Donor Proliferation as Insurance against Aid Shocks: Lower Risk of Civil War?

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Abstract

The proliferation of governmental and non-governmental organizations that provide aid to developing countries causes harm to program performance and bureaucratic institutions. This paper investigates an overlooked positive side effect of donor proliferation. With an increasing number of donors, exposure to negative aid shocks decreases, along with the risk this poses for political stability. I use data on 141 recipient countries and all OECD bilateral aid donors for the years 1970-2007 to test hypotheses about the relationship between donor fragmentation and armed political conflict. An endogenous switching model shows that donor fragmentation reduces the risk of aid shocks, and that aid shocks lead to an increased risk of conflict. There is also evidence for an endogenous dampening of aid shocks in the run-up to conflict episodes.

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1 Introduction

The proliferation of governmental and non-governmental organizations that provide aid to developing countries has been at the center of recent academic and policy debates (e.g. Aldasoro *et al.* 2010; Easterly 2007). There is evidence that donor fragmentation has negative consequences, both for the efficacy of aid (Djankov *et al.* 2009), and for the domestic institutions in recipient countries (Morss 1984; Knack and Rahman 2007).

While these negative effects are real and have potentially serious consequences, donor fragmentation may have largely overlooked positive side effects. Highly concentrated donor structures mean that unexpected aid shortfalls by one main donor can do serious harm to overall aid flows to a recipient country. This extreme form of aid volatility can come at a steep price in terms of disruption to investment flows, the government budget, and public services.

By making a recipient country less dependent on a single donor, or a small group of donors, donor proliferation can serve to reduce the risk of severe shocks to aid flows. While negative aid volatility has been associated with a range of economic ills, I concentrate on a particular form of political fallout. Nielsen *et al.* (2011) show that negative aid shocks substantively increase the risk of armed political conflict. In this paper, I explore to what extent donor fragmentation reduces the risk of armed conflict as a consequence of aid shocks.

In the following, I first develop the theoretical framework that ties donor fragmentation to aid shocks and onset of violent political conflict. I then present results from a statistical analysis of 141 recipient countries of bilateral official development aid (ODA) from 1970 to 2007. Fitting an endogenous switching model to this data shows that donor fragmentation substantively reduces the chances of severe negative aid shocks. This in turn reduces the likelihood of civil conflict onset, after we account for endogenous determination of aid shocks. I also find that donors reduce the volatility of aid in the run-up to political crisis. The conclusion summarizes the findings, and gives outlooks for future work.

2 Donor Fragmentation as Insurance Against Armed Political Conflict

Much work has concentrated on the connection between aid volatility and economic growth. An number of studies finds that volatility reduces growth (Lensink and Morrissey 2000; Kharas 2008), but there is also evidence for positive growth effects of upside volatility (Hudson and Mosley 2008). Aid volatility tends to be pro-cyclical (Pallage and Robe 2001; Bulíř and Hamann 2003, 2007), with the potential to disrupt financing of government programs and infrastructure spending (Agénor and Aizenman 2010; Arellano *et al.* 2009).

The political consequences of aid shocks have received much less attention. In this paper, I concentrate on the risk of political destabilization brought about by aid shocks. Nielsen *et al.* (2011) show that severe reversals of aid levels lead to substantively higher probability of internal armed conflict. They argue that sudden severe drops in aid provisions shift the balance of power between the government and rebel groups in the rebels' favor. The government's inability to commit to the terms of a bargain that favors the rebels once aid flows are restored leads to bargaining breakdown.

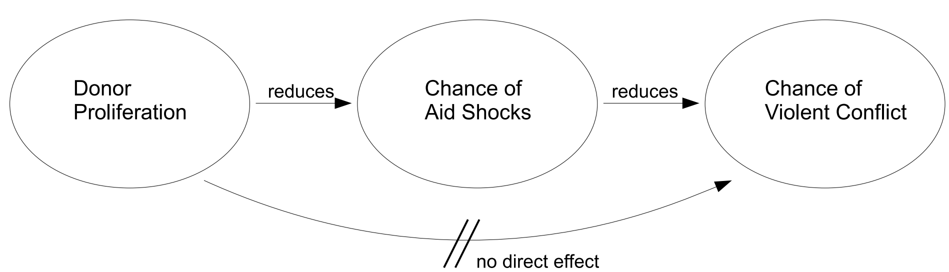
Another plausible causal mechanism that links aid shocks to violent conflict arises if aid is given for political reasons. In other work I demonstrate that uncertainty about donor commitments to stability can lead recipient governments to rely too much on aid to deal with political unrest (Steinwand 2010a). If requirements surpass what the donor is willing to pay, or aid drops for exogenous reasons, rebellion cannot be avoided.

The study of donor fragmentation has received much prominence recently. From the perspective of policy makers, the question of donor fragmentation has direct implications for the way aid programs are administered. With increasing numbers of aid providers administrative requirements tend to increase as well, overburdening local authorities (Easterly 2007). This tendency has been well documented also on the sectoral level (Frot and Santiso 2010).

Academic interest has focused on the effects of donor fragmentation on economic development, and government institutions. Duplication of aid programs, together with increased administrative burdens in local bureaucracies leads to reduced growth performance (Djankov *et al.* 2009). Increased administrative requirements also directly affect recipient country institutions. Knack and Rahman (2007) find that higher donor fragmentation is associated with deteriorating institutional performance. There is also some evidence that it increases corruption (Djankov *et al.* 2009). Hudson and Mosley (2008) note that donor fragmentation should serve to reduce aid volatility. They provide some simple descriptive statistics to underscore this point.

Their findings provide a useful starting point for my analysis. I am theorizing that because donor fragmentation reduces aid volatility, it helps to protect against unexpected aid shocks. This in turn should serve to reduce the risk of violent political conflict. The causal pathway of this relationship is illustrated in figure 1. In order to develop testable hypothesis, we now explore the theoretical linkages between the individual steps in this causal chain in more detail.

Figure 1: Causal Pathway



We can think of aid shocks as extreme realizations of aid volatility. Following common practice, I conceptualize aid volatility as deviation from an expected value. The expected value in turn is either a statistical trend or informed by earlier aid commitments. To demonstrate the relationship between donor fragmentation and aid volatility, I follow Hudson and Mosley (2008).

Let X be the total aid provided by just one donor, with expected (average) payout $E(X) = \mu$. The volatility of this aid is simply its variance, $Var(X)$. Now assume the same donor gives X, but divided into two parts of equal size, $X_{1/2}$. We then can decompose $Var(X)$ into

$$Var(X) = Var(2X_{1/2}) = 2Var(X_{1/2}) + 2Cov(X_{1/2}, X_{1/2}) = 4Var(X_{1/2}). \tag{1}$$

This results obtains because the two halfs $X_{1/2}$ perfectly co-vary with each other.

Consider now the case where the same amount of aid is provided by two donors, $i = 1, 2$, each giving equal aid shares of size $X^i_{1/2}$. Thus, average total aid provision is unchanged $E(X^1_{1/2} + X^2_{1/2}) = \mu$, but total volatility is given by

$$Var(X^1_{1/2} + X^2_{1/2}) = Var(X^1_{1/2}) + Var(X^2_{1/2}) + 2Cov(X^1_{1/2}, X^2_{1/2}). \tag{2}$$

This expression is almost always less than the variance in the one-donor case (1). Only if $X^1_{1/2}$ and $X^2_{1/2}$ perfectly co-vary do we have $2Cov(X^1_{1/2}, X^2_{1/2}) = Var(X^1_{1/2}) + Var(X^2_{1/2})$, and (1) and (2) become equal. Since in reality such perfect correlation never occurs, increasing the number of donors always serves to decrease the volatility of aid flows.

Can a reduction in volatility contribute to reducing the chance of severe aid shocks and thus lower the risk of violent conflict? To answer the first part of this question we only need to realize that increased variability leads to higher probability mass being found in the tails of a distribution. Any extreme event located in the tails therefore becomes less likely as the variance of the distribution decreases.[1] This gives us our first testable hypothesis.

Hypothesis 1: Greater donor fragmentation reduces the chance of severe negative aid shocks.

How about the relationship between aid shocks and the probability of conflict? Typical models of conflict treat the decision to fight as related to the reservation value for peace. If the expected payoffs from fighting for the would-be rebels, including the costs in terms of life and property, seem more promising than the alternatives, fighting is a rational decision.

Aid shocks enter this scenario as realizations of a stochastic process. Actors have expectations about future aid allocations, and condition their behavior accordingly. Once an aid shock is observed, uncertainty about the current state of the world is resolved. For example, if a rent-seeking recipient government expects donors to provide aid in support of domestic stability, it will extract more rents from the economy for itself, knowing that donors will pay for important services to the suffering population (Steinwand 2010a). In the face of an aid shock, such policies are not easily reversed, and potential rebel groups spring into action.[2]

Formally, a rebel group fights after observing an aid shock if

$$D(Aid) = F(Aid) - SQ(Aid) > 0, \qquad (3)$$

where $F(Aid)$ is the expected utility from fighting, $SQ(AID)$ is the expected utility of remaining at peace, and the difference between the two is $D(Aid)$. Both utilities can be a function of realized aid provisions, as aid either influences relative government capabilities or is used as subsidy to the population. Both causal pathways affect the outcome in the same

[1] Consider for example a random variable X that is distributed normal with mean zero and variance σ^2, $X \sim (0, \sigma^2)$. Let's define $X_e = -2$ as extreme negative event. The probability of this event occurring is $Pr(x < -2) = 0.0786$ if $\sigma^2 = 2$, but decreases to $Pr(x < -2) = 0.0227$ for $\sigma^2 = 1$.

[2] Equally, uncertainty about the state of the world *tomorrow* can make it rational to go to war *today* after observing an aid shock. This is because of the government cannot commitment to stick to the terms of today's bargain if it finds itself in a better position (with more aid) tomorrow.

fashion, since less aid makes fighting more attractive and staying at peace less attractive, i.e. $\partial SQ(Aid)/\partial Aid > 0$ and $\partial F(Aid)/\partial Aid < 0$. The probability of conflict is the $ex-ante$ probability of observing an aid shock (after which fighting occurs deterministically). Thus, the probability of conflict is

$$Pr\left(\text{Conflict}\right) = Pr\left(D^{*}(Aid) > 0\right), \tag{4}$$

where $D^{*}(Aid)$ varies with the realization of Aid. $D^{*}(Aid) = 0$ defines the reservation value for peace. If we rewrite the probability of fighting in terms of the cumulative distribution function of Aid, and the derived random variable $D^{*}(Aid)$, we have $Pr(D^{*}(Aid) > 0) = F_{D^{*}(Aid)}(0)$. Note that the distribution described by $F_{D^{*}(Aid)}$ is not centered on zero, because on average the peace condition is met. Higher aid volatility leads to increases in $Var(D^{*}(Aid))$. And since the reservation value for peace is fixed at 0, this in turn causes increases in $Pr\left(D^{*}(Aid) > 0\right)$. Higher aid volatility thus increases the risk of an aid shock, and in turn the probability of conflict. Since only negative deviations from expected aid flows will trigger violent conflict, we concentrate on this aspect for our second hypothesis.

Hypothesis 2: Negative aid shocks lead to an increased risk of violent conflict.

Before finally putting the individual causal steps together, we need to address the question whether donor fragmentation affects the probability of conflict in other ways than through aid shocks. One potential candidate for such influence is economic growth. We know that fragmentation leads to decreased growth performance. However, while GDP per capita is a consistent and powerful explanatory variable for the propensity of civil war in cross-sectional studies, we have no comparable results for GDP *growth*. Some countries with low GDP per capita have managed to 'take-off', with high growth rates on a path of economic convergence (Pritchett 1997). Other poor countries, especially those Sub-Saharan Africa since the 1970s, have experienced decades of anemic growth or even decline. Without clear theoretical prediction, we take a conservative position and say that no direct effect of donor fragmentation on violent conflict exists. We leave it to the empirical analysis to demonstrate otherwise.

Hypothesis 3: Higher donor fragmentation reduces the risk of violent conflict by lowering the probability of aid shocks. There is no direct effect of fragmentation on conflict.

In the next section, I first discuss the data and the appropriate statistical setup to test the hypotheses develop here. I then present results from the empirical analysis.

3 Empirical Analysis

Data

To test the the hypotheses developed in the previous section I assemble a new data set covering all 141 countries that have received official development aid (ODA) between 1970 and 2007. Calculating moving averages and taking lags effectively reduces the years in the analysis to 1975-2008.

I begin with coding aid volatility. The first choice concerns the measure of aid flows. I use bilateral net ODA flows per capita, taken from the OECD's International Development Statistics (2009). Net flows measure total aid disbursements minus repayments of non-concessional loans. Unlike aid commitments or gross disbursements, looking at net flows gives an accurate picture of the total free resources from aid available in a given year. Using cross-sectional aid data requires that we standardize aid flows. I divide aid per GDP to make the economic impact of aid shortfalls comparable across countries.

Next, I calculate a four-year sliding mean of the aid variable. I measure volatility as deviation from this trend, adding a one-year lag. The resulting variable takes the form

$$\Delta y_{t_0} = y_{t_0} - \frac{1}{4}\sum_{j=1}^{4} y_{t_{-j}}. \tag{5}$$

This conceptualization follows the standard approach in the literature on aid volatility.[3] Given the time-series nature of the data, it makes sense to conceptualize volatility as deviation from a trend rather than raw changes in aid flows.

I follow Nielsen *et al.* in coding aid shocks as indicator variable that is set to 1 for observations in the lower 15th percentile of Δy_{t_0}, and 0 otherwise.[4]

My key independent variable is donor fragmentation. I follow a widespread practice and calculate the Herfindahl-Hirschman index (HHI) of aid shares. The HHI is calculated by taking the sum of squared aid shares of all donors, i.e. $HHI = \sum_i aid_i^2/total\ aid$, where i indexes all donors who give aid. It ranges from 0 to 1. I do not convert the measure by subtracting it from 1, i.e. 0 stands for absolute fragmentation and 1 for absolute concentration.

The HHI has the advantage of accounting for fragmentation in the sense of increases in the numbers of donors, while correcting for relative size of aid share. For example, when moving from one to two donors with equal aid share, the index falls from 1 to 0.5. However, if aid allocated by the two donors splits 3/4 to 1/4, the index only drops to 0.63, accounting for the larger influence of the main donor.

In my data, the most fragmented aid goes to Central & South Asia (mean HHI = 0.276). Aid to Sub-Saharan Africa and South America is similar in structure (mean HHI Africa = 0.286, mean HHI S. America= 0.298). A second group of regions has more concentrated aid. HHI values cluster around 0.40. This group includes Central America & the Caribbean

[3] I only deviate in using a moving average instead of the Hodrick-Prescott (HP) filter to calculate the trend. The HP filter was developed for the analysis of business cycles, and privileges long-term over short-term fluctuations (Hodrick and Prescott 1997). Ultimately, the choice of smoother is somewhat arbitrary. I run all regressions also with 5 year moving averages, without substantively changing results.

[4] I also run all regressions using the 5th percentile, with substantively unchanging results.

(mean HHI = 0.381), Europe (mean HHI = 0.413), and the Middle East & North Africa (mean HHI = 0.414). Countries in Oceania receive the most concentrated aid (mean HHI = 0.471). The data bear out the much discussed increase of fragmentation over time. Average HHI starts from 0.411 in the 1970s, but drops to 0.352 in the 1980s, and 0.324 in the 1990s. However, this trend reverses after 2000, with an average HHI=0.307 for the years to 2007. It is of course possible that this reversal masks the massive growth of non-governmental organizations providing aid since the end of the Cold War.

I include only aid from 22 bilateral OECD donors into the analysis. While growth in multilateral institutions and NGOs contributes to donor fragmentation, bilateral aid is more discretionary in character in terms of political payoffs for donors. Shocks to bilateral aid should therefore have a greater impact on political stability than multilateral aid shocks.

Since I seek to test the causal pathway depicted in figure 1, I am estimating a two equation model. The first equation has the aid shock indicator as dependent variable, while equation two models the occurrence of violent conflict.[5] Both dependent variables are binary. We can summarize this model as

$$Y^{*1}_{i,t_0} = g(t_0) + X_{i,t_{-1}}\beta + u_{i,t_{-1}} \tag{6}$$

$$Y^{*2}_{i,t_1} = h(t_1) + Y^{1}_{i,t_0}\theta + Z_{i,t_0}\gamma + v_{i,t_0}, \tag{7}$$

where $Y^{*j},\ j = 1, 2$, are unobserved latent variables for aid shocks and conflict, with observed realizations

$$Y^{j}_{i} = 1 \text{ if } Y^{j}_{i} \geq 0, \tag{8}$$

$$Y^{j}_{i} = 0 \text{ otherwise.} \tag{9}$$

[5] A single equation with conflict as dependent variable and an interaction term design for aid shocks and donor fragmentation would not allow us to account for the possible endogeneity of aid shocks.

The terms $g(t_0)$ and $h(t_1)$ represent the baseline hazard of aid shocks and conflict initiation (Box-Steffensmeier and Jones 2004). I model these using third-order polynomials of the years since the last conflict/aid shock (Carter and Signorino 2010). The conflict variable has a lead of one year, to ensure the sequence of event from aid shock to conflict is in the right order. Likewise, the right-hand side of the aid shock equation is lagged by one year. Aid shocks are included as endogenous variable in equation 7. A measure of donor fragmentation is included on the right-hand-side in both equations 6 and 7.

Including aid shocks in the conflict equation raises the question of reverse causation. If donors change aid flows in anticipation of conflict, aid shocks will be endogenously determined. In this case, we would have a situation similar to a selection setup (Heckman 1979), with the difference that the endogenous variable does not lead to censoring, but to regime switching.[6]

Are there theoretical reasons to expect endogeneity? While Nielsen *et al.* discount this possibility, anecdotal evidence suggests otherwise. For example, donors sometimes freeze funding during periods of political tensions, which in turn can be a precursor to organized political violence. Examples include electoral disputes, border conflicts with neighboring states, or military coups.[7] This would lead to a positive endogenous relationship between conflict and aid shocks.

At the same time, we also know that aid has been used to actively support incumbent regimes, not only during the Cold War. For example, it still is a mainstay of French foreign policy to underwrite the internal security of its client states in sub-saharan Africa. Under this premise, the threat of political violence would make aid shocks actually less likely (or lead to positive aid 'bumps'), leading to negative endogeneity between conflict and aid shocks.

The proper model to account for this form of endogeneity is an endogenous switching

[6] In addition, the dependent variable in the outcome equation is binary.

[7] Since our measure of conflict only picks up episodes that have passed the 25 deaths per year threshold, even nominally violent events such as coups run the risk of not immediately registering.

model that allows for correlation of the disturbance terms u_i and v_i (Miranda and Rabe-Hesketh 2006). This model has the advantage that a simple likelihood-ratio test can reveal the presence of endogeneity. It also is generally identified. However, I follow good practice by meeting theoretically motivated exclusion restrictions (Sovey and Green 2009).

As a variable that is correlated with aid shocks but not with conflict, I use the real effective exchange rate of the US dollar against a basket of international currencies (REER) (Source: The World Bank Group 2011). Since the aid data in the analysis is denominated in US dollars, movements in the REER will have an immediate measurement effect on parts of total aid not provided by the US. The instrument is somewhat weak, but is statistically significant in the analysis.[8]

While no statistical test for the exogeneity of an instrument exists, it seems highly unlikely that the relative strength of the US dollar has a direct effect on violent conflict. For all non-American aid, the US dollar only serves as denominator, and thus will not affect the value of aid provisions. For aid given in US dollars, currency effects due to purchasing power variation vis-à-vis other countries should be minimal, since American aid has a notoriously high tying rate (Jepma 1991).

I employ a standard battery of other independent variables that are important predictors of civil conflict. The variable most robustly associated with conflict across studies is GDP per capita. It is measured as purchasing power parity relative to a basket of US goods (source: Heston *et al.* 2009).

Results

We begin our analysis by estimating equations 6 and 7 separately. In the absence of better theoretical guidance, I am including the same independent variables for conflict onset and aid shocks, with addition of the US real effective exchange rate. The results are reported in

[8] The correlation between the exchange rate and aid shocks is $r = -0.102$.

table 1. Model 1 shows that higher donor concentration is associated with a greater chance of aid shocks, in line with hypothesis 1. A stronger dollar decreases the chance of aid shocks. This is in line with the logic of aid flows being denominated in US dollars, and thus becoming less volatile nominally as the dollar strengthens. Rich and more democratic countries were also more likely to have more steady aid flows. This is suggestive for the endogeneity of shocks and conflict, since wealth and good governance also play a big role in the causation of conflict.

This is reflected in model 2, where conflict is the dependent variable. Rich countries are less likely to experience organized violence, though democracy is not statistically significant. Land area has the expected positive effect. British colonies are also less likely to experience conflict. Great donor concentration is associated with a decrease in the probability of conflict, which seems to contradict our prediction from hypothesis 3. However, the variable enters the analysis directly, not accounting for the effect of donor concentration on aid shocks. Most importantly, aid shocks have a positive sign, but fail to reach statistical significance. Thus, without further efforts, I am not able not able to reproduce the core finding from Nielsen *et al.* (2011), using an expanded data set and different variable definitions.

Does the lack of statistical significance of aid shocks disappears when we account for the possibility of endogenous aid shocks? The results are reported in model 3. In the aid shock equation, there is not much change. Coefficient estimates retain the same order of magnitude, and statistical significance. Very similar in the conflict equation. The control variables remain unchanged. Donor concentration still reduces the probability of conflict, even though we are now also modeling the variable's influence on aid shocks. Since the aid shock coefficient stays statistically insignificant, and even decreases somewhat in magnitude, this causal pathway from donor concentration to conflict appears closed. It remains to note that the model does not find evidence of endogeneity, with the correlation between aid shocks and conflict being small and statistically not significant.

Table 1: Regression Results

Aid Shock	1	2	3	4	5
Donor	0.487^{*}		0.295^{*}	0.280	0.733^{**}
Concentration	(0.271)		(0.155)	(0.421)	(0.225)
US REER	-0.0230^{**}		-0.0129^{**}	-0.0131^{**}	-0.0114^{**}
	(0.00542)		(0.00301)	(0.00409)	(0.00447)
GDP p.c.	-0.0426^{**}		-0.0254^{**}	-0.0338^{**}	-0.0183^{**}
	(0.00586)		(0.00329)	(0.00551)	(0.00402)
Land Area	-2.10×10^{-7}		-1.57×10^{-7}	-5.03×10^{-7}	4.99×10^{-7}
	(1.17×10^{-6})		(6.43×10^{-7})	(8.74×10^{-7})	(1.11×10^{-6})
Democracy	-0.0772^{**}		-0.0465^{**}	-0.0335	-0.0731^{**}
	(0.0271)		(0.0155)	(0.0212)	(0.0244)
French Colony	-0.121		-0.0419	-0.0499	0.0913
	(0.137)		(0.0709)	(0.106)	(0.122)
British Colony	0.0781		0.0730	0.0686	.0918
	(0.124)		(0.0709)	(0.0928)	(0.115)
Population	$-1.19 \times 10^{-8**}$		$-6.33 \times 10^{-9**}$	$-6.59 \times 10^{-9**}$	$-1.14 \times 10^{-8*}$
	(3.93×10^{-9})		(2.02×10^{-9})	(2.21×10^{-9})	(6.00×10^{-9})
Conflict					
Aid Shock		0.208	0.133	-0.220	0.679^{**}
		(0.177)	(0.187)	(0.227)	(0.320)
Donor		-0.906^{**}	-0.428^{**}	1.14	-0.473
Concentration		(0.460)	(0.218)	(0.927)	(0.363)
GDP p.c.		-0.0266^{**}	-0.0115^{**}	-0.0178^{**}	-0.0101^{**}
		(0.00774)	(0.00350)	(0.00625)	(0.00430)
Land Area		$1.43 \times 10^{-6*}$	$6.59 \times 10^{-7*}$	5.03×10^{-8}	$1.72 \times 10^{-6**}$
		(7.66×10^{-7})	(3.99×10^{-7})	(5.52×10^{-7})	$(6.42) \times 10^{-7}$
Democracy		0.0666	0.0333	0.00378	0.0660^{**}
		(0.0427)	(0.0207)	(0.0278)	(0.0329)
French Colony		-0.0695	-0.0251	-0.116	0.00705
		(0.184)	(0.0923)	(0.127)	(0.140)
British Colony		-0.435^{**}	-0.223^{**}	-0.260^{**}	-0.235
		(0.186)	(0.0902)	(0.113)	(0.159)
Population		-7.94×10^{-10}	-3.16×10^{-10}	1.13×10^{-10}	$-1.48 \times 10^{-9*}$
		(9.11×10^{-10})	(4.58×10^{-10})	(5.93×10^{-10})	(2.21×10^{-9})
ρ	n.a.	n.a.	-0.0196	0.199	-.294
			(0.127)	(0.156)	(0.196)
n	3597	3643	3657	1811	1846

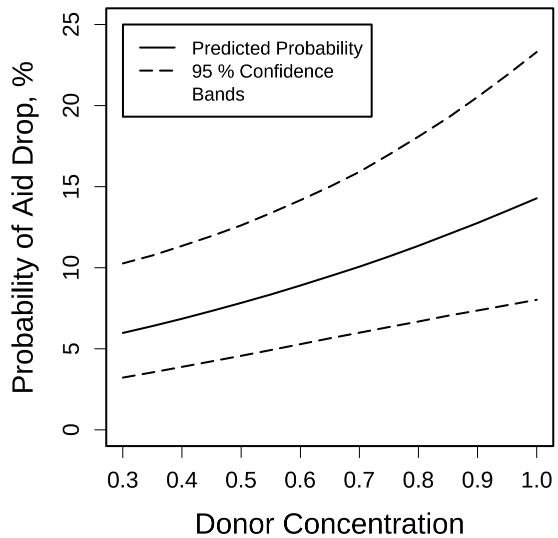
In a next step, I disaggregate the analysis according to the degree of donor concentration. The unexpected finding that higher donor concentration has a direct pacifying effect on conflict suggest donor self-selection plays a role. If conflict prone aid recipient countries attract a greater number of donors, this could result in relatively high levels of donor fragmentation. As a corollary, more peaceful countries should have more concentrated donor systems. Under this selection scenario, the theorized pacifying effect of donor fragmentation would be the strongest in countries with the highest observed donor concentrations, even though these countries are relatively peaceful. To see if this is true, I divide the sample into two parts. I use the median of the donor fragmentation variable (at about 0.3) to divide the sample into one part with high donor fragmentation and one part with low donor fragmentation.

Model 4 reports results for high donor fragmentation, and model 5 for low donor fragmentation. Looking first at the aid shock equations of both models, there are some very interesting differences. In model 4, the donor concentration variable loses statistical significance. This makes intuitive sense, because by construction donors in this sub-sample are more fragmented. Within this group, further fragmentation has little effect on reducing the probability of aid shocks. In contrast, it is in model 5, the group of concentrated donors, that fragmentation has a significant and substantively sizable effect on reducing the probability of aid shocks. Figure 2 shows the marginal effect of a change in the donor concentration variable. At a Herfindahl-Hirschman index value of 0.3, the threshold level for inclusion into the subsample, each 0.1 point increment adds about 0.6 percentage points to the risk of experiencing an aid shock. This marginal effect increases to about 1.5 percentage points when we approach an HHI of 1.0.[9] Other variables in the aid shock equation remain largely unchanged.

In the conflict equation, the aid shock variable displays a remarkable bifurcation. In

[9]These number were generated using a profile of variables for a country at the first quartile of income and population, the 3rd quartile of land area, and median democracy score, time since the last aid shock, and US real effective exchange rate.

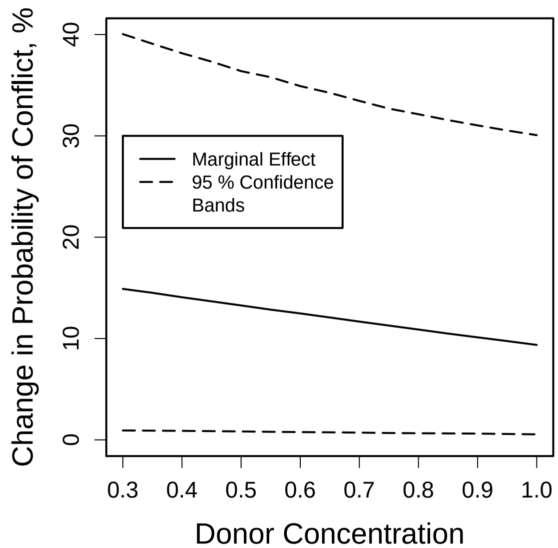
Figure 2: Predicted Probability of Aid Shocks



model 4, with low values of donor concentration, aid shocks still are statistically insignificant, but with reversed coefficient sign. This is in line with the donor self-selection story. For high donor concentrations (model 5), aid shocks finally reach statistical significance and make conflict more likely. The substantive effect of the variable is moderate. Figure 3shows that an aid shock adds between 10 and 15 percent to the probability of conflict onset, depending on donor concentration. However, it should be noted that this decrease is not statistically significant, as the donor concentration variable falls below conventional significance levels in model 5. The other control variables in the conflict equation remain largely unchanged, with the notable exception of democracy. In sub-sample with high donor concentration, democracy is associated with increased conflict onset. The reason for this is not readily apparent.

Overall, model 5 provides support for hypotheses 1 and 2. Before looking at hypothesis 3, we should note that model 5 identifies negative endogeneity between conflict and aid shocks, albeit at low levels of statistical significance ($p = 0.106$). This again is in line with

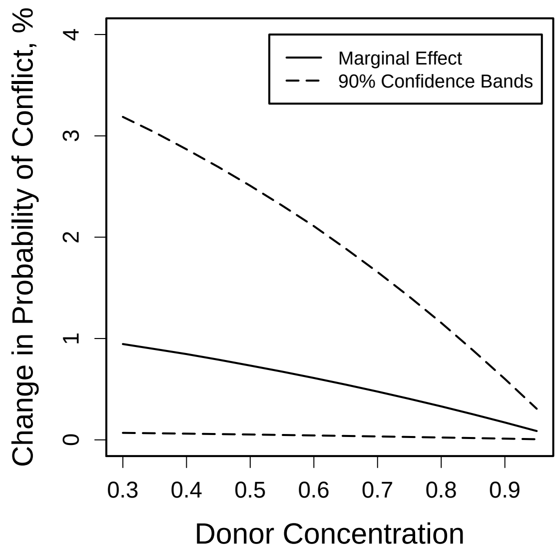
Figure 3: Predicted Probability of Conflict



the selection logic, as donors try to reduce downward aid volatility in the up-run to conflict events.

Let's now look how donor fragmentation affects conflict onset via the path of reducing aid shocks. The counterfactual we need to consult draws on both the conflict and aid shock equations. The predicted probability of conflict is given by $Pr(Conflict) = Pr(Conflict \mid Aid\ Shock) * Pr(Aid\ Shock) + Pr(Conflict\ |No\ Shock) * Pr(No\ Shock)$. Varying the donor concentration variable across its range in the sub-sample from 0.3 to 1 and taking first differences, we can calculate the marginal effect of donor concentration on the probability of conflict. The result is summarized in figure 2. We recover only a weak relationship. The effect of moving from a fully fragmented to fully concentrated donor system never increases the probability of conflict by more than one percentage point. The effect is also only weakly statistically significant on the 10 percent level. Thus, we do not find empirical support for the core hypothesis 3. Donor fragmentation only reduces the risk of conflict in a minimal fashion.

Figure 4: Effect of Donor Concentration on Conflict



Given that we were able to identify an important role of donor fragmentation for aid shocks, as well as for the role of aid shocks in conflict initiation, the lack of evidence for the interlinked causal pathway remains somewhat of a puzzle. Most likely, individual effect sizes are insufficiently large and further attenuate when we condition the effect of aid shocks on the probability of aid shocks occurring. This problem might be mitigated when we address the rare event nature of civil conflict (less than 4% of observations) and donor self-selection. If we correctly model the processes that put countries at an increased risk of conflict, we can better study the role of donor fragmentation and aid shocks in this environment.

4 Conclusion

This paper started from the premise that donor fragmentation has potentially positive side effects on aid volatility. It then went on to show that increased fragmentation should reduce the risk of severe aid shocks and the concomitant risk of violent political conflict. The empirical analysis finds support for individual elements of this relationship but not for the entire causal chain.

The analysis revealed some evidence that that donors self-select into fragmented or centralized donor systems. This suggest an important role for donor coordination. In the existing debate, coordination is often described as panacea to combat the proliferation of aid organizations and programs. However, the negative effect of fragmentation on aid volatility shows that the *content* of coordination might be critically important for the resulting policy effects. Coordination that leads to higher correlation between the aid flows will increase overall aid volatility and the risk of aid shocks. In this scenario, a recipient country might be better off with an uncoordinated and more fragmented donor system.

On the other hand, if donors manage to offset each others' shortfalls, coordination will also have beneficial effects for aid volatility. Unfortunately, the prospect of this seem rather dim. The processes through with aid is allocated differ substantively from donor to donor. In addition, coordination typically happens on a local level and between administrative entities of different donor countries that do not have control over aid allocations. There are indications that coordination on a higher political level sometimes happens, resulting in individual donors becoming lead donors for specific recipient countries (Steinwand 2010b). Lead donors might internalize the costs of volatility and thus work to reduce it. We still know little about lead donorship, and more research is needed. Overall, the connection between donor fragmentation and aid volatility deserves more attention in the academic and policy communities.

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