Donor Competition for Aid Impact, and Aid Fragmentation

Kurt Annen and Luc Moers

Abstract

We show that donors that maximize relative aid impact spread their budgets across many recipient countries in a unique Nash equilibrium. This aid fragmentation result is robust to the introduction of fixed costs, even if they are improbably large. In equilibrium, smaller donors have less fragmented aid, and behave better from an efficiency viewpoint. We present evidence that our theoretical results are in line with cross-country correlations. Our analysis has important policy implications: First, short of ending donors’ maximization of relative aid impact, agreements to better coordinate aid allocations are not implementable. Second, since policies to increase donor competition in terms of aid effectiveness risk reinforcing relativeness, they may well backfire, as any such reinforcement increases aid fragmentation.

JEL classification: D70, F35, H87, O19

In following up the Declaration, we will intensify our efforts to provide and use development assistance ... in ways that rationalise the often excessive fragmentation of donor activities. (OECD 2005, 2).

This paper analyzes the strategic interaction of donors of foreign aid and its effects on the allocation of aid across recipient countries. It is widely recognized that aid in the typical developing country is highly fragmented. The quote at the top of this page, taken from the Paris Declaration (OECD 2005), which intends to improve aid effectiveness, clearly identifies aid fragmentation as a problem. This raises an important question: Why is aid fragmented? To our knowledge, the literature does not contain any formal models or empirics that could explain. We provide such a model. We also present empirical evidence that cross-country correlations are in line with the results of our model.

Using a game-theoretic framework, we show that donors that maximize relative aid impact—donor competition—spread their budgets across many recipient countries in a unique Nash equilibrium. In equilibrium, aid is fragmented. If aid giving has fixed costs before it can have any impact, which is the case in reality, this equilibrium still results. In this case, it is always inefficient, because of multiplication of fixed costs. However, we show that the equilibrium may be inefficient even without fixed costs. Our

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model illustrates that this inefficiency is higher the more equal donors’ budgets are. In equilibrium, smaller donors have less fragmented aid and behave better from an efficiency viewpoint.

Our model is relevant when donors care about the impact of their aid disbursements relative to the impact of other donors. Under the various motivations (dimensions of impact) of donor aid that the literature has come up with (see Maizels and Nissanke (1984), for an early example), this certainly seems the case. For example, if aid impact means buying geopolitical influence, the one donor (say, the US) in a given recipient country (or region, say, Central Asia) wants to come out on top of the other donors (say, China and Russia) in that country, and vice versa. Similar pressures among donors are at play if the aid motivation is mostly in its commercial impact (one donor wanting more trade and/or FDI than the others) or donor agent satisfaction (one donor wanting to “push out” a larger aid portfolio than the others).1

We argue that such “relativeness” is not only relevant under the above interpretations of aid impact but also under the traditional interpretation: aid effectiveness on poverty reduction in recipient countries. This arises because it is difficult to assess a donor’s absolute effect on poverty reduction. In the need to answer questions of “how big is big” in terms of aid impact, relative donor comparisons seem indispensable. As a result, donor aid impact evaluations often imply benchmarking to other donors. Increasingly, “aid watchers” have come to the fore, who aim to publicly expose precisely the relative effectiveness of donors. This has increased the publication of donor rankings, assessing and comparing aid practices among donors (see, e.g., Birdsall and Kharas 2010; Knack et al. 2011; Easterly and Williamson 2011; Roodman 2012). Birdsall and Kharas (2010, 10) for example note: “Our approach is to assess the quality of aid by benchmarking countries and agencies against each other in each year” (Birdsall and Kharas 2010, 2), and the “target audience includes also the senior management of individual aid agencies, looking to benchmark themselves against others.” Knack et al. (2011) report that “there is evidence that donors do in fact pay attention to these rankings and care about public perceptions.” Accordingly, for example, the Australian Council for International Development (ACFID) has recently identified benchmarks to compare their aid program with internationally agreed standards and good practice (ACFID 2014). In this report Australia’s aid practices are systematically compared to the ones of other bilateral donors.

From a policy perspective, our analysis first of all implies that, short of ending relativeness, agreements to better coordinate aid allocations are not implementable, as donors have strong incentives to deviate. Second, since policies to increase donor competition in terms of aid effectiveness risk reinforcing relativeness, they may well backfire, as any such reinforcement increases aid fragmentation. In this sense, good intentions can have perverse effects. For example, two commonly discussed ways to increase aid effectiveness, namely, improving aid impact evaluations, and increasing donor coordination, can work against each other if improved aid impact evaluations lead to stronger relativeness and thus donor competition for aid impact.

I. Donor Coordination in Practice: Fragmentation

The typical donor gives aid to many developing countries, and the largest bilateral donors in the world operate in virtually every developing country that receives a positive amount of aid, and so do some of the largest multilateral donors, as reflected in figure 1.2 On the horizontal axis, we show each donor’s

1 The last motivation is even often relevant within donor bureaucracies, where one sectoral/regional department (say, energy/Africa) competes with the others (say, human development/Asia) for a given budget, which confers status on the “winning” donor agents within that bureaucracy.

2 Contrary to Official Development Assistance (ODA), which is a net concept, we focus on actual disbursements of new aid money flowing into a developing country, and call it “Gross Aid.” This is because the question we are asking is about the allocation decision of donors of their current budgets. Specifically, this measure excludes debt forgiveness. We also exclude food and humanitarian aid. All our empirical results are similar with or without food and humanitarian aid. However, one may argue that having aid from many donors at the same time, i.e., aid fragmentation, is desirable in a social emergency in a recipient country. Specifically, we thus calculate: Gross Aid=Grants–Grants: Debt

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share of the global aid budget in 2011. The vertical axis shows the number of recipient countries that received a positive amount of aid from a given donor in 2011. The size of the circles measures the ratio of gross aid to Gross National Income (GNI) of donors. A total of 148 developing countries received a positive amount of gross aid in 2011. Among the bilateral donors, Japan disbursed about 11.1 billion US$ to 142 of the 148 aid-recipient countries, the US about 15.6 to 133, Canada 1.75 to 128, Germany 6.5 to 136, France 6.15 to 129, and the UK 4.95 to 129. Among the multilateral institutions, the EU Institutions disbursed about 13 billion US$ to 146 countries, the UN 2 to 140, the World Bank a little more than 10 to 80, and the IMF about 1.5 to 29.

In fact, aid fragmentation has substantially increased in the last 50 years, the period since the OECD Development Assistance Committee (DAC) was established. The average bilateral donor disbursed aid to about 20 recipient countries in 1960 but 87 in 2011. When focussing only on donors that already provided aid in 1970 (when the lionshare of the large donors was already operational), the 2011 number is roughly 115.

The number of donors in the average recipient country has also substantially increased. In 1960, there were less than 3 bilateral donors in the typical recipient country. In contrast, in 2011, this number was almost 23. When only considering the 16 1970-donors, this number was about 12 in 2011. The divergence between these two numbers has increased, which illustrates the arrival on the scene of new donors. This trend may have accelerated recently, with the rise of some emerging markets as donors themselves, in particular China.3 Even countries with a small aid share often have many donors, as shown in figure 2.

Figure 1. Number of Recipient Countries and Global Aid Budget Shares

Source: Authors’ analysis based on data sources discussed in the text.

Forgiveness+ODA Gross Loans–Rescheduled Debt–Food Aid–Humanitarian Aid. The data was obtained from the OECD (http://stats.oecd.org/Index.aspx?DataSetCode=Table2A). Notice that all other data used in this paper is from the World Development Indicators (WDI) retrieved January 2014 if not stated otherwise.

3 These emerging donors do not report aid data to the DAC. On the basis of a literature review, Walz and Ramachandran (2010) report that overall aid estimates for non-traditional donors vary greatly and are somewhere between 11 and 41.7 billion US$, or 8 and 31 percent of ODA from DAC donors. For China, they note that aid estimates range anywhere from 1.5 to 25 billion US$. If the upper estimate is accurate, it ranks as the second largest bilateral donor after
This figure shows recipients' aid as a percentage of the global bilateral aid budget on the horizontal axis and the number of bilateral donors on the vertical axis. The size of the circles measures GNI per capita (PPP-adjusted) in recipient countries. For example, Gambia, with an aid share of just above 0.05 percent, has 28 bilateral donors. Moldova, with a share of 0.22 percent, has 31 donors out of the 39 bilateral donors that disbursed positive amount of aid in 2011. Afghanistan, with a share of 8.4 percent is the largest recipient of bilateral aid in 2011, and it counts 36 out of the 39 donors. Also, countries with an above median policy quality, as measured by the World Bank Country Policy and Institutional Assessment (CPIA), and a below median income level, as measured by GNI per capita), with 27 donors, have a statistically significant larger number of donors than recipients that do not satisfy these two characteristics, which have 21 donors on average.

According to the commonly used Herfindahl index, aid fragmentation substantially increased between 1960 and 2011, as illustrated in figure 3. It largely did so between 1960 and 1980. After 1980, aid fragmentation is still increasing but at a substantially lower rate. This is simply because, by 1980, all bilaterals as well as multilaterals in the world that are able to give large aid amounts had arrived on the scene. When comparing the development of fragmentation of all donors with that among the 1970-donors, one can see that it is essentially determined by the latter. In particular, the increasing entrance of new donors since 1980 did not directly increase fragmentation much. The reason is that the aid budgets of the new donors are generally small. However, note that we do not capture emerging donors such as China in our data.

the US. Using non-DAC data, excluding China, Dreher et al. (2011) compare aid allocations of DAC and emerging donors, but the descriptive statistics show that the aid amounts of the emerging donors that they can cover are quite small.

4 We measure fragmentation as one minus the Herfindahl index as done in Knack and Rahman (2007), so that an increase in our index represents an increase in fragmentation.
The OECD has dedicated a specific website to the theme of “aid fragmentation and donor orphans,” with links to a large set of documents demonstrating the increased levels of aid fragmentation. It states that aid fragmentation “can seriously impair the effectiveness of aid. The current pattern of how aid is delivered and received shows aid splintered across too many donors, each with their own processes and priorities, working in often overlapping relationships with each other. Not only is this pattern complex to understand and coordinate, it also creates transaction costs and administrative burdens for recipient countries. This trend is spreading across the development cooperation landscape.”

At the same time, the costs of fragmentation in terms of aid effectiveness (multiplication of donors’ fixed costs; claims on recipients’ scarce capacity; miscoordination of projects and policies) have led to increasing rhetoric focusing on improving donor coordination, especially since the Paris Declaration of 2005. As the Declaration puts it: “Excessive fragmentation of aid at global, country or sector level impairs aid effectiveness. A pragmatic approach to the division of labour and burden sharing increases complementarity and can reduce transaction costs” (OECD 2005, 6). More good intentions are stated in increasing the focus on results: “Managing for results means managing and implementing aid in a way that focuses on the desired results and uses information to improve decision-making” (OECD 2005, 7). Such intentions were reinforced in the “Accra Agenda for Action” (OECD 2008b) to accelerate and deepen implementation of the Paris Declaration. This, in turn, was based on the official evaluation itself, that “gave ministers at Accra a sobering answer: some progress has been made, but not enough” (OECD 2008a, 3). The most recent official evaluation (OECD 2011), and subsequent Fourth High-Level Forum on Aid Effectiveness (Busan, South Korea) essentially reach the same conclusion.

What we have then, in practice, is aid fragmentation increasing historically, yet officially stated intentions increasingly recognizing its detriment to aid effectiveness. Even though formal models and empirics that explain donor fragmentation are absent from the literature as we read it, some clues behind this state of affairs can be found there. This is what we turn to in the next section.

II. Background Literature

There is a large literature on both aid effectiveness and aid allocation. The mostly empirical literature on aid effectiveness is generally read as showing ambiguous results (Bourguignon and Sundberg 2007; Rajan and Subramanian 2008; Clemens et al. 2012; Roodman 2015). However, as Bourguignon and Sundberg (2007, 316) note this ambiguity of results “is not surprising given the heterogeneity of aid motives, the limitations of the tools of analysis, and the complex causality chain linking external aid to final outcomes.”

In trying to explain donor fragmentation, this paper zooms in on one possible reason for the ambiguity of results in the aid effectiveness literature: donor competition for aid impact. Most relevant for our paper is therefore the literature that concentrates on explaining donor aid allocation. This literature has substantiated the “heterogeneity of aid motives” that we described in the introduction (e.g., Maizels and Nissanke 1984; Ludborg 1998; Alesina and Dollar 2000).

However, there are only a few papers that study the strategic interaction among donors, which we put at the heart of our model. Torsvik (2005) analyzes a game in which the Samaritan dilemma may be reinforced by donor coordination unless donors can credibly enforce conditional aid contracts. However, in his model cooperation or noncooperation is not an equilibrium outcome as in our model. Mavrotas and Villanger (2006) study strategic donor behavior in the context of multilateral agencies using a game theoretic framework. However, their focus is different from ours as in their model donors attempt to influence recipient behavior, an aspect that is absent in our model. In their purely empirical analysis Round and Odedokun (2004) find a positive “peer pressure” effect among donors in terms of size of the aid budget. Similarly, Frot and Santiso (2011), using a concept from the finance literature, find evidence of aid “herding” among donors. Our paper can be seen as investigating a potential cause of such aid herding, and concomitant aid fragmentation: donor competition for aid impact.

An emerging literature is confirming adverse effects of aid fragmentation. For example, Knack and Rahman (2007) show that aid fragmentation reduces bureaucratic quality in developing countries as more aid agencies poach qualified staff away from recipient governments. Knack and Smets (2013) show theoretically and empirically that a higher level of aid fragmentation leads to more aid tying among donors. According to both these papers, aid fragmentation reduces aid effectiveness. There is also direct empirical evidence that suggests that aid fragmentation reduces aid effectiveness (e.g., Annen and Kosempel 2009; Djankov et al. 2009). These papers estimate aid-growth regressions including an interaction term between aid and aid fragmentation, and find a significant negative coefficient on the interaction term.

Burnside and Dollar (2000) investigate both aid effectiveness and aid allocation. They find that aid has a positive impact on growth in poor countries with “good” fiscal, monetary, and trade policies, but has little effect without such policies present. However, these variables only have a small impact on the allocation of aid, which is the combined effect of no impact for bilateral, and a significant impact for multilateral aid. These findings suggest a large potential for improving aid effectiveness by reorienting aid allocations toward poor recipient countries with good policies. Although the robustness of the results in Burnside and Dollar (2000) has been questioned in subsequent research (Easterly et al. 2004), this paper has nevertheless had a profound impact on donor practices across the world, as documented by Easterly (2003).

The more recent literature on aid allocation indeed suggests that donor motives have become less heterogeneous, in targeting aid on poorer countries with better policies (Dollar and Levine 2006; Claessens et al. 2009), which may strengthen competition among donors. A sequence of papers has ranked donor practices more generally (Easterly and Pフトze 2008; Birdsall and Kharas 2010; Easterly and Williamson 2011; Knack et al. 2011; Roodman 2012), and in accordance with the Burnside and Dollar finding, “poverty-selectiveness” and “policy-selectiveness” are criteria that codetermine these rankings, an inherently relative concept.
III. Model

Against the background of the above, we can now develop our model that offers an explanation for aid fragmentation in the strategic interaction of donors. Consider a situation with \( d \) donors and \( r \) recipients. For now we assume that \( d = r = 2 \). We relax this assumption later. Each donor \( i = 1, 2 \) chooses an aid allocation \( a_i = (a_i^1, a_i^2) \) such that \( a_i^1 + a_i^2 \leq t_i \), where \( a_i^j \) denotes the aid from donor \( i \) to recipient \( j \). The parameter \( t_i > 0 \) measures the aid budget of donor \( i \). Recipient \( j \) receives total aid \( a_j = a_j^1 + a_j^2 \). Let \( a = ((a_1^1, a_2^1), (a_1^2, a_2^2)) \) denote the aid allocation profile, and let \( A \) be the set of all possible aid allocation profiles.

Aid given to recipient country \( j = 1, 2 \) has an impact, where impact is measured by the recipient-specific impact function \( f_j(a_j) \). Assume that \( f_j(0) = 0 \), \( f_j'(a_j) > 0 \), and \( f_j''(a_j) < 0 \), \( \forall a_j \geq 0 \). Thus, additional aid always increases impact, at a diminishing rate. The assumption of diminishing returns of aid impact is intuitively plausible, since absorptive capacity in the typical developing country is limited. It is also supported by empirical papers on aid effectiveness that have estimated a decreasing marginal impact of aid on growth. Specifically, these studies include a squared term of foreign aid in the regression analysis, and find that it has a negative sign (Burnside and Dollar 2000; Collier and Dollar 2001; Clemens et al. 2012). Note also that aid enters linearly and additively into the impact functions. Complementarity of aid across donors is ruled out by assumption. However, this assumption is useful in the context here as it implies that the aid technology is “fragmentation neutral.” For example, if we were to use a technology as in Cordella and Dell’Ariccia (2007), where developmental efforts by two providers—in their case the recipient government and a donor—enter as two additive concave functions, then more fragmented aid leads to a higher impact as compared to less fragmented aid. Our assumption of adding aid efforts linearly (no complementarity between donors) assures that our fragmentation result is not driven by an assumption related to technology. Finally, our setup implicitly assumes that aid impact in a given recipient country does not vary across donors. This assumption is reasonable as we focus on aid efforts across donors that can benefit from donor coordination. Aid impact is a public good for the donors.

Total impact of aid of all donors across recipients is then given by

\[
X(a) = f_1(a_1^1) + f_2(a_2^2). \tag{1}
\]

Let the net aid impact of donor 1 be defined by

\[
X_1(a) = X((a_1, a_2)) - X((0, 0), a_2). \tag{2}
\]

The net impact of donor 2 is defined similarly. That is, the net impact of a given donor’s aid is the difference between total impact with and without the aid of that donor. Thus, it measures to what extent a donor “makes a difference.” Note that this definition of net aid impact corresponds to the typical understanding in aid evaluations. These look at the difference in outcomes with and without the existence of a given aid project. It follows endogenously from this setup that the net impact of a donor decreases in the amount of aid by the other donor. Inspecting (2) reveals that \( X_1 \) decreases in \( a_2 \). Increasing aid by donor 2 always increases total impact \( X \), but it decreases the net impact of donor 1. Thus, more of that total impact gets attributed to donor 2—\( X_2 \) increases in \( a_2 \)—and less of that total impact gets attributed to donor 1—\( X_1 \) decreases in \( a_2 \). Aid shares between the two donors determine how the total aid impact gets attributed between the two donors.

From a normative point of view, we are interested to know whether a given aid allocation, \( a \), maximizes total impact, \( X \). This point of view is clearly justified under the traditional interpretation of aid impact, as aid effectiveness on poverty reduction in recipient countries. If changing \( a \) to \( a' \) reduces overall poverty, then such a change is desirable. To maximize total impact, we solve

\[
\max_{a^1, a^2} X(a) \quad \text{s.t.} \quad a^1 + a^2 \leq t, \tag{3}
\]

where \( t \equiv t_1 + t_2 \). Strict concavity and monotonicity of the impact functions implies that \( X(a) \) is concave and strictly increasing, and the optimization problem has a unique solution. Let the unique solution to
this problem be \( a(t) = (a^1(t), a^2(t)) \). The function \( a^i(t) \) denotes the optimal aid supply to recipient \( j \) as a function of the budget \( t \). We henceforth refer to “efficiency” in terms of aid allocations that maximize total impact.

**Definition 1 (Efficiency).** An aid allocation, \( a \in A \), is efficient if \( a^1 + a^2 = a^1(t) \) and \( a^1 + a^2 = a^2(t) \). Let \( A^* \) denote the set of all efficient aid allocation profiles.

Note that the set \( A^* \) is not a singleton. There are many aid allocations among the two donors such that they together provide the efficient aid supply \( a^i(t) \) to each recipient \( j \). We first analyze the model without fixed costs of aid giving, and then with.

**Donors Maximize Net Aid Impact**

Assume that each donor \( i=1,2 \) simultaneously chooses its aid allocation \( a_i \) to maximize net aid impact. Each donor solves the problem

\[
\max_{a_i} X_i(a) \quad \text{s.t.} \quad a_i^1 + a_i^2 \leq t_i. \tag{4}
\]

This setup produces a two-player game. The following result can be proven.

**Proposition 1.** When donors \( i=1,2 \) maximize net aid impact \( X_i \), then the set of all Nash equilibrium aid allocations equals \( A^* \).

**Proof.** See appendix. \( \square \)

When donors maximize net aid impact, the game has multiple equilibria, as shown in the appendix. This suggests that “donor coordination” can work as an equilibrium selection device. For example, international donor summits may be seen as meetings to discuss which equilibrium donors should select. In addition, the analysis suggest that any agreement reached is implementable. However, since any Nash equilibrium is efficient according to proposition 1, donor coordination is irrelevant in terms of aid effectiveness, and only affects the distribution of total aid over donors in a recipient country. Note that this will change in the presence of fixed costs.

**Donors Maximize Relative Net Aid Impact**

Consider now what happens if donors care about relative instead of absolute net aid impact, as we have argued in the introduction and literature review. We define “relative net aid impact” of donor \( i \) as

\[
V_i = \frac{X_i}{X_1 + X_2}. \tag{5}
\]

\( V_i \) measures what difference the aid of donor \( i \) makes relative to the difference the aid of the other donor makes. The larger the net impact of the one donor relative to the other, the larger is \( V_i \).

Donors now allocate their aid budget in order to maximize \( V_i \) instead of \( X_i \). We thus use relative net aid impact \( V_i \) to model the notion of “donor competition.” \( X_1(a_1) \) is strictly increasing in \( a_1 \) and it is strictly concave. In contrast, \( X_2(a_1) \) is strictly decreasing in \( a_1 \). Together, this implies that \( V_1 \) is strictly increasing in \( a_1 \). In addition, for any given \( a_2 \), there is a unique \( a_1 \) that maximizes \( X_1 \) subject to the budget constraint. In fact, \( a(t) - a_2 \) maximizes \( X_1 \), given an allocation \( a_2 \) that exhausts the entire budget \( t_2 \). Assume now there is a unique \( a_1 = a_1 \) that minimizes \( X_2 \) subject to the budget constraint given \( a_2 \), and assume that \( a_1 = a(t) - a_2 \). Then \( a_1 \) maximizes \( V_1 \), as it maximizes \( X_1 \) and minimizes \( X_2 \). We can show that an \( a_2 \) exists such that \( a(t) - a_2 \) minimizes \( X_2 \) and maximizes \( X_1 \). Differentiating \( X_2 \) with respect to \( a_1 \) yields

\[
f_1'(a_1 + a_2) - f_1'(a_1) < 0, \forall j. \tag{6}
\]

If \( a_2 = a(t) - a_1 \), then \( a_1 + a_2 = a(t) \), which implies that the first term in (6) is identical for all \( j=1,2 \). In order to minimize \( X_2 \), the second term in (6) needs to be equalized across all \( j \). The unique \( a_1 \) that

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6 In special cases, it may be though.
achieves this is $a_1 = a(t_1)$. Thus, given $a_2 = a(t) - a(t_1)$, $V_1$ has a unique global maximum at $a_1 = a(t_1)$. Similarly, given $a_1 = a(t) - a(t_2)$, $V_2$ has a unique global maximum at $a_2 = a(t_2)$. We are now able to state our first result:

**Proposition 2.** Assume that impact functions are such that $a(t)$ is linear in $t$. Then the game has a unique Nash equilibrium at $(a(t_1), a(t_2)) \in A^r$. In this equilibrium, recipients receive identical budget shares from both donors: Aid is perfectly fragmented in terms of budget shares. The equilibrium aid allocation is efficient.

**Proof.** If $a(t)$ is linear in $t$, then $a(t_1 + t_2) = a(t_1) + a(t_2)$ or $a(t) - a(t_1) = a(t_2)$, which establishes $(a(t_1), a(t_2))$ as the unique Nash equilibrium using the observations described above. Linearity in $t$ implies that the budget share of donor $i$ going to recipient $j$, $\frac{a_i'(t_i)}{t_i}$ is constant for all $i = 1, 2$.

Thus, when the donors’ objective shifts from maximizing absolute to relative net aid impact, we move from multiple equilibria to a unique equilibrium. The key property of this equilibrium is that aid is perfectly fragmented in terms of budget shares. Note also that in equilibrium, each donor allocates aid “as if” it is the only donor in the game. This equilibrium is still efficient absent any fixed costs, but the assumption that $a(t)$ is linear in $t$ implies that each donor allocates aid to every recipient country.

However, such linearity is a strong assumption. It is satisfied when $X(a)$ is homothetic in $a$—which, for example, is the case when recipients have identical impact functions. Thus, in order for proposition 2 to hold, one needs to assume that scaling up or down the global aid budget does not affect efficient aid shares to recipient countries. It is not hard to find reasons why this may not be the case. First, as mentioned in section II, aid impact typically differs depending on policy quality in recipient countries, that is, aid impact functions are non-identical. Second, for small enough aid budgets, it is likely that in an efficient allocation some recipient countries will get zero aid (corner solution). Both suggest that total aid impact $X(a)$ is nonhomothetic.

To analyze the game for cases where $a(t)$ is nonlinear in $t$, it is convenient to convert each donors’ constrained optimization problem into an unconstrained one by using the fact that donors will exhaust their entire budget. In this case, $a_i^2 = t_i - a_i^1$. The optimization problem thus reduces to an optimization problem with one variable. Differentiating (5) with respect to $a_1$, setting this expression to equal or smaller than zero, and simplifying yields the Kuhn-Tucker condition for donor 1:

$$ (1 - V_1)X'_1 - V_1 X'_2 \leq (>) 0, \quad a_1 \geq 0, \quad (a_1 = t_1), $$

where $X'_1 = f'_1(a_1 + a_2) - f'_2(t - a_1 - a_2)$ and $X'_2 = X'_1 + f'_2(t_1 - a_1) - f'_1(a_1)$. The first-order condition for donor 2 is defined similarly. Differentiating once more with respect to $a_1$ and simplifying yields the second-order condition

$$ \frac{\partial^2 V_1}{(\partial a_1)^2} = (1 - V_1)X''_1 - V_1 X''_2, $$

which needs to be smaller than zero. Assume that this condition is satisfied. Every allocation that satisfies the first-order condition then satisfies the second-order condition, which implies that the donor’s optimization problem has a unique solution. We are now able to state our next result:

**Proposition 3.** Assume that impact functions are such that $a(t)$ is nonlinear in $t$. If $t_1 = t_2$, then the game has a unique Nash equilibrium at $(a(t_1), a(t_2))$. In this equilibrium, aid is perfectly fragmented in the sense that every recipient country receives half of its total aid from donor 1 and 2. The equilibrium aid allocation is inefficient.

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7 In the following analysis, we drop the superscript and set $a_i^j \equiv a_i$. Similarly, we set $a_i^1(t) \equiv a(t)$ and $a_i^2(t) \equiv t - a(t)$.

8 Note that a sufficient but not necessary condition for the second order condition to be satisfied is that $f''_i(a) \geq 0 \forall i$. 

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Proof. $t_1 = t_2$ implies that each donor $i$ can assure $V_i = .5$. Any $V_i \neq .5$ cannot be part of an equilibrium. The first-order condition in (7) reduces to

$$V_1(f'_1(a_1) - f'_2(t_2 - a_1)) \leq (>)0, \quad a_1 \geq 0, \quad (a_1 = t_1).$$

This condition is satisfied for $a_1 = a(t_1)$. Strict concavity in $f$ assures that $a(t_1)$ is unique. The same insight applies to donor 2. The allocation $(a(t_1), a(t_2))$ is the unique Nash equilibrium.

Note that the equilibrium aid allocation is no longer efficient now that $a(t)$ is nonlinear in $t$, even before fixed costs. For example, when there are recipients where $a(t_i) = 0$ for $i = 1,2$, whereas $a(t) > 0$, then these recipients receive no aid in equilibrium, while they would receive a positive amount of aid if donors were to maximize net impact instead of relative net impact. This would occur, for example, if donors perceive that aid has a larger impact in poor countries with good policies. Each donor then concentrates its aid on those recipients, ignoring the fact that the presence of other donors lowers the marginal impact such that aid could have a larger impact when also given to countries with less favorable policy environments. Thus, perversely, individual donors drive to maximize impact relative to other donors by concentrating on poor countries with good policies leads to higher aid fragmentation and inefficiency in the Nash equilibrium of all donors. We will make use of this in our empirics.

The first-order conditions defined in (7) implicitly define the best-response functions of the game. For an allocation $a_2 = 0 < a(t_2)$, a relatively large (small) donor will allocate strictly less (more) than $a(t_1)$ to recipient $j$. In fact, if $V_1$ is sufficiently large, donor 1’s best response may be to give zero aid to recipient $j$ if donor 2 gives zero aid to this recipient. A similar insight applies to the case when $a_2 = t_2 > a(t_2)$. Thus, for a large donor, the more aid the other donor gives to a recipient, the more aid it gives to this very same recipient as its best-response. Of course, this is contrary to best responses observed in proposition 1, as more aid by one donor leads to less by the other there. For a small donor, the direction of its best response depends on exactly how small a donor is. If $V_1$ is close to $.5$ when the other donor gives little aid to recipient $j$, then the slope of donor 1’s best response is positive. In contrast, if $V_1$ is small no matter $a$, then this slope is negative for any $a_2 \in [0, t_2]$. For a relatively small donor, more aid to a recipient by the other donor leads to less aid to that recipient as its best response. Thus, we obtain that for relatively small donors there is strategic substitutability of aid, while for relatively large donors there is strategic complementarity. Note also that these observations imply that best-response functions intersect exactly once. Thus, the game has a unique Nash equilibrium for any $t_1, t_2 > 0$.

One can illustrate the uniqueness of the equilibrium, and the inefficiency of the equilibrium allocation graphically as in figure 4, showing best-response functions for the case with donors with nonidentical budgets, and for a specification of impact functions where $a(t)$ is nonlinear in $t$. The $(a(t) - a(t))$-line in the graph shows all possible combinations of aid between donor 1 and 2 to recipient 1 that maximize total impact. The equilibrium allocation in the figure is strictly below that line. Donor coordination in this situation would make overall aid impact larger. However, a coordinated aid allocation is not a Nash equilibrium, and therefore not implementable.

We can establish the following comparative statics result:

**Proposition 4.** Assume that impact functions are such that $a(t)$ is nonlinear in $t$. Let $t_1 = 0t$ and $t_2 = (1 - 0)t$. Without loss of generality assume that $0 \geq .5$. Then, the inefficiency in the unique equilibrium aid allocation is the highest when $\theta = .5$ and it is nonincreasing in $\theta$ for all $\theta \in [.5, 1]$.

**Proof.** See appendix.

---

9 A more technical version of this discussion is deferred to the appendix.
This proposition implies that an unequally distributed global aid budget over donors is better for efficiency than more equally distributed aid budgets. It suggests that, in equilibrium, smaller donors behave differently from larger donors. We will make use of this in our empirics.

**Introducing Fixed Costs**
Our model so far shows that the global aid allocation will be inefficient if \( a(t) \) is nonlinear in \( t \), even before the incorporation of another important fact related to the disbursement of aid: Aid giving is costly. For example, when a donor starts to operate in a recipient country it incurs fixed costs, without which it has no impact. Such costs initially include getting familiar with a recipient country, setting up a local office, contacts with the government and other institutions, etc. Beyond that, a donor will at least face some fixed costs, such as wages and building of a local office in a recipient country. Easterly and Williamson (2011) note that donor transparency on overhead is dismal but estimate that the average ratios of administrative costs, and salaries and benefits to aid disbursements, are 0.17 and 0.12, respectively. However, they also find a wide variance, indicating that fixed costs can be quite large. The question then arises whether our results survive if we add fixed costs to the game.
In order to see the impact of fixed costs on the equilibrium aid allocation, assume that fixed costs amount to more than half of a donor’s budget. It is then no longer feasible for a donor to operate in both recipient countries. We can show that donor fragmentation is still likely to occur even under this extreme assumption. If donors coordinate their aid—that is, donor 1 operates in recipient country 1 and donor 2 operates in recipient country 2—then the net impacts for donor 1 and 2 are $X_1 = f_1(t_1)$ and $X_2 = f_2(t_2)$, respectively, where $1 - \tau > 0.5$ is the share of a donor’s budget used to cover fixed costs. If both donors operate in recipient country 2 then $X_1 = f_2(t(t_1 + t_2)) - f_2(t_2)$ and $X_2 = f_2(t(t_1 + t_2)) - f_2(t_1)$. Assume that $f_1(a) < f_2(a)$ for all $a \geq 0$. Thus, recipient 2 is the high-impact country. It is easy to see that, if donors have equal budgets, each donor gives aid to the high-impact recipient in the unique Nash equilibrium. In this case, aid coordination would yield a strictly lower net aid impact for the donor who were to give aid to country 1. This donor has a beneficial deviation, which is to shift its aid from recipient 1 to recipient 2. In fact, with donors with equal budgets, aid fragmentation is always the unique equilibrium, no matter how large fixed costs are. In this equilibrium, one recipient receives all the aid, while the other receives nothing.

In contrast, with donors with different budgets the game may no longer have an equilibrium in pure strategies. In this case, given that the large donor gives aid to recipient 2, then it is a best response for the large donor to give aid to the very same country. Thus, we are in a situation in which the large donor wants to operate where the small is, while the small donor wants to operate where the large donor is not. The game will have an equilibrium in mixed strategies. If donor 2 gives aid to recipient 1 with probability $q$ and donor 1 gives aid to recipient 1 with probability $p$, then the change in payoff for a marginal change in $q$ given $p$ for donor 1 equals:

$$p[V_1(0, 0) + V_1(t_1, t_2) - V_1(0, t_2) - V_1(t_1, 0)] - V_1(0, 0) + V_1(t_1, 0).$$

If $V_1(0, 0) > V_1(t_1, 0)$ we still obtain our fragmentation result, because for $p=0$, donor 1’s best-response is to set $q=0$. Furthermore, if $t_1 = t_2$ the term in the square brackets equals zero, which implies that the expression is negative for all $p \in [0, 1]$. We confirm the unique equilibrium to give all aid to recipient 2 in this case. If donor 1 is sufficiently smaller than donor 2, then $V_1(0, 0) < V_1(t_1, 0)$. In this case, donor 1’s best response is to set $q=1$ if $p=0$, and to set $q=0$ if $p=1$. However, there will be a unique $p^* \in (0, 1)$ so that any $q \in [0, 1]$ is a best response. If $(q^*, p^*)$ denotes the Nash equilibrium in mixed strategies, then aid will be fragmented with probability $q^*p^* + (1 - q^*)(1 - p^*) > 0.5$. Thus, we obtain the result that the probability of aid fragmentation is always larger than .5 no matter the relative size of donors’ budgets.

Fixed costs introduce noncontinuities into the problem. Best-response functions jump at the point where donors move from allocating aid to one country to two countries. For small enough costs, there will still be an intersection point of best-response functions, and the analysis in the previous subsection is not affected in the sense that aid remains perfectly fragmented in the equilibrium. However, as we have now seen, if fixed costs are larger, we may no longer have an equilibrium in pure strategies. This, though, can only happen if donors have different budgets, and aid fragmentation still remains likely then. In the case of donors with equal budgets aid always remains fragmented in equilibrium no matter the magnitude of fixed costs.

The coordination of aid allocations is now desirable not only to avoid the inefficiencies described in the previous subsection but also those created due to multiplication of fixed costs. However, the model shows that a donor agreement that seeks to avoid these inefficiencies is still unlikely to be implemented.

---

10 When recipient countries are identical, then \(\frac{V_1(0, 0) - V_1(t_1, 0)}{V_1(0, 0) + V_1(t_1, t_2) - V_1(0, t_2) - V_1(t_1, 0)} = 0.5\), in which case this expression has its minimum that equals .5.
Introducing More Recipients and More Donors

The analysis so far is based on a world with two donors and two recipients. In reality, of course, these numbers are higher. This raises the question how our results are affected by increasing the number of donors and recipients.

Increasing the number of recipients while keeping the number of donors at two does not produce qualitatively new insights, as long as recipients have different impact functions. If impact functions are identical, and donors have to incur sufficiently large fixed costs, equilibria appear where one donor focuses on one group of countries whereas the other donor focuses on another group. However, as pointed out before, the assumption of identical impact functions of recipients is difficult to justify.

Consider now the case with more donors, while keeping the number of recipients at 2. If there are \( d \) donors, then the first-order condition for donor \( i \) described in (7) changes to

\[
(1 - V_i)X_i' - V_i \left( \sum_{k=i}^{d-1} X_k' \right) \leq (>)0, \quad a_i \geq 0, \quad (a_i = t_i).
\]

A donor’s problem now is to choose its aid allocation to maximize its own impact while minimizing the sum of the impact of the other donors. \( V_i \) still functions as a weight between these two concerns. As before, donors with a relatively large budget are more concerned about reducing the impact of other donors in their aid allocation decision than donors with a relatively small budget. In order to see how increasing the number of donors affects the equilibrium, consider the example of two equally large donors plus two equally small donors with a budget that is 20 times smaller than the budget of the two large donors.11 In this example, there is a unique equilibrium in which the two large donors fragment by giving aid to both recipients, and the two small donors concentrate their aid efforts on the recipient that receives “too little” aid in terms of efficiency from the large donors. In this equilibrium, the two large donors mainly compete with each other, while their aid allocation decisions are only marginally affected by the allocations of the small donors.

The question then arises whether the two small donors compete against each other like the two large donors do. In order to analyze this, assume now that, instead of having one recipient that receives “too little” aid from the large donors, there are two such recipients. That is, we have a world of three recipients and four donors in total. In this numeric example, the unique equilibrium is that the two small donors each split their budget between the two recipients that receive “too little” aid from the large donors. Thus, small donors also compete against each other in equilibrium. However, if donors have to incur large enough fixed costs, then “coordinated aid” among the small donors appears as an equilibrium. In our simulation, fixed costs of 2 percent of total budget per recipient were enough to generate this “coordinated” equilibrium. Note that these fixed costs are small enough that it is clearly feasible for small donors to operate in all recipient countries, but they choose not to. In this equilibrium, the two large donors allocate aid to all three recipients, while the two small donors each give aid to a different one of the two recipients that receive “too little” aid from the large donors. We will make use of this in our empirics.

Moving toward a world with more than two recipients and donors, the model thus predicts that small donors care more about maximizing their own aid impact in recipient countries than large donors do. The latter always keep their aid allocations fragmented, whereas the former, already at small fixed costs, start coordinating their aid allocations to improve efficiency. This is nicely in line with the empirical finding by Alesina and Dollar (2000) that aid allocations of the largest donors (US, Japan, France, in their data) are most “distorted” from an efficiency viewpoint, whereas notably the Nordic countries

11 Reality is more extreme: in 2009, the budget of the average donor was about 108 and 65 times smaller than the budget of the US and Japan, respectively, the two largest donors in that year.
seem to care more about efficiency. However, our model also suggests that the smaller donors, like the Nordics, would start behaving in a similarly distorted manner if they were the larger. Perversely, making smaller, “better” donors larger could thus actually deteriorate the overall efficiency of global aid.

**IV. Empirical Evidence**

The main prediction of our model is that aid is fragmented in equilibrium. In section I, we already showed that aid is fragmented, and that fragmentation has increased over time. However, there are other implications of the model that we can explore in the data. The model suggests that relatively small donors choose to have less recipients and their aid allocations among the fewer recipients is less fragmented. Moreover, it suggests that increased relativeness should lead to increased fragmentation.\(^\text{12}\)

Regarding the different behavior of smaller donors, figure 1 already indicated that they tend to give aid to fewer countries than larger donors. A Poisson regression between the number of recipients of a donor and its share in the global aid budget for the year 2011 shows a significant positive relationship (see column I in table 1).\(^\text{13}\) However, this correlation may be simply driven by (budgetary) feasibility, as for example fixed costs may make it difficult for small donors to operate in a large number of recipient countries.\(^\text{14}\) In order to control for feasibility, we include the donors’ GDP per capita as a control. Column II reports the result with this control, and we can see that there is still a statistically significant positive relationship between budget share and the number of recipients, although somewhat smaller than in Column I, which was to be expected. Column III reports panel regression results. The advantage of this analysis is that we can control for donor-fixed effects. Our result prevails: A larger share in the global aid budget is associated with more aid recipients given the income level of donors and given donor-fixed effects that may affect the number of recipients.

Although smaller donors allocate aid to fewer countries on average, it is not clear whether their aid is less fragmented. For example, smaller donors could cluster in the same recipient countries and as a group have highly fragmented aid in these countries. In order to test whether this is the case, we divide donors into two groups for each year between 1980 and 2011: We rank their total budgets and then form groups of eight among the donors with the 16 highest budgets.\(^\text{15}\)

We calculate aid fragmentation for each recipient country in each year for both groups and for both groups take the average across recipients for each year. Figure 5 shows that aid fragmentation is always higher for the eight largest donors compared to the other group of donors. This difference is significant for most years. Column IV in table 1 replicates figure 5 for the year 2011 in a cross-section regression. It confirms that aid fragmentation is significantly higher among the 8 largest donors as compared to the other group. Column V in table 1 replicates figure 5 as a panel regression. The advantage here is that we

\[12\] We limit this empirical section to bilateral donors. For multilaterals, since executive boards consisting of many countries take their operational decisions, competition may largely take place within these boards.

\[13\] We use a Poisson regression with heteroskedastic-robust standard errors in columns I and II and with cluster-robust standard errors in column III. Poisson regressions are appropriate here as we deal with count data that is bounded below (at zero) and above (at about 150, the maximal number of possible aid recipients). Note that using OLS regressions instead of Poisson regressions gives qualitatively identical results.

\[14\] In figure 1, the case of South Korea is the extreme case demonstrating that a relatively small donor can have a very large number of aid recipients. There are other examples: In 2009 Canada disbursed aid to 137 recipients, in 1995 Belgium to 121, in 2001 the Netherlands to 133, in 2007 Greece to 119, etc. These examples suggest that it is feasible for small donors to give aid to a large number of recipients.

\[15\] Note that the Herfindahl index is sensitive to the number of donors. For this reason, we form groups of equal size. These 16 donors together controlled 99 percent and 94 percent of the global aid budget in 1980 and 2011 respectively. In 1980 the top eight donors controlled about 87 percent of the global aid budget, whereas in 2011 this number changed to 80 percent. In 2011, there are many more small donors compared to 1980, but they control only a very small fraction of the global aid budget.
Table 1. Larger Donors vs. Smaller Donors

<table>
<thead>
<tr>
<th></th>
<th>No. of recipients</th>
<th>Aid fragmentation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(I)</td>
<td>(II)</td>
</tr>
<tr>
<td>Global budget share</td>
<td>0.06***</td>
<td>0.04***</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Lagged GDP pc (log)</td>
<td>0.25***</td>
<td>0.18</td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
<td>(0.17)</td>
</tr>
<tr>
<td>8 Largest donors</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>4.35***</td>
<td>1.85*</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(1.01)</td>
</tr>
<tr>
<td>Donor FE</td>
<td>no</td>
<td>no</td>
</tr>
<tr>
<td>Recipient FE</td>
<td>no</td>
<td>no</td>
</tr>
<tr>
<td>Time FE</td>
<td>no</td>
<td>no</td>
</tr>
<tr>
<td>N</td>
<td>38</td>
<td>37</td>
</tr>
<tr>
<td>Pseudo-R-squared</td>
<td>0.15</td>
<td>0.22</td>
</tr>
<tr>
<td>Chi-squared</td>
<td>14.81</td>
<td>20.66</td>
</tr>
<tr>
<td>R-squared</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F statistic</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Columns I, II, and III report results of Poisson regressions with the number of aid recipients as the dependent variable. Columns I and II use the sample of 37 bilateral donors in 2011, which includes DAC and non-DAC donors. Column III uses the same sample but in a panel between 1961 and 2011. Regressions I and II use heteroskedastic-robust standard errors, and regression III uses cluster-robust standard errors at the donor level—all reported in parenthesis. Columns IV and V report OLS regressions with aid fragmentation (1 minus Herfindahl index) as the dependent variable. Cluster-robust standard errors at the recipient level reported in parenthesis. Significance levels: *: 10 percent **: 5 percent ***: 1 percent.

Source: Authors’ analysis based on data sources discussed in the text.

Figure 5. Aid Fragmentation and Relative Donor Size

Source: Authors’ analysis based on data sources discussed in the text.
can use recipient fixed-effects. We find that aid fragmentation is significantly higher in the group of the 8 largest donors as compared to the other group. The point estimate suggests a difference of 10 percentage points. We conclude that the correlations reported in table 1 are consistent with the prediction of our model that smaller donors choose to have fewer recipients and that aid of smaller donors is less fragmented among those fewer recipients.

Our model also predicts that increased relativeness should lead to increased fragmentation. As discussed in the introduction and literature review, there has been an increase in the publication of donor rankings. In these rankings measures of “aid-selectivity” play a crucial role (see Birdsell and Kharas 2010; Easterly and Williamson 2011; Knack et al. 2011; and Roodman 2012, for four recent examples). Its basic idea is that donors allocate their aid to countries in which they can be more effective. Burnside and Dollar (2000) was most influential in this respect, focussing donors on poor recipient countries with good policies, as documented by Easterly (2003). Both policy and poverty selectivity have thus become more important in donors’ aid allocation decisions. Given that aid selectivity plays an important role in donor rankings, which are inherently relative measures of donor performance, our model explaining aid fragmentation should apply better to aid-selective donors than to donors that are not aid selective as measured in these rankings.

To measure aid selectivity, we use the Commitment to Development Index (CDI), produced and updated every year since 2003 by the Center for Global Development (CGD), estimating aid selectivity as part of their quality assessment of donors’ aid efforts in their donor ranking.16 We take the aid selectivity measure from the CDI and divide donors into two groups for every year between 2006 and 2011: aid selective donors and non-aid selective donors. The selectivity measure in the CDI captures to what extent aid is targeted at poor and well-governed countries. Thus, the CDI selectivity measure captures the policy and poverty selectivity of a donor’s aid allocation, in line with Burnside and Dollar (2000). We classify a donor as being “aid-selective” ($S = 1$), if this aid selectivity measure is above the median value in a given year; as “non aid-selective” if not ($S = 0$). Table 2 shows how donors do in terms of aid-selectivity by showing their average between 2006 and 2011. A donor with a value of 1, which includes most of the Nordic countries, and some other small donors, indicates that these donors have always been classified as aid-selective in all the years. In contrast, a value of zero indicates that a donor has always been classified as non-aid selective in all the years. Noteworthy, the United States has a value of zero.

Specifically, we can now use the CDI aid selectivity measure to test the prediction of our model that aid fragmentation among aid-selective donors should be higher as compared to non-aid selective donors particularly in recipient countries that fare well on the selectivity criterion used by the donors. A recipient country with a good policy environment should thus attract more fragmented aid from the aid-selective donors as compared to non-aid-selective donors. Likewise, a poorer recipient country should attract more fragmented aid from aid-selective donors as compared to non-aid-selective donors.

To test this hypothesis, we calculate a fragmentation measure for aid-selective and non-aid-selective donors in each recipient country for each year between 2006 and 2011. We then estimate the following model:

$$\text{FRAG}_{i,t,S} = \beta_0 + \beta_1 S + \beta_2 \text{GNIpc}_{i,t-1} + \beta_3 \text{POL}_{i,t-1} + \beta_4 S \times \text{POL}_{i,t-1} + \beta_5 S \times \text{GNIpc}_{i,t-1} + \phi_t + \tau_t + \epsilon_{i,t,S},$$

where FRAG measures aid fragmentation in recipient country $i$ in year $t$ for aid-selective donors ($S = 1$) and non-aid-selective donors ($S = 0$). The variables GNIpc and POL measure income level and policy selectivity.

---

16 See Roodman (2012) for an exact description of the methodology used to derive the CDI. The data can be found at http://www.cgdev.org/initiative/commitment-development-index/inside.
quality in recipient country \( i \) in the year \( t-1 \) respectively. In our panel regressions, we include recipient- and time fixed effects. As we have two observations for each recipient country in a given year, we use cluster-robust standard errors also for our “cross-section” regressions. For our income measure we use GNI per capita (PPP adjusted), and for our policy measure we use two measures: The World Bank CPIA measure, and World Governance Indicators (WGI) developed by Kaufmann, Kraay, and Mastruzzi.\(^{17}\) Note that CDI uses WGI as its policy measure, and Knack et al. (2011) use CPIA.

Our main interest is in the interaction terms with \( S \) (aid selectivity): We should find a negative interaction term with respect to GNIpc and a positive interaction term with respect to POL. Table 3 shows the results. The first three regressions report the results for the year 2011, and the other three regressions report the results using data between 2006 and 2011, when including recipient- and time-fixed effects. Columns I and IV use the CPIA as the policy measures, and the remaining columns use WGI.

\(^{17}\) The data for WGI can be accessed at the following link: http://info.worldbank.org/governance/wgi/index.aspx#home.

Table 2. Donor Ranking in Aid Selectivity

<table>
<thead>
<tr>
<th>Rank</th>
<th>Donor</th>
<th>Avg. ( S )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Denmark</td>
<td>1.00</td>
</tr>
<tr>
<td>1</td>
<td>Finland</td>
<td>1.00</td>
</tr>
<tr>
<td>1</td>
<td>Iceland</td>
<td>1.00</td>
</tr>
<tr>
<td>1</td>
<td>Ireland</td>
<td>1.00</td>
</tr>
<tr>
<td>1</td>
<td>Luxembourg</td>
<td>1.00</td>
</tr>
<tr>
<td>1</td>
<td>Netherlands</td>
<td>1.00</td>
</tr>
<tr>
<td>1</td>
<td>New Zealand</td>
<td>1.00</td>
</tr>
<tr>
<td>1</td>
<td>Portugal</td>
<td>1.00</td>
</tr>
<tr>
<td>1</td>
<td>Sweden</td>
<td>1.00</td>
</tr>
<tr>
<td>1</td>
<td>Switzerland</td>
<td>1.00</td>
</tr>
<tr>
<td>1</td>
<td>France</td>
<td>0.83</td>
</tr>
<tr>
<td>11</td>
<td>Japan</td>
<td>0.83</td>
</tr>
<tr>
<td>11</td>
<td>United Kingdom</td>
<td>0.83</td>
</tr>
<tr>
<td>14</td>
<td>Australia</td>
<td>0.50</td>
</tr>
<tr>
<td>14</td>
<td>Austria</td>
<td>0.50</td>
</tr>
<tr>
<td>14</td>
<td>Belgium</td>
<td>0.50</td>
</tr>
<tr>
<td>14</td>
<td>Canada</td>
<td>0.50</td>
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<tr>
<td>14</td>
<td>Israel</td>
<td>0.50</td>
</tr>
<tr>
<td>19</td>
<td>Germany</td>
<td>0.33</td>
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<tr>
<td>19</td>
<td>Hungary</td>
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<td>Norway</td>
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<td>22</td>
<td>Italy</td>
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<tr>
<td>22</td>
<td>Poland</td>
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<tr>
<td>24</td>
<td>Cyprus</td>
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<td>24</td>
<td>Czech Republic</td>
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<tr>
<td>24</td>
<td>Greece</td>
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<td>24</td>
<td>Korea</td>
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<td>24</td>
<td>Lithuania</td>
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<td>24</td>
<td>Slovak Republic</td>
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<td>24</td>
<td>Spain</td>
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<tr>
<td>24</td>
<td>Turkey</td>
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<tr>
<td>24</td>
<td>United Arab Emirates</td>
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</tr>
<tr>
<td>24</td>
<td>United States</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Notes: Donor is classified as “Aid Selective” (\( S=1 \)) if ranked in the top half according to the aid selectivity measure calculated by the “Commitment to Development Index” (CDI); “Non-Aid Selective” if not (\( S=0 \)). The measure reported above is the average of \( S \) between 2006 and 2011.

Source: Authors’ analysis based on data sources discussed in the text.
Columns III and VI show the results using WGI as the policy measure but using the sample that matches the one used in the CPIA regressions. In all the regressions, the interaction-terms have the expected sign and are statistically significant at the 5-percent level or less, except in one specification, where the interaction term with WGI is not significant. In line with our model, these results suggest that the relationship between poverty and aid fragmentation is significantly different for aid selective donors compared to non-aid-selective donors. The same is true for the relationship between policy and aid fragmentation. For non-aid selective donors, the relationship between poverty and fragmentation is either not significant, or significant with the wrong sign. For example, in column III the coefficient for GNIpc is significant at the 1-percent level but it has a positive sign. The same conclusion applies to the relationship between policy and aid fragmentation. For non-aid selective donors, the relationship between poverty and fragmentation is significantly different for aid selective donors compared to non-aid-selective donors. The same is true for the relationship between policy and aid fragmentation.

For non-aid selective donors, the relationship between poverty and fragmentation is either not significant, or significant with the wrong sign. For example, in column III the coefficient for GNIpc is significant at the 1-percent level but it has a positive sign. The same conclusion applies to the relationship between policy and fragmentation for non-aid selective donors. In contrast, the relationship between poverty and fragmentation for aid-selective donors has the expected sign and it is statistically significant in all regressions. These results are reported under “GNIpc | S = 1.” The relationship between policy and aid fragmentation is always positive for aid-selective donors, as expected, but coefficients are significant only in the “cross-section” regressions. These results are reported under “POL | S = 1.” We infer that our results are robust for poverty, but less so for policy, although the coefficient in all the regressions has the expected sign. We also observe that overall, aid-selective donors exhibit a higher level of aid

### Table 3. Aid Selectivity and Aid Fragmentation for “Aid-Selective” and “Non-Aid-Selective” Donors

<table>
<thead>
<tr>
<th>Dependent variable: aid fragmentation (1-Herfindahl)</th>
<th>Year 2011</th>
<th>Years 2006–2011</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(I)</td>
<td>(II)</td>
</tr>
<tr>
<td>S</td>
<td>0.16</td>
<td>0.90***</td>
</tr>
<tr>
<td></td>
<td>(0.32)</td>
<td>(0.31)</td>
</tr>
<tr>
<td>Lagged real GNIpc (log)</td>
<td>0.05*</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Lagged CPIA (log)</td>
<td>−0.24*</td>
<td>−0.07</td>
</tr>
<tr>
<td></td>
<td>(0.14)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Lagged WGI</td>
<td>−0.07</td>
<td>−0.13***</td>
</tr>
<tr>
<td></td>
<td>(0.14)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>CPIA × S</td>
<td>1.04***</td>
<td>(0.24)</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>GNIpc × S</td>
<td>−0.17***</td>
<td>−0.09**</td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>WGI × S</td>
<td>0.13**</td>
<td>0.28***</td>
</tr>
<tr>
<td></td>
<td>(0.19)</td>
<td>(0.22)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.39**</td>
<td>0.32</td>
</tr>
<tr>
<td></td>
<td>(0.19)</td>
<td>(0.22)</td>
</tr>
<tr>
<td>Recipient FE</td>
<td>no</td>
<td>no</td>
</tr>
<tr>
<td>Time FE</td>
<td>no</td>
<td>no</td>
</tr>
<tr>
<td>POL</td>
<td>S = 1</td>
<td>0.80***</td>
</tr>
<tr>
<td></td>
<td>(0.23)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>GNIpc</td>
<td>S = 1</td>
<td>−0.12***</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.20</td>
<td>0.08</td>
</tr>
<tr>
<td>N</td>
<td>148</td>
<td>250</td>
</tr>
</tbody>
</table>

Notes: Dependent variables are aid fragmentation measured by one minus the Herfindahl index for aid-selective and non-aid-selective donors. All regressions use OLS with clustered standard errors in parenthesis. Significance levels: *: 10 percent **: 5 percent ***: 1 percent.

Source: Authors’ analysis based on data sources discussed in the text.
fragmentation as the coefficient of the dummy variable $S$ is positive in five out of the six specifications. Finally, when comparing columns II and III, and V and VI, we observe that the interaction terms and the coefficients GNIpc $|S = 1$ and POL $|S = 1$ increase in absolute value when changing from the full sample with WGI as a policy measure to the CPIA sample. This is relevant as the CPIA measure is published for “IDA-elegible” countries only, and these countries are all low-income countries. Thus, our finding of increased aid-selectivity leading to an increased aid fragmentation seems particularly relevant for IDA-elegible countries.

To conclude, the correlations reported in table 3 are in line with the predictions of our model. The evidence thus points to possible unintended consequences of making donors more accountable in terms of their aid selectivity. Increased aid selectivity may lead to increased aid fragmentation, and if aid fragmentation reduces aid effectiveness, this policy may in fact backfire and make aid less effective.

V. Conclusion

Aid fragmentation remains high, and has in fact increased, despite increasing rhetoric against it, which begs an explanation. This fragmentation can be seen as one of the reasons for the ambiguous results in the aid effectiveness literature.

Our model shows how competition among donors for aid impact, in any dimension, inherently leads to aid fragmentation. The equilibrium aid allocation may be inefficient even without fixed costs, and this inefficiency increases in the equality of donors’ budgets. In equilibrium, smaller donors have less fragmented aid, and behave better from an efficiency viewpoint. Moreover, the model explains how attempts, such as recently undertaken, to better evaluate donor impact via “measurable results,” and target aid on countries with higher “policy quality” and poverty, however well-intended, can backfire in more fragmentation and less efficiency, because they may well increase relativeness. Our empirics are in line with the results of the model.

Our model thus essentially says that efforts to improve donor coordination are doomed to failure, since they do not change the incentives underlying donors’ strategic interaction, unless they end relativeness. We do not want to be read as suggesting that an aid monopoly would be the best of all worlds, as, clearly, some competition between donors is healthy, but we show that the competitive forces push towards a fragmented and inefficient equilibrium.

This points to the importance of avoiding relativeness in evaluating aid impact. Donor coordination is a feasible equilibrium outcome in our model only if donors care about their absolute and not relative impact. Thus, the development of absolute standards in evaluating aid impact seems crucial. Note that, to the extent that emerging donors, such as China, are reinforcing the general focus on relativeness, their emergence will inherently lead to more fragmented and less effective aid according to our model.

Finally, note that, focussing on explaining donor fragmentation, our model says nothing about aid-recipient behavior. An interesting extension of our model could be to investigate feedback mechanisms from donor competition to aid-recipient behavior and vice versa. This could for example shed light on the effectiveness of donor conditionality. Svensson (2003) notes that conditionality essentially does not work, because the threat of not disbursing is not credible. He stresses that the outcome could be improved by explicitly linking aid allocation and disbursement decisions by donors, and, in his conclusion, wonders why the donor community then has not introduced such a link. Our model suggests this could be because of the competition for aid impact among the donors themselves. This divides the donors, and, in practice, the recipient will know and play that. Thus, the implications of the competitive forces that lead to donor fragmentation may be even more damaging than “just” the inefficiencies we found modeling the donor side while abstracting from the recipients’ game.
Appendix

Proof of Proposition 1. Comparing (1) with (2) yields the insight that maximizing total net impact is identical to maximizing total impact since the negative term in (2) does not depend on donor $i$’s choice. Total impact is given by

$$X(a_1,a_2) = \sum_{j=1}^{2} f_j(a'_1 + a'_2).$$

Forming a Lagrangian yields

$$L(a_i) = \sum_{j=1}^{2} f_j(a'_1 + a'_2) + \lambda_i(t_i - a'_1 - a'_2^2).$$

Strict monotonicity in the impact functions implies that donor $i$ will always disburse the entire budget $t_i$. For each donor $i=1,2$, the Kuhn-Tucker conditions are given by

$$f'_j(a'_1 + a'_2) - \lambda_i \leq 0 \quad d'_i \geq 0, \quad \forall j = 1,2,$$

and

$$t_i - a'_1 - a'_2^2 = 0.$$ (9)

Since the aid of each donor enters additively into the impact functions, for any given $a \in A$, $f'_j$ in (9) is identical for both donors. This implies that in a solution to the optimization problem, we must have that $\lambda_1 = \lambda_2$, because the constraint is binding for both donors. Furthermore, the sum of aid disbursed by the two donors equals $t_1 + t_2 = t$, which implies that $\lambda_1 = \lambda_2 = \chi(t)$, where $\chi(t)$ denotes the shadow price of aid when solving the problem in (3). The marginal aid impact of an extra budget dollar is the same as in the unique solution of the optimization problem in (3). Thus, any $a \in A^*$ constitutes a solution to the system of equations described in (9) and (10) for both donors simultaneously. Any allocation $a \in A^*$, therefore, can be established as a Nash equilibrium. In contrast, an allocation $a \notin A^*$ cannot be a Nash Equilibrium. In this case, (9) must be violated for at least one donor. □

Description of Best-Response Functions. Using implicit differentiation of (6), we obtain:

$$\frac{\partial a'_1}{\partial a'_2} = \frac{(1 - 2V_1)X'' - \frac{\partial V_1}{\partial a'_2}(X'_1 + X'_2)}{(1 - V_1)X'' - V_1X''_2}. $$ (11)

The sign of $\frac{\partial a'_1}{\partial a'_2}$ is determined by the sign of the numerator as we know that the sign of the denominator is negative (second-order condition). Differentiating, using the fact that $V'' = 0$, and simplifying yields that the sign of $\frac{\partial V_1}{\partial a'_2}$ is equal to the sign of the expression

$$V_1(f'_2(t_1 - a_1) - f'_1(a_1)) + (1 - V_1)(f'_2(t_2 - a_2) - f'_1(a_2)). $$ (12)

This expression (12) equals zero at $(a(t_1),a(t_2))$. We rewrite the first-order conditions in (7) as

$$(1 - 2V_1)(f'_1(a_1 + a_2) - f'_2(t - a_1 - a_2)) + V_1(f'_1(a_1) - f'_2(t_1 - a_1)) \leq 0.$$ (13)

Consider now an allocation $a_2 = 0 < a(t_2)$. Then, $V_t(a(t_1),a_2) < (>)0$ if $V_1 > (<) .5$ at this allocation, which means that a relatively large (small) donor will allocate strictly less (more) than $a(t_1)$ to recipient $j$. In fact, if $V_1$ is sufficiently large, donor 1’s best-response may be to give zero aid to recipient $j$ if donor 2 gives zero aid to this recipient.

A similar insight applies to the case when $a_2 = t_2 > a(t_2)$. If $V_t(a(t_1),a_2) > (>) .5$, then $a_1(a_2) > ( <) a(t_1)$. $\frac{\partial a_1}{\partial a_2} > 0$ if $V_1(a_1,a_2) > .5$ for any $a_2$ that exhausts the entire budget $t_1$. Thus, for a large donor, the more aid the other donor gives to a recipient, the more aid it gives to this very same recipient as its best-response. Of course, this is contrary to best responses observed in proposition 1, as more aid by one donor leads to less by the other there. For a small donor, the sign of $\frac{\partial a_1}{\partial a_2}$ depends on exactly how small a donor is. In fact, if $V_1$ is close to .5 when the other donor gives little
aid to a recipient $i$, then $\frac{\partial a_i}{\partial t_1} > 0$. If $V_1$ is small, then $\frac{\partial a_1}{\partial t_2} < 0$ for any $a_2 \in [0, t_2]$. For relatively small donors, more aid to a recipient by the other donor leads to less aid as their best-response. Thus, we obtain that for relatively small donors there is strategic substitutability, while for relatively large donors there is strategic complementarity. Note also that these observations imply that best-response functions intersect exactly once. Thus, the game has a unique Nash equilibrium for any $t_1, t_2 > 0$.

Proof of Proposition 4. The parameter $\theta$ measures donor 1’s share of the global aid budget $t$. Without loss of generality assume that $a(t)$ is convex in $t$. This implies that $t - a(t)$, the aid amount distributed to recipient 2, is concave in $t$. Note that because both $f_1$ and $f_2$ are strictly increasing, $a(t)$ and $t - a(t)$ is non-decreasing in $t$. Then, $a(\theta t) + a((1 - \theta)t) < a(t)$ for all $\theta \in (0, 1)$ and the difference $A(\theta) \equiv a(t) - [a(\theta t) + a((1 - \theta)t)]$ does not increase in $\theta$ for all $\theta \in [.5, 1]$. The fact that $A(\theta)$ is non-increasing in $\theta$ for all $\theta \in [.5, 1]$ implies that total aid impact $X(a(t), a((1 - \theta)t))$ is non-decreasing in $\theta$ for all $\theta \in [.5, 1]$. Consider now the first-order condition when $a = (a(\theta t), a((1 - \theta)t))$. If $\theta = .5$, the first-order condition is satisfied for both donors and we have a Nash equilibrium. Consider now a global budget with $\theta > .5$. Then $V_2(a) < 0$, and $V_2(a) > 0$. Given $a$, it is a best-response for donor 1 to decrease and for donor 2 to increase the aid to recipient 1. If the adjustment process to the equilibrium leads to an increase and decrease of aid in identical magnitudes, then $X$ remains unchanged, and efficiency is not affected by this adjustment process. Assume there is such an equilibrium where $a_1 = a(\theta t) - \Delta$ and $a_2 = a((1 - \theta)t) + \Delta$, with $\Delta > 0$. In this allocation, starting from $a$, donor 1 transfers the amount of $\Delta$ from recipient 1 to recipient 2 thereby increasing inefficiency, and donor 2 transfers the amount of $\Delta$ from donor 2 to donor 1 thereby removing the increased inefficiency created by donor 1. Then, $X_1 = X(a) - f_1(a_1 + \Delta) - f_2((t - \theta t) - a_2 - \Delta) > X_2(a)$ and $X_2 = X(a) - f_1(a_1 - \Delta) - f_2((t - \theta t) - a_1 - \Delta) > X_2(a)$. This, however, cannot be an equilibrium as donor 1 has a beneficial deviation given donor 2 allocates $a_2 = a((1 - \theta)t) + \Delta$. For example, to allocate $a_1 = a(\theta t)$ it will strictly decrease $X_2$ and it will strictly increase $X_1$, thereby increasing $V_1$. Note that the same logic applies to an adjustment process where donor 1 decreases its aid amount to recipient 1 by more than donor 2 does. This implies that in a Nash equilibrium, $a^*$, we must have that $X(a^*) > X(a)$. Since $X(a)$ is (weakly) increasing in $\theta \in [.5, 1]$, $X(a^*)$ must be (weakly) increasing in $\theta \in [.5, 1]$.

References


18 This corresponds to the situation depicted in figure 4. In equilibrium, recipient 1 receives less aid than efficient.


