dummy that captures a internal conflicts occuring in the direct neighborhood of country i at t.

Policy: In line with Hausmann et al. (2005), we measure changes in political institutions using the Polity IV index (Marshall and Jaggers 2009). The Polity IV dataset assigns a score ranging from -10 to 10 for each country-year beginning 1800, where higher values indicate a larger degree of democracy. Along the manual, positive or negative regime changes are annual changes by at least three unit points in the respective direction.

Economic reforms are crudely proxied using a dummy for openess. Constructed by Sachs and Warner (1995), we use the updated data from Wacziarg and Welch (2008). Although originally designed to capture trade liberalization, we argue that these liberalizations are accompanied by substantial changes in economic fundamentals and serve as an adequate proxy for changes in economic policy (Hausmann et al., 2005).

Geopolitics: Finally, we use three dummies that capture changes in geopolitics. To capture the changing logic of aid allocation following the collapse of the Soviet Union (Kanbur, 2003), $coldwar_t = 1$ for all t up to 1990 and 0 for subsequent years. $indep_{it} = 1$ if country i declared independence in t. As 9/11 is associated with the securitization of aid (Wood 2005), $post2001_t = 1$ for all t after 2001. To allow for a delayed response to year-specific events, all dummies are also coded 1 for $t \ldots t + 2$[11].

4.3 Drivers of aid acceleration

Table 3 presents a step-wise inclusion of the event variables for a regression based on aggregate aid accelerations. In Column I, we report the baseline specification using the two immediate conflict variables. International conflicts are significantly associated with aid accelerations, while internal conflicts are statistically insignificant. The difference between both types of conflicts becomes once more apparent when including spill-overs (Column II). Countries bordering neighbors subject to international conflicts are significantly more likely to experience sudden aid inflows, while the association is not significant for neighbors with internal conflicts.

In contrast to negative regime changes, positive regime changes are significantly associated with aid accelerations, albeit at a low significance level ($p = 0.034$). Economic

[11] This is a standard procedure in Hausmann et al. (2005). As the choice of lag introduces additional degrees of freedom, we conduct robustness checks with different lags (Section 3.).

reforms - proxied as transitions towards openess - exert no statistically significant association with the probability of aid accelerations (Column III). Geopolitical events such as the declaration of independence are significantly associated with aid accelerations (Column IV). International conflicts, their spill-overs and positive regime changes remain statistically significant once controlling for regional fixed effects (Column V). In addition, the Cold War coefficient turns significant, arguably since Cold War aid accelerations were mostly confined to a few regions (Berger et al., 2010).

Even though the interpretation of non-linear models is not straightforward, it is worthwhile to examine the economic significance of the coefficients. With other variables held constant at their means, the marginal effect of an international war and its spill-over on the probability of an aid acceleration is 10.8% and 7.2%, respectively: For an "average country" in an "average year", the outbreak of an international conflict raises the probability of an aid acceleration by about 11% points. Even if the country itself is not experiencing an international conflict, the occurence of such in a bordering country raises the probability by around 7% points. The marginal effect of independence is of similar magnitude (9%) but the coefficient for positive regime changes is small (3.5%).

In order to gauge the differences between our event study and conventional averaging, we compare the aid accelerations approach (Table 4, Column I) to standard OLS specifications that use various period averages for aid growth (Roodman, 2007). The results based on averaging tend to diverge from the results of the event study. Most of the explanatory variables are fragile upon changes in the averaging period (Column II-V): The coefficient for international conflicts, for example, is insignificant using annual averages, positive significant using 5 year averages, negative significant using 7 year averages and insignificant again using 10 year averages. Once more, the results suggest that existing work based on averages might have masked a range of short-run responses, with results possibly driven by artifacts of averaging over longer periods.

4.4 Do donors coordinate?

In Table 5, we report the regression by donor breakdown using the full specification (Table 3, Column V). Even though missing values and different time periods complicate a comparison between the regressions, the results at least indicate that donors within the OECD Development Assistance Committee (DAC) follow different allocation rules: Out of the ten largest DAC donors, the coefficient for international conflict and positive

regime change is only significant for five donors. The coefficient for economic reforms, for example, is only significant for Japan and Spain but point to different directions. As another example, while the spill-over coefficient for internal conflicts is positive and significant for USA, Japan and Norway, the estimated coefficient for Sweden points to the opposite direction. Overall, Sweden appears to allocate aid very differently, being the only country with a significant spill-over coefficient for internal conflicts.

The disaggregation also suggests that the "net" effect for accelerations based on total aid flow masks a diverse range of counteracting allocation rules. While the spill-over term for internal conflicts is significant for four of the ten largest DAC donors, the opposing signs render the overall coefficient insignificant for predicting aggregate aid accelerations. Similarly, the aggregate results would suggest a significant positive coefficient for the declaration of independence but the disaggregation shows that countries such as United Kingdom, Japan and Netherlands alone tend to do the opposite.

If all countries aimed to allocate aid according to similar "efficiency" criteria (Collier and Dollar, 2002b), this result would be discouraging. The case of the European Union (EU) provides a striking example of a possible coordination problem. Despite the repeatedly declared efforts in harmonizing foreign and security policy, aid allocation is not only incoherent but the competing aid flows tend to offset each other. This renders the overall EU aid accelerations highly unpredictable by our model.

To illustrate this, Table 6 reports a step-wise regression with accelerations based on the pooled EU aid flows. Unlike the baseline regression in Table 3 that exhibited a distinct pattern for the prediction of aid accelerations, none of the event variables - conflicts, wars, geopolitical shifts - turn out to be statistically significant predictors for the EU. Only the coefficient for Cold War turns out significant once controlling for regions. If the EU acted as a unitary donor, however, one would expect clearer allocation rules.

While the underlying reasons (coordination failure, political interests etc.) for the competing behaviour is unclear, it is possible to examine which countries allocate aid along similar rules by examining how often growth accelerations coincide between donors. A simple approach is to calculate the Jaccard index for the binary acceleration indicator and examine the resulting similarity matrix. Table 7 presents the results for EU donors: Within the EU, the aid accelerations of United Kingdom and Netherlands are most synchronized (0.079), followed by the French-German and German-UK aid flows (0.07). While Sweden and Norway are often aggregated as the "Scandinavian donors" (Alesina

and Dollar, 2000), the similarity index between their aid accelerations is actually relatively low (0.029). The most dissimilar aid accelerations are between Germany and Netherlands (0.009), followed by Germany-Spain (0.011) and Sweden-UK (0.014).

4.5 Robustness checks

As macroeconomic studies are notoriously prone to fragility (Roodman, 2007; Jarocinski and Ciccone, 2009), we do robustness checks to check the validity of our results:

We replace the UCDP/PRIO conflict variable with a measure based on the Major Episodes of Political Violence (MEPV) data (Marshall 2010). In contrast to binary indicators from UCDP/PRIO, the MEPV data assigns different intensities to the conflicts. We generate proxies for international and internal conflicts based on the distinction between interstate MEPV and "societal" MEPV[12]. The main results for international war and their spillovers remain stable but the coefficient for internal wars turns significant (Table 8, Column II). This, however, is driven by the different coding scheme of the MEPV, where some international conflicts were coded as internal conflicts[13]. We also replace the Polity IV proxies using a similar measure based on the Freedom House dataset. The coefficient for positive regime changes remains stable, with negative regime changes turning marginally significant (Column III).

In addition, we alter the filter rule by reducing the 9th decile cut-off to an 8th decile cut-off and remove the lag, instead coding the period around an acceleration as accelerations as well (Hausmann et al., 2005). Again, the main results remain stable (Column IV), providing evidence that the results are not artifacts of the filter. Finally, we re-estimate the probit model using the linear probability model (LPM) and a Tobit specification but the results again do not change substantially (Column V-VI).

5 Conclusion

This study examines the relationship between aid accelerations and domestic events. By drawing upon a methodology from the growth literature, we depart from conventional approaches, focusing on specific events rather than period averages: Our findings suggest

[12]Interstate MEPV is the sum of international violence and international war, while "societal" MEPV is the sum of civil violence and war and ethnic violence and war.

[13]The Soviet invasion in Afghanistan, for example, is coded as an internal conflict in the MEPV.

that events such as wars, regime changes and geopolitical shifts are statistically significant predictors of aid accelerations. We also find evidence for spill-overs, where countries that neighbor war-torn countries are almost as likely to have an aid acceleration - even in absence of a conflict spill-over. By disaggregating aid flows, we find indicative evidence for competing aid allocation rules. In the case of the EU, these competing rules offset each other, rendering the overall aid flows highly idiosyncratic.

Even though our empirical strategy does not identify causal effects *per se*, our evidence is at least more causal than existing correlations: By exploiting the temporal dimension using the event-based approach, we argue that the causation runs from domestic events to donor response. While temporal sequence need not necessarily reflect causation[14], it is unlikely that the outbreak of large domestic events (e.g. a civil war) is driven by the anticipated subsequent influx of aid. Since aid accelerations often coincide with specific domestic events, it is further possible to complement the quantitative study with qualitative case studies in order to more reliably infer to causality. This is another advantage of our approach in comparison to average-based regressions.

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6 Appendix

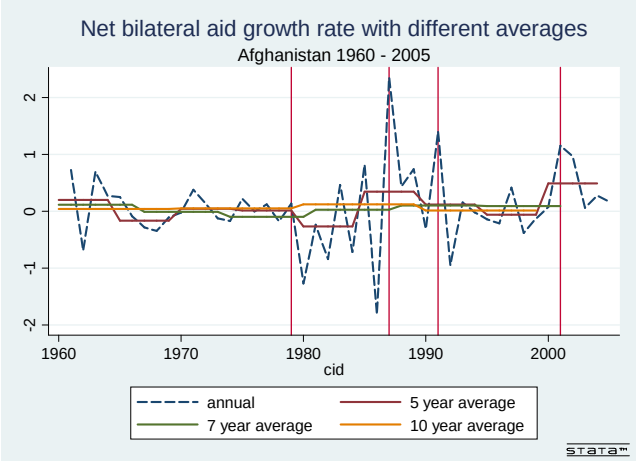
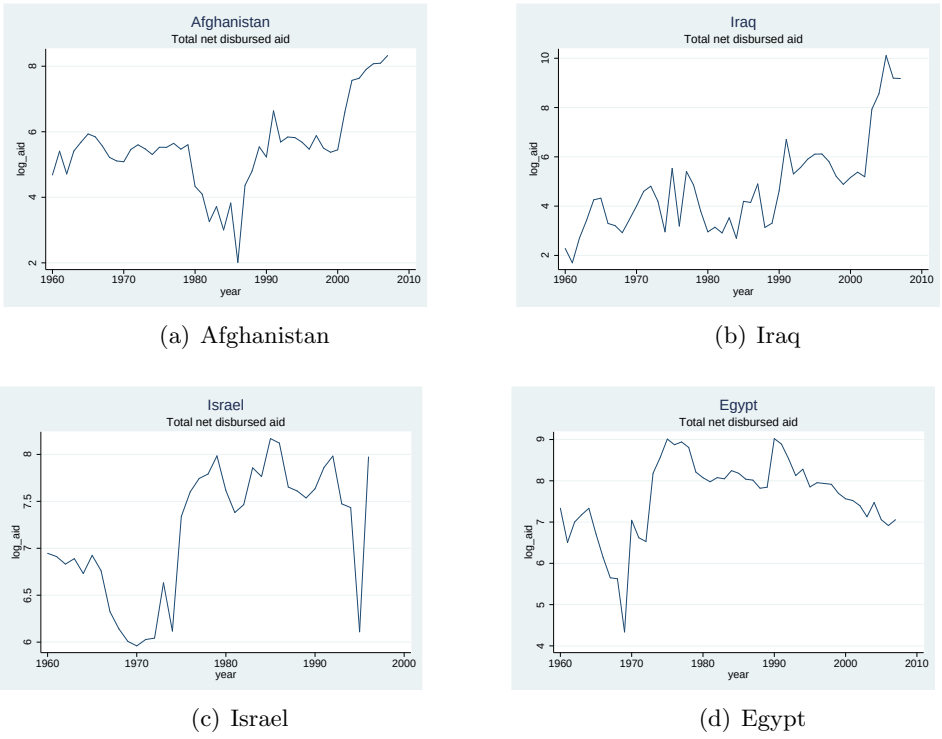


Figure 1: Net bilateral aid (OECD DAC) growth rate with different period averages. First break in 1979 coincides with the Soviet Invasion, second break coincides with the withdrawal in 1987, third break coincides with the Afghanistan War 2001.

	Std of dev. from trend	1st diffs. CoV	Stdev	Mean	Median abs. 2nd diffs.*100	Trend R^2
Aid from all donors						
Mean	1.208	57.145	1.231	0.081	-1.697	0.055
Median	0.649	9.039	0.677	0.057	-0.956	0.014
Standard deviation	1.167	165.025	1.166	0.127	7.596	0.087
Aid from USA						
Mean	2.090	85.474	2.110	-0.012	-1.173	0.005
Median	2.078	30.367	2.099	0.007	0	0.005
Standard deviation	1.297	166.481	1.295	0.156	23.102	0.074
Aid from GBR						
Mean	1.879	1089.28	1.902	-0.011	-5.1	0.031
Median	1.920	21.890	1.947	-0.014	0	0.005
Standard deviation	0.958	123.768	0.955	0.148	26.2	0.073
Aid from GER						
Mean	1.673	80.52	1.704	0.017	0.07	0.043
Median	1.444	17.88	1.466	0.063	-0.1	0.013
Standard deviation	1.108	524.79	1.122	0.223	35.99	0.072
Aid from FRA						
Mean	1.594	66.088	1.613	0.018	0.131	0.030
Median	1.316	24.367	1.325	0.028	0	0.006
Standard deviation	1.126	118.418	1.129	0.121	37.228	0.053
Aid from SWE						
Mean	2.171	189.159	2.216	0.053	-3.677	0.046
Median	2.222	25.813	2.277	0.052	0	0.007
Standard deviation	1.047	1086.34	1.048	0.119	50.332	0.102

Table 1: Evidence for aid volatility - summary statistics (within volatility)



(a) Afghanistan (b) Iraq

(c) Israel (d) Egypt

Figure 2: Selected time series of total aid inflow (net aid disbursed, constant 2009 USD)

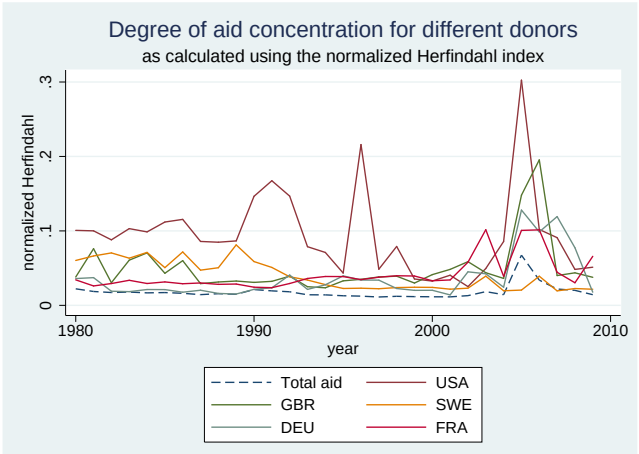
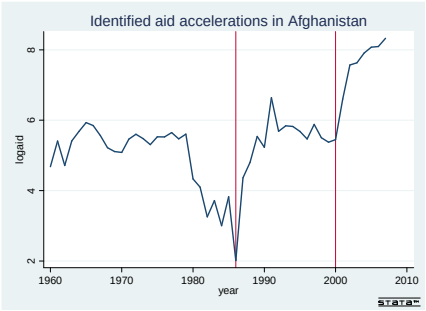
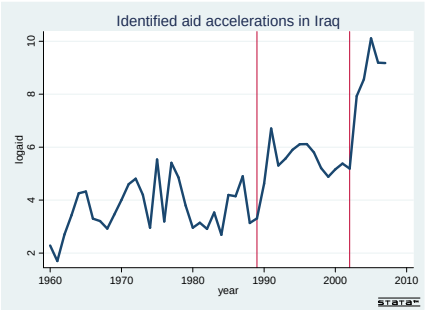


Figure 3: Degree of aid concentration for different donors (between volatility)



(a) Afghanistan



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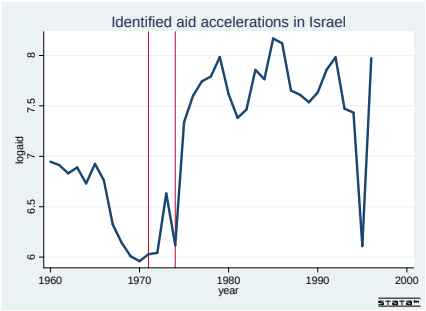

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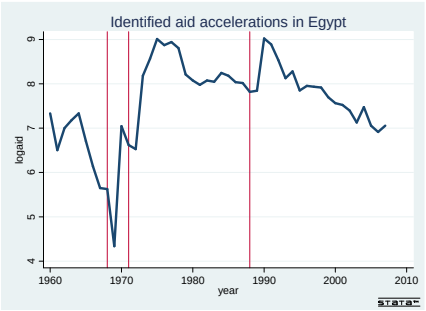
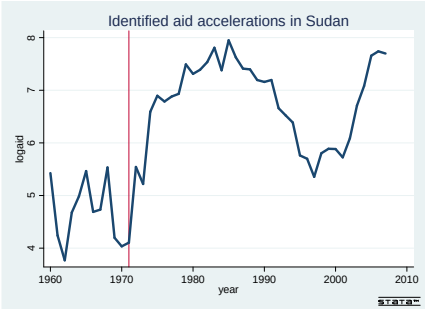
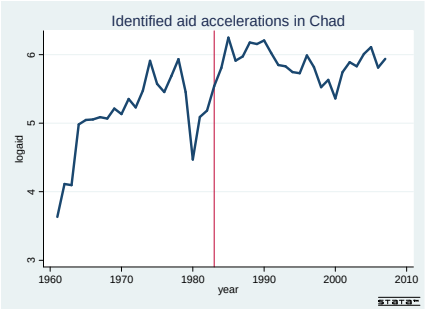


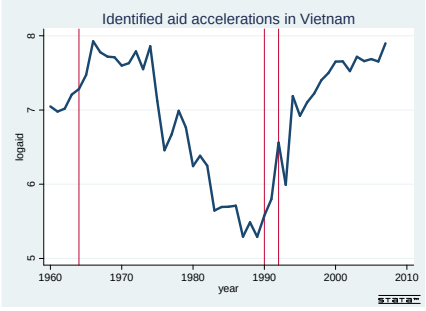
(d) Egypt



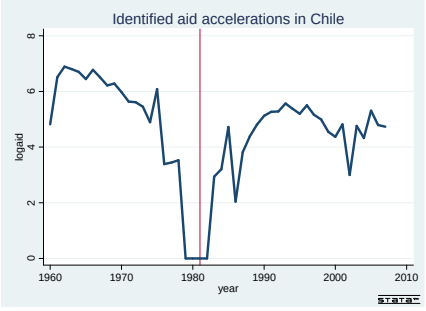
(e) Sudan



(f) Chad



(g) Vietnam



(h) Chile

Figure 4: Selected time series and the detected aid accelerations.

	1960	1970	1980	1990	2000	Sum
E. Europe and C. Asia	0	0	1	3	0	4
	(0)	(0)	(0.1)	(0.04)	(0)	(0.02)
M. East and N. Africa	6	11	9	4	3	33
	(0.04)	(0.05)	(0.04)	(0.01)	(0.01)	(0.03)
S. Asia	3	5	1	3	3	15
	(0.02)	(0.02)	(0.004)	(0.01)	(0.01)	(0.01)
West Europe	1	0	0	0	0	1
	(0.001)	(0)	(0)	(0)	(0)	(0.001)
N. America	0	0	0	0	0	0
	(0)	(0)	(0)	(0)	(0)	(0)
Sub.S. Africa	12	27	8	11	9	67
	(0.08)	(0.12)	(0.03)	(0.03)	(0.05)	(0.06)
L. America and Carib.	5	11	16	15	10	57
	(0.03)	(0.05)	(0.07)	(0.05)	(0.06)	(0.05)
Other	8	11	9	7	3	38
	(0.05)	(0.05)	(0.04)	(0.03)	(0.02)	(0.04)
Sum	35	65	44	43	28	215
	(0.04)	(0.05)	(0.03)	(0.03)	(0.04)	(0.04)

Table 2: Frequency of aid accelerations across regions

Notes: Unconditional probability (frequency divided by number of country-years) in brackets below.

	Base (I)	Spill (II)	Policy (III)	Geopol. (IV)	Region FE (V)
prio_inter1	0.108+	0.115+	0.113+	0.113+	0.108+
	(3.41)	(3.61)	(3.56)	(3.56)	(3.41)
prio_intra1	0.030	0.030	0.028	0.030	0.035
	(1.19)	(1.18)	(1.13)	(1.21)	(1.36)
prio_inter3x		0.071+	0.072+	0.068+	0.072+
		(3.13)	(3.19)	(3.04)	(3.18)
prio_intra3x		0.008	0.008	0.008	0.010
		(0.49)	(0.46)	(0.50)	(0.57)
poschange3			0.036**	0.031*	0.035**
			(2.12)	(1.84)	(2.09)
negchange3			0.012	0.004	0.008
			(0.53)	(0.19)	(0.36)
econlib_pos3			0.026	0.022	0.025
			(0.94)	(0.82)	(0.90)
coldwar				0.017	0.101**
				(0.36)	(2.53)
independence				0.091+	0.091+
				(2.94)	(2.96)
post2001				0.074	0.079
				(1.43)	(1.51)
Region FE	No	No	No	No	Yes
Pseudo R^2	0.034	0.037	0.038	0.040	0.044
N	4838	4838	4838	4838	4838

Table 3: Sustained and unsustained accelerations with controls

Notes: Estimated by probit. Coefficients shown are marginal probabilities evaluated at the sample means. Numbers in parenthesis are robust t-statistics. * $p < 0.1$, ** $p < 0.5$, + $p < 0.01$. All regressions include time dummy variables. Constant not reported.

	Event (I)	Ann. aid grwth(II)	5 yr avg (III)	7 yr avg (IV)	10 yr avg (V)
prio_inter1	0.108+	0.111	0.077	0.046	0.032
	(3.41)	(1.35)	(1.37)	(1.12)	(0.58)
prio_intra1	0.035	-0.005	0.001	-0.016	0.012
	(1.36)	(-0.16)	(0.04)	(-0.50)	(0.63)
prio_inter3x	0.072+	0.006	0.108**	-0.042*	0.001
	(3.18)	(0.21)	(2.04)	(-1.72)	(0.06)
prio_intra3x	0.010	-0.016	-0.014	-0.018	-0.044*
	(0.57)	(-0.60)	(-0.77)	(-0.79)	(-1.85)
poschange3	0.035**	-0.005	0.002	0.033*	-0.016
	(2.09)	(-0.20)	(0.12)	(1.76)	(-1.10)
negchange3	0.008	0.068	0.010	0.028	-0.035
	(0.36)	(1.64)	(0.26)	(1.09)	(-0.68)
econlib_pos3	0.025	-0.056	0.033	0.011	0.006
	(0.90)	(-1.14)	(0.94)	(0.36)	(0.15)
coldwar	0.025	0.135	0.005	0.054**	
	(0.90)	(1.20)	(0.25)	(2.23)	
independence	0.091+	0.193+	0.021	0.019	0.083
	(2.96)	(2.99)	(0.23)	(0.54)	(1.02)
post2001	0.079*	0.056			
	(1.51)	(0.75)			
(Pseudo) R^2	0.044	0.019	0.059	0.072	0.09
N	4838	5168	982	734	473

Table 4: Comparing aid accelerations against average aid flows

Notes: Estimated by probit (Column I) and OLS (Column II-V). For Column I, coefficients shown are marginal probabilities evaluated at the sample means. Numbers in parenthesis are robust t-statistics (clustered at country level for OLS). * $p < 0.1$, ** $p < 0.5$, + $p < 0.01$. All regressions include time dummy variables and region fixed effects. Constant not reported.

	All (I)	USA (II)	FRA (III)	GER (IV)	GBR (V)	JPN (VI)	ESP (VII)	NLD (VIII)	SWE (IX)	NOR (X)	CAN (XI)
prio_inter1	0.108+	0.090+	0.089**	0.124+	0.038	-0.012	0.166*	0.116+	-0.014	0.050	0.029
	(3.41)	(2.73)	(2.42)	(3.97)	(1.17)	(-0.43)	(1.83)	(2.97)	(-0.42)	(1.26)	(0.82)
prio_intra1	0.035	0.038	0.005	-0.027	0.001	0.028	-0.019	-0.033	0.001	0.027	-0.042
	(1.36)	(1.44)	(0.19)	(-1.22)	(0.01)	(1.09)	(-0.47)	(-1.31)	(0.04)	(1.03)	(-1.60)
prio_inter3x	0.072+	-0.023	-0.024	-0.029	0.036	-0.006	-0.081	0.027	0.057**	-0.022	0.034
	(3.18)	(-0.94)	(-0.93)	(-1.46)	(1.63)	(-0.30)	(-1.34)	(1.18)	(2.03)	(-0.77)	(1.52)
prio_intra3x	0.010	0.038**	-0.005	-0.003	-0.026	0.029*	0.031	0.009	-0.050**	0.031*	-0.027
	(0.57)	(2.17)	(-0.31)	(-0.23)	(-1.45)	(1.72)	(0.92)	(0.52)	(-2.32)	(1.68)	(-1.42)
poschange3	0.035**	0.038**	0.140	0.004	-0.014	0.042**	0.019	0.035*	0.033*	0.007	0.055+
	(2.09)	(2.15)	(1.61)	(0.28)	(-0.82)	(2.34)	(0.70)	(1.88)	(1.71)	(0.40)	(3.08)
negchange3	0.008	-0.013	0.066	0.036	-0.054**	0.036	-0.055	-0.093+	0.037	-0.012	-0.031
	(0.36)	(-0.54)	(0.42)	(1.53)	(-2.22)	(1.37)	(-1.16)	(-3.58)	(1.15)	(-0.45)	(-1.25)
econlib_pos3	0.025	-0.028	0.032	-0.038	0.020	-0.053**	0.112**	-0.015	-0.029	0.005	0.038
	(0.90)	(-1.03)	(1.13)	(-1.62)	(0.73)	(-2.05)	(2.32)	(-0.57)	(-1.06)	(0.19)	(1.27)
coldwar	0.025	0.035	-0.108	0.037	-0.044	0.017	(dropped)	-0.050	-0.061	-0.047	-0.053
	(0.90)	(0.75)	(-1.13)	(0.76)	(-0.73)	(0.27)		(-0.44)	(-0.92)	(-0.64)	(-0.71)
independence	0.091+	-0.058	-0.042	-0.023	-0.106+	-0.117+	(dropped)	-0.094**	-0.025	(dropped)	0.031
	(2.96)	(-1.44)	(-0.77)	(-0.69)	(-2.95)	(-2.93)		(-2.35)	(-0.41)		(0.77)
post2000	0.079*	0.068	0.120**	0.177+	0.164+	-0.007	0.257+	0.052	-0.054	-0.050	0.156**
	(1.51)	(1.35)	(2.30)	(3.11)	(2.75)	(-0.15)	(3.33)	(1.09)	(-1.28)	(-1.12)	(2.53)
Pseudo R^2	0.044	0.059	0.045	0.044	0.038	0.034	0.057	0.059	0.037	0.027	0.041
N	4838	4229	3519	4516	4444	4213	1210	3755	3017	3100	4008

Table 5: Predicting aid accelerations by donor country

Notes: Estimated by probit. Coefficients shown are marginal probabilities evaluated at the sample means. Numbers in parenthesis are robust t-statistics. * $p < 0.1$, ** $p < 0.5$, + $p < 0.01$. All regressions include time dummy variables and region fixed effects. Constant not reported.

	Base (I)	Spill (II)	Policy (III)	Geopol. (IV)	Region FE (V)
prio_inter1	-0.006	-0.005	-0.005	-0.005	-0.005
	(-0.42)	(-0.39)	(-0.38)	(-0.38)	(-0.37)
prio_intra1	0.017	0.018	0.017	0.017	0.018
	(1.24)	(1.28)	(1.22)	(1.22)	(1.30)
prio_inter3x		0.003	0.003	0.003	0.004
		(0.28)	(0.31)	(0.32)	(0.38)
prio_intra3x		-0.011	-0.010	-0.011	-0.010
		(-1.06)	(-1.05)	(-1.05)	(-1.01)
poschange3			0.011	0.011	0.011
			(1.20)	(1.20)	(1.20)
negchange3			-0.005	-0.005	-0.003
			(-0.40)	(-0.39)	(-0.26)
econlib_pos3			0.001	0.001	0.0003
			(0.01)	(0.01)	(0.02)
coldwar				0.046	0.051**
				(1.52)	(2.53)
independence				-0.002	-0.002
				(-0.15)	(-0.14)
post2000				0.120**	0.041
				(2.09)	(1.28)
Region FE	No	No	No	No	Yes
(Pseudo) R^2	0.039	0.040	0.041	0.041	0.043
N	5034	5034	5034	5034	5034

Table 6: Predicting aggregate EU aid accelerations

Notes: Estimated by probit. Coefficients shown are marginal probabilities evaluated at the sample means. Numbers in parenthesis are robust t-statistics. * $p < 0.1$, ** $p < 0.5$, + $p < 0.01$. All regressions include time dummy variables and region fixed effects. Constant not reported.

	ESP	NLD	NOR	FRA	GBR	SWE	GER
ESP	1	0.060	0.029	0.045	0.039	0.009	0.011
NLD	0.060	1	0.042	0.047	0.079	0.047	0.009
NOR	0.029	0.042	1	0.045	0.040	0.027	0.044
FRA	0.045	0.047	0.045	1	0.051	0.050	0.070
GBR	0.039	0.079	0.040	0.051	1	0.014	0.061
SWE	0.009	0.047	0.027	0.050	0.014	1	0.050
GER	0.011	0.009	0.044	0.070	0.061	0.050	1

Table 7: Proximity matrix for aid accelerations

Notes: Calculated using the Jaccard index.

	Base (I)	MEPV (II)	Freedom (III)	Filter (IV)	LPM (V)	Tobit (VI)
prio_inter1	0.108+					
	(3.41)					
prio_intra1	0.035					
	(1.36)					
prio_inter3x	0.072+					
	(3.18)					
prio_intra3x	0.010					
	(0.57)					
poschange3	0.035**	0.038**				
	(2.09)	(2.22)				
negchange3	0.008	-0.005				
	(0.36)	(-0.25)				
econlib_pos3	0.025	0.027	0.021	0.011	0.008	0.009
	(0.90)	(0.98)	(0.78)	(0.42)	(0.31)	(0.30)
coldwar	0.025	0.088**	0.090**	0.068	0.059	(dropped)
	(0.90)	(2.25)	(2.25)	(1.55)	(1.31)	
independence	0.091+	0.116+	0.132+	0.099**	0.098**	0.115**
	(2.96)	(2.94)	(3.23)	(2.43)	(2.11)	(2.10)
post2000	0.079*	0.066	0.088	0.068	0.060	(dropped)
	(1.51)	(1.39)	(1.66)	(1.25)	(1.46)	
mepv_inter1		0.027+	0.027+	0.032+	0.047+	0.056+
		(3.39)	(3.41)	(3.99)	(3.39)	(3.29)
mepv_intra1		0.014**	0.014**	0.014**	0.016**	0.019**
		(2.44)	(2.49)	(2.36)	(2.08)	(2.07)
mepv_inter3x		0.022+	0.021+	0.023+	0.028**	0.033**
		(2.91)	(2.82)	(2.91)	(2.45)	(2.44)
mepv_intra3x		-0.005	-0.004	-0.009	-0.009*	-0.010*
		(-0.93)	(-0.89)	(-1.60)	(-1.84)	(-1.86)
free_pos3			0.034+	0.028**	0.029**	0.033**
			(2.74)	(2.18)	(2.29)	(2.31)
free_neg3			0.036*	0.031	0.032	0.037
			(1.79)	(1.48)	(1.56)	(1.58)
(Pseudo) R^2 0.044	0.046	0.047	0.045	0.04	0.03	
N	4838	4742	4742	4675	4675	4675

Table 8: Predicting total aid accelerations

Notes: Estimated by probit. Coefficients shown are marginal probabilities evaluated at the sample means. Numbers in parenthesis are robust t-statistics. * $p < 0.1$, ** $p < 0.5$, + $p < 0.01$. All regressions include time dummy variables and region fixed effects. Constant not reported.