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Donor Competition for Aid Impact, and Aid Fragmentation

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Abstract

This paper shows that donors that maximize relative aid impact spread their budgets across many recipient countries in a unique Nash equilibrium, explaining aid fragmentation. This equilibrium may be inefficient even without fixed costs, and the inefficiency increases in the equality of donors' budgets. The paper presents empirical evidence consistent with theoretical results. These imply that, short of ending donors' maximization of relative aid impact, agreements to better coordinate aid allocations are not implementable. Moreover, 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.

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Contents Page

"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, page 2).

"... there is no unity in the foreign aid community. A high-level official says, "If I say something critical and get kicked out and nobody joins me... in the end it's my organisation that will lose access to the country"" (International Crisis Group, 2011, page 27).

1 Introduction

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 first 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 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 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.

It is important to stress at the outset that our model applies whatever the exact interpretation of aid impact. In particular, it does not hinge on its more cynical interpretations, such as impact on aid managers own income or status, donors' own commerce or geopolitical influence. The fragmented and

inefficient equilibrium also results under the traditional interpretation of aid impact: Aid effectiveness on poverty reduction in recipient countries. Since this is most striking, we henceforth assume that the traditional interpretation of aid impact applies.

The second quote above illustrates what drives these results: Donors worry about the impact of their actions relative to other donors. This donor competition for aid impact partly arises because it is very hard to measure a donor's absolute impact on poverty reduction in a recipient country. Thus, in their need to justify aid budgets, donors use aid impact comparisons with other donors in order to make their case. Moreover, increasingly, "aid watchers" have come to the fore, who aim to publicly expose precisely the relative effectiveness of donors. For example, there is an increase in the publication of donor rankings, assessing and comparing aid practices among donors, and there is evidence that these rankings affect donor behavior. As well, with the rise of non-traditional, emerging donors, such as China, relativeness seems to be increasing more generally, both under the traditional and more cynical interpretations of aid impact.

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. Such agreements are "cheap talk" in game-theoretic terms (only). 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 donor competition for aid impact.

The rest of this paper is structured as follows: Section 2 provides some background on the development of aid fragmentation, and the efforts by the aid community to improve coordination. Section 3 relates our paper to the literature. Section 4 develops the theoretical model, and states the main results. Section 5 provides empirical evidence. Section 6 concludes.

2 Donor Coordination in Practice: Fragmentation

Figure 1 summarizes the current global gross aid allocation among donors.[1] On the horizontal axis, we show each donor's share of the global aid budget in 2009, the most recent year for which we have comprehensive data. The vertical axis shows the number of recipient countries that received a positive amount of aid from a given donor in 2009. The size of the circles measures the ratio of gross aid to Gross National Income of donors. First, we see that the typical donor gives aid to many developing countries. A total of 142 developing countries receives a positive amount of gross aid. Among the bilateral donors, Japan disbursed about 11 billions US$ to 140 of the 142 aid-recipient countries, the US about 18 to 138, Canada 1.9 to 137, Germany 5.8 to 136, France 4.9 to 129, and the UK 4.6 to 127. Among the multilateral institutions, the EU Institutions disbursed about 9.3 billions US$ to 141 countries, the UN 1.8 to 140, the World Bank a little more than 11 to 79, and the IMF about 2.5 to 38. Thus, we can conclude that the largest bilateral donors in the world operate in virtually every developing country that received a positive amount of aid in 2009, and so do some of the largest multilateral donors: Aid is certainly fragmented.

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 donor disbursed aid to about 20 recipient countries in 1960, but 85 in 2009. When focussing only on donors that already provided aid in 1970 (when the lionshare of the large donors was already operational), the 2009-number is roughly 105.

The number of donors in the average recipient country has also substantially increased. In 1960, there were less than 3 donors in the typical recipient

[1] 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 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).

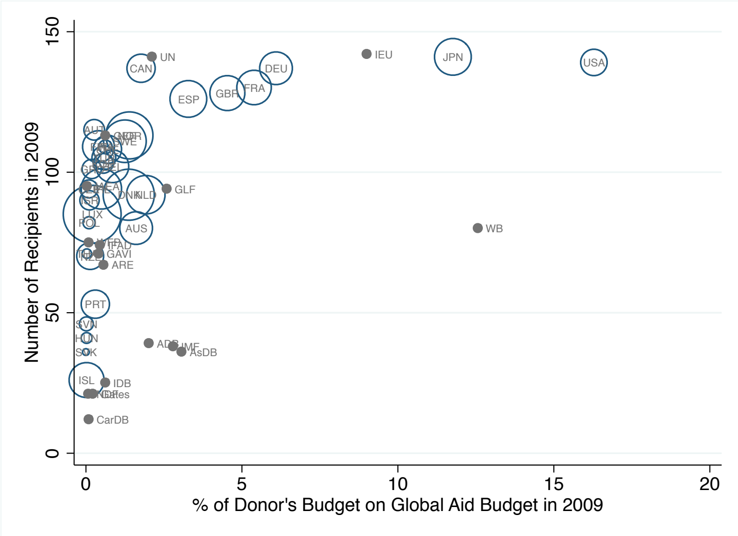

Figure 1: Number of Recipient Countries and Global Aid Budget Shares

country. In contrast, in 2009, this number was almost 30. When only considering the 22 1970-donors, this number was about 16 in 2009. The divergence between these two numbers has increased, which illustrates the arrival on the scene of new donors. Although this cannot be captured in the data, this trend may have accelerated recently, with the rise of some emerging markets as donors themselves, in particular China.[2]

Figure 2 shows the development of aid fragmentation between 1960 and 2009 according to the commonly used Herfindahl index (H), confirming that fragmentation substantially increased (i.e., concentration measured by H decreased). 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,

[2]These emerging donors do not report aid data to the DAC, and we are not aware of any credible estimates of their size. 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 billions US$, or 8 and 31 percent of ODA from DAC donors. For China, they note that aid estimates range anywhere from 1.5 to 25 billions US$. If the upper estimate is accurate, it ranks as the second largest bilateral donor after the US.

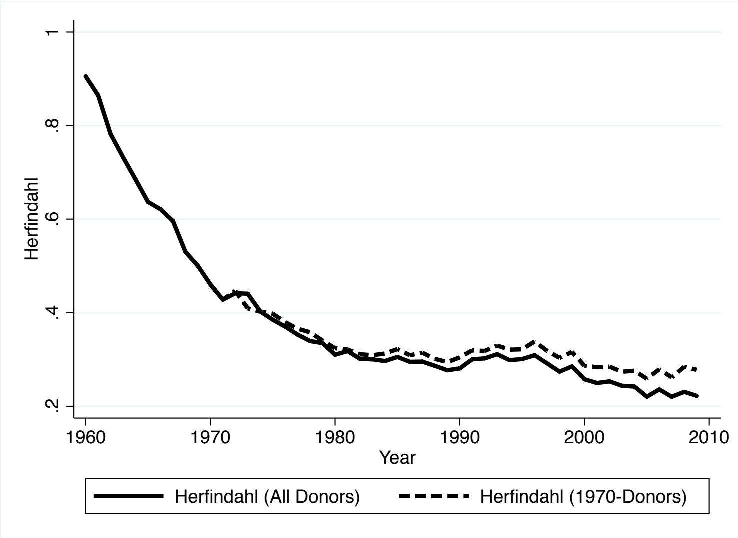

Figure 2: Global Aid Herfindahl Index

one can see that it is essentially determined by the latter. In particular, the increasing entrance of new donors since 1980 did not directly decrease H much. The reason is that the aid budgets of the new donors are generally small. However, keep in mind that we cannot capture emerging donors such as China in our data, which could be causing a stronger decrease in H as we speak.

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 focussing on improving donor coordination, especially since the Paris Declaration.[3] 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, page 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

[3]Aid fragmentation can adversely affect the performance of recipient countries also through other channels than aid effectiveness. 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.

decision-making" (OECD, 2005, page 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, page 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.

3 Background Literature

The large, mostly empirical literature on aid effectiveness is generally read as showing ambiguous results (Bourguignon and Sundberg, 2007; Rajan and Subramanian, 2008). Our reading does not differ, which forms the main inspiration for this paper. However, as Bourguignon and Sundberg (2007, page 316) note, really, 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, our paper zooms in on one possible reason for the ambiguity of results in the aid effectiveness literature, at the start of the causality chain in the "black box". This can be seen as a follow-up on earlier joint work including one of us: Annen and Kosempel (2009) find that the technical-assistance component of aid does have a positive and significant impact on economic growth, unless it is highly fragmented. Most of the aid effectiveness literature, all the way back to Bauer's (1972) classic, concentrates on political-economy problems on the recipient side.[4] While this

[4]Bauer (1972), one of the most ardent critics of aid, essentially argues that poverty reflects harmful political regimes that introduce distortionary policies for the benefits of a narrow political elite. Perversely, he argues, aid can actually cause a poverty trap if it strengthens these governments so they can stay in power. The more formal wave of aid effectiveness literature goes back to Boone (1996), who also puts the political regime of

remains highly relevant, the donor side itself can surely also create problems for aid effectiveness, and this is the entry point for our paper.

This brings us to the other main strand in the aid literature, which concentrates on explaining, again mostly empirically, donor aid allocation. This literature has substantiated the "heterogeneity of aid motives" (e.g., Ludborg, 1998; Alesina and Dollar, 2000; Svensson, 2003). Four broad classes of aid motives come to the fore, to a different extent for different donors. Of course, aid can be given for the reason implied by the word itself: to help, genuinely to reduce poverty in the recipient country. At the risk of being called naively idealistic, we might say this provides donors with the "correct" incentives. However, donors can also give aid based on "incorrect" incentives: geopolitical (strategic, military), or commercial motives (trade, foreign investment) of the donor country, or donor agent satisfaction (managerial salary, status, for "pushing aid out the door"). We read this literature as suggesting that all four motives are at play, but most strongly the first two. Recognizing that aid motives combine to create donor competition for aid impact, whatever its exact interpretation (depending on the motive), we concentrate on the strategic interaction among donors, an aspect that has been absent from the literature.

Checking the aid allocation literature for formal models related to ours, we found only one. It is a rather old paper that is hardly cited in the modern literature, even though it remains relevant: Dudley and Montmarquette (1976) develop and test a model of aid supply, considering aid as a good that is indirectly consumed by the residents of the donor country. The supply of aid is then explained by the demand by the donor country for its aid impact in the recipient country. That is, aid is in the donor's utility function, which is maximized. Although certainly related, their model does not focus on the strategic interaction among donors that we put at the heart of our model, which tries to explain aid fragmentation among donors, not aid supply of a donor. We found one, recent paper, Frot and Santiso (2011), that does concentrate on the interaction among donors, but it is exclusively empirical. Using a concept from the finance literature, they find evidence of aid "herding" among donors. Additionally, they find that this herding is mostly "pure" as it does not seem to occur for observable reasons (though we note that their list of variables used as observables seems incomplete). In their conclusion, they note that their study "leaves for future research the funda-

the aid recipient at the heart of his finding of lack of aid effectiveness.

mental question of the motivations for donors to herd" (Frot and Santiso, 2011, page 71). Our paper can be seen as investigating a potential cause of such aid herding, and concomitant aid fragmentation: donor competition for aid impact.

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 towards 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). Recently, a sequence of papers has ranked donor practices more generally (Easterly and Pfutze, 2008; Birdsall and Kharas, 2005; Knack et al., 2011; Easterly and Williamson, 2011), confirming both the lack of progress in aid coordination in spite of increasing rhetoric noted in the previous section, as well as some of the differences among donors noted in this section. Like Burnside and Dollar (2000) had its impact on donor behavior, donors are also watching these rankings.

In the context of our paper, it is crucial to note that the literature summarized above suggests that donors compete trying to maximize their relative aid impact. This is most easily discerned if the aid motive lies in its geopolitical impact: 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 or Russia) in that country, and vice versa. Similar pressures among donors are at play if the aid motive 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). Such donor competition for aid impact is the game even if the correct incentives are at play, as we will assume in what follows. Partly because it is very hard to measure a donor's absolute aid impact on poverty reduction in a recipient country, in practice, a donor that needs to evaluate its impact does so relative to the others. Moreover, the increased attention to allocation of aid on the basis of performance (Dollar and Levine, 2006; Bourguignon and Sundberg, 2007), as measured by the strength of recipient-country policies

("a la" Burnside and Dollar (2000)) and the monitorable results they deliver, strengthens relativeness among donors. The same is true for the recent papers that rank donor practices, as any ranking is an inherently relative concept.

The aid fragmentation result from our model, developed in the next section, occurs precisely under this donor competition for aid impact. We thus zoom in on this one potential explanation of aid fragmentation, in a literature that, as described, does not contain any explanation so far.[5]

4 Model

Consider a situation with d donors and r recipients. For now we assume that $d = r = 2$. We relax this assumption in section 4.4. 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 $a^j = a_1^j + a_2^j$. 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. This is 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 (Clemens et al., 2004; Burnside and Dollar, 2000; Collier and Dollar, 2001). The assumption of diminishing returns of aid impact is also intuitively plausible, since absorptive capacity in the typical developing country is limited.

[5] Of course, that does not preclude the possibility of other contributing explanations. For example, a "common pool problem" in the aid industry might help explain aid fragmentation. Precisely because it is difficult to measure aid impact, a donor would need only participate with a small amount of aid to claim the benefits of participation (and it keeps "plausible deniability" of responsibility for any failure that way). However, this would seem to imply that each donor would want to be as small as possible in as many countries as possible, and this is not what we observe in reality: the typical donor distribution in recipient countries includes various large donors as well as many small. Neither has this potential explanation been worked out in the literature.

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

$$X(a) = f_1(a^1) + f_2(a^2). \tag{1}$$

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. Of course, the 'counterfactual' $X((0,0), a_2)$ is often difficult to measure, which is partly why we have argued that donors maximize relative instead of absolute impact, but let us abstract from this for now.

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.[6] 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 $a^j(t)$ 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 $a_1^1 + a_2^1 = a^1(t)$ and $a_1^2 + a_2^2 = a^2(t)$. Let A^* denote the set of all efficient aid allocation profiles.*

Note that the set A^* is not necessarily a singleton. Depending on the properties of the impact functions, there are many aid allocations among the

[6]Note that this notion of 'efficiency' may be questionable if X refers to a more cynical interpretation of aid impact.

two donors such that they together provide the efficient aid supply $a^j(t)$ to each recipient j. We first analyze the model without fixed costs of aid giving, and then with.

4.1 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 i 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 2-player game. The following result can be stated.

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 A. □

When donors maximize net aid impact, the game has multiple equilibria, as shown in Appendix A. This suggests that 'donor coordination' can work as an equilibrium selection device if each donor maximizes its net impact. 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.

4.2 Donors Maximize Relative Net Aid Impact

Assume now, as we have argued, that donors care about relative instead of absolute net aid impact. 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 $a_1 = \hat{a}_1$ that minimizes X_2 subject to the budget constraint given a_2, and assume that $\hat{a}_1 = a(t) - a_2$. Then $\hat{a}_1$ 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

$$f_j'(a_1^j + a_2^j) - f_j'(a_1^j) < 0, \quad \forall j. \tag{6}$$

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 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 $(a(t_1), a(t_2)) \in A^*$. 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, $\frac{a^j(t_i)}{t_i}$ 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. 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 3, aid impact typically differs depending on policy quality in recipient countries, i.e., 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 non-homothetic.

To analyze the game for cases where $a(t)$ is non-linear 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.[7] 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:

$$(1 - V_1)X_1' - V_1 X_2' \leq (>)0, \quad a_1 \geq 0,\ (a_1 = t_1), \tag{7}$$

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.[8] 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 non-linear 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.*

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

[8] Note that a sufficient but not necessary condition for the second order condition to be satisfied is that $f_j'''(a^j) \geq 0\ \forall j$.

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

$$V_1(f_1'(a_1) - f_2'(t_1 - a_1)) \leq (>)0, \quad a_1 \geq 0, \ (a_1 = t_1).$$

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 non-linear in t, even before fixed costs. These inefficiencies can be quite substantial. 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.

Studying (7) more carefully yields another insight. It demonstrates donors' concern for two things: First, a donor cares about its own net impact, because (7) includes X_1'. Second, a donor cares about the net impact of the other donor, because (7) also includes X_2'. A donors allocates aid to maximize its own impact while minimizing the impact of the other donor. The relative size of the donor, as measured by V_1, serves as a weight between these two concerns. For example, if V_1 is small no matter the allocation $a \in A$, then donor 1 is small relative to donor 2. In this case, donor 1 allocates aid mostly to maximize its own net impact with little concern of its effect on the aid impact of donor 2: $V' \approx X_1' \ \forall j$. Here, donor 1 behaves in a similar way as described in Proposition 1. Donor 1 allocates aid as closely as possible to the efficient allocation $a(t)$ given a_2. In contrast, if V_1 is large, then a donor's concern shifts towards allocating aid in order to minimize the impact of the other donor rather than maximizing its own net impact.

The first-order conditions defined in (7) implicitly define the best-response

functions of the game.[9] 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 $t_1, t_2 > 0$.

Figures 3 and 4 show best-response functions for the case with donors with identical and non-identical budgets respectively, and for a specification of impact functions where $a(t)$ is non-linear in t. The figures, first, confirm the uniqueness of the equilibrium. Second, the equilibrium allocation in the figures is inefficient. 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 both figures is strictly below that line. Note that, in this example, the inefficiency occurs because impact functions are such that, for a small enough budget, we have a corner solution in which recipient 1 receives zero aid and recipient 2 receives all aid. Here, we see that donor competition leads to an inefficiency. 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. Third, a comparison of Figure 4 with 3 shows how a change of the distribution of aid budgets over donors away from equality affects their behavior. In Figure 4, donor 2 has 40 percent of the global aid budget. Donor 2's best-response function is negatively sloped suggesting more aid by donor 1 leads to less aid by donor 2. The opposite is the case for donor 1, who controls

[9] A more technical version of this discussion is deferred to Appendix A.

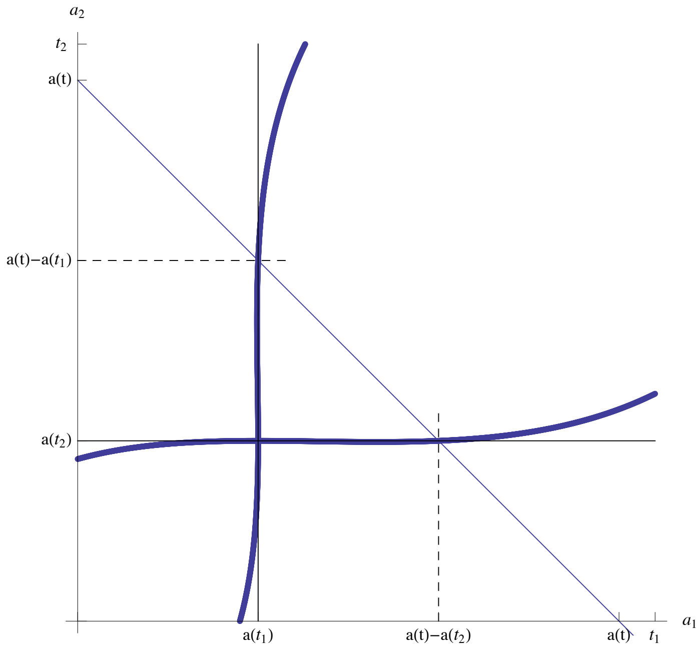

Figure 3: Best-Response Functions with Identical Donors

60 percent of the global aid budget. More aid by donor 2 leads to more aid by donor 1. Comparing the equilibrium in Figure 4 with 3 suggests that inequality of donors' budgets improves efficiency, because the smaller donor's best-response function shifts the equilibrium closer towards the $(a(t) - a(t))$-line. We can establish the following comparative statics result:

Proposition 4. *Assume that impact functions are such that $a(t)$ is non-linear in t. Let $t_1 = \theta t$ and $t_2 = (1-\theta)t$. Then, the inefficiency in the unique equilibrium aid allocation is the highest when $\theta = .5$ and it (weakly) decreases in θ for all $\theta \in [.5, 1]$.*

Proof. See Appendix A. □

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.

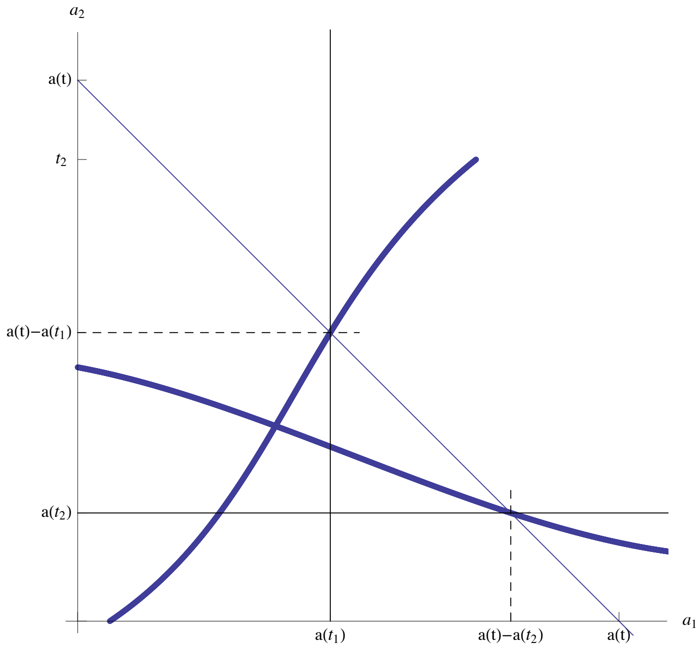

Figure 4: Best-Response Functions with Non-Identical Donors

4.3 Introducing Fixed Costs

Our model so far shows that the global aid allocation will be inefficient if $a(t)$ is non-linear 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 – i.e., 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 $X_1 = f_1(\tau t_1)$ and $X_2 = f_2(\tau t_2)$ respectively, where $\tau > 0.5$ is the share of a donor's budget used to cover fixed costs. If both donors operate in recipient country 2 then $X_1 = f_2(\tau(t_1+t_2)) - f_2(\tau t_2)$ and $X_2 = f_2(\tau(t_1 + t_2)) - f_2(\tau t_1)$. 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 a small enough donor to give aid to recipient 1. However, given that the small donor gives aid to recipient 1, 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 p and donor 1 gives aid to recipient 1 with probability q, then the change in payoff for a marginal change in q given p for donor 1 equals:

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

If $V_1(0,0) > V_1(\tau_1, 0)$ 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 $V_1(0,0) < V_1(\tau_1, 0)$. 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

$q^*p^* + (1-q^*)(1-p^*) > 0.5$.[10] 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 essentially introduce non-continuities 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. With fixed costs, any aid fragmentation automatically implies an inefficiency, which increases with the extent of fragmentation. The model, however, shows that an agreement that seeks to avoid these inefficiencies is still unlikely to be implemented.

4.4 Introducing More Recipients and More Donors

The analysis so far is based on a world with 2 donors and 2 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 2 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 focusses on one group of countries whereas the other donor focusses 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

[10] When recipient countries are identical, then $\frac{V_1(0,0)-V_1(\tau t_1,0)}{V_1(0,0)+V_1(\tau t_1,\tau t_2)-V_1(0,\tau t_2)-V_1(\tau t_1,0)} = 0.5$, in which case this expression has its minimum that equals .5.

i described in (7) changes to

$$(1 - V_i)X_i' - V_i(\sum_{k \neq i}^{d-1} X_k') \leq (>)0, \quad a_i \geq 0, \; (a_i = t_i).$$

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 – as analyzed in Figure 3 – 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 case, 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

[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.

that receive 'too little' aid from the large donors. We will make use of this in our empirics.

Moving towards 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 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.

5 Empirical Evidence

The main prediction of our model is that aid is fragmented in equilibrium (sections 4.2 and 4.3). In section 2, we already showed that aid is indeed 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 also suggests that aid is less fragmented among relatively small donors (section 4.4). Moreover, it suggests that increased relativeness should lead to increased fragmentation (section 4.2). In line with, for example, Alesina and Dollar (2000), we limit our empirical presentation to bilateral donors, since this constitutes the cleanest test of our model. For multilaterals, since executive boards consisting of many countries take their operational decisions, any competition takes place within these boards. That is, unlike for bilaterals, in a strict sense, we cannot observe the game that our model intends to reflect.[12]

Regarding the different behavior of smaller donors, Figure 1 already indicated that they tend to give aid to fewer countries than larger donors. An OLS regression between the number of recipients of a donor and its share in the global aid budget shows a significantly positive relationship (see Column (I) in Table 1). However, this correlation may by simply driven by (bud-

[12] We ran all regressions in this section for multilaterals as well, and results, available on request, were indeed not in line with our model.

getary) feasibility, as for example fixed costs may make it difficult for small donors to operate in a large number of recipient countries.[13] In order to control for feasibility, we include the maximal number of recipients a donor had in the years between 1960 and 2009 as a control.[14] Columns (II) and (III) in Table 1 report these results in a cross-section and panel regression respectively. The coefficient for the 'Global Budget Share' drops substantially when including this control, but it remains positive and significant. However, most likely the control we use is too strong as the disbursement capability as measured by their historical maximum of aid recipients is partly explained by strategic considerations as in our model. Donors with identical disbursement capability still have more recipients when their global budget share is larger.

Although smaller donors allocate aid to fewer countries on average, it is not clear whether their aid is less fragmented according to H. For example, smaller donors can 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 three groups for each year between 1980 and 2009: We rank their total budgets and then form groups of six among the donors with the 18 highest budgets.[15] We calculate H for each recipient country in each year for each of the groups and take the average across all recipient countries for each year. Figure 5 shows that aid fragmentation is always higher (i.e., H lower) for the 6 largest donors compared to the other

[13]In Figure 1, the case of Canada is the extreme case demonstrating that a relatively small donor can have a very large number of aid recipients. There are other examples: In 1995, Belgium disbursed aid to 121 recipients, in 2001 the Netherlands to 133, in 2005 South Korea to 128, in 2007 Greece to 119, etc.

[14]The most straightforward control would be to include donor aid budgets into the regression. However, this variable is highly correlated with 'Global Budget Share' producing problems of multicollinearity.

[15]Note that H is sensitive to the number of donors. For this reason, we form groups of equal size. These 18 donors together controlled 100 percent and 97 percent of the global aid budget in 1980 and 2009 respectively. In 1980 the top 6 donors controlled about 83 percent of the global aid budget, whereas the other two groups controlled 14 percent and 3 percent respectively. In 2009, these numbers changed to 76 percent, 15 percent, and 6 percent. We see that the top 6 donors control a large part of the global aid budget, and that this share has decreased only slightly in the last 30 years. In 2009, there are many more small donors compared to 1980, but they control only a very small fraction of the global aid budget. We also see that aid fragmentation increased between 1980 and 2009 for all groups, although there is no clear trend identifiable for the smaller donors starting in the mid 1990s. Note that reducing the group size to 5 donors or increasing it to 7 donors does not affect the main message of Figure 5

Table 1: Larger Donors vs. Smaller Donors

Dependent Variable:	Nr. of Recipients			Herfindahl Index	
	(I)	(II)	(III)	(IV)	(V)
Global Budget Share	5.26***	1.03*	0.56***		
	(1.25)	(0.51)	(0.17)		
Max. Nr. of Recipients		0.83***	1.05***		
		(0.05)	(0.03)		
6 Largest Donors				-0.09***	-0.09***
				(0.03)	(0.01)
Third 6 Largest Donors				-0.02	0.02***
				(0.03)	(0.01)
Constant	83.08***	6.65	-36.67***	0.55***	0.58***
	(4.97)	(5.28)	(4.95)	(0.02)	(0.00)
R-squared	0.36	0.93	0.77	0.03	0.03
F statistic	17.68	192.51	77.65	6.31	236.36
N	33	33	771	415	12215

Dependent variable in Columns (I), (II), and (III) is the number of aid recipients for each donor. Dependent variable in Columns (IV) and (V) is Herfindahl Index in each recipient country for the donor groups of the 6 largest, second 6 largest, and third 6 largest donors. Significance levels : $*$: 10 $**$: 5 percent $***$: 1 percent. Robust standard errors are in parenthesis. Columns (I), (II), and (IV) show cross section results for the year 2009. Columns (III) and (IV) show panel data results between 1980 and 2009.

two groups of donors. We reject the Null that the difference between H for the middle group and the group of the top donors is not larger than zero at the 5 percent level or lower for all years except 1993 and 1994. The group of the second 6 largest donors almost always exhibits higher aid fragmentation than the group of the third 6 largest donors, although the difference is not statistically significant for most years. Column (IV) in Table 1 replicates Figure 5 for the year 2009 in a cross-section regression. It confirms that aid fragmentation is significantly higher among the 6 largest donors as compared to the other two groups. Column (V) in Table 1 replicates Figure 5 as a panel regression. We find that aid fragmentation is significantly higher in the group of the 6 Largest Donors as compared to the group of the second 6 largest donor, and aid fragmentation is significantly lower for the group of the third 6 largest donors as compared to the group of the second 6 largest donors. The main message of this analysis is in line with the suggestion of our model

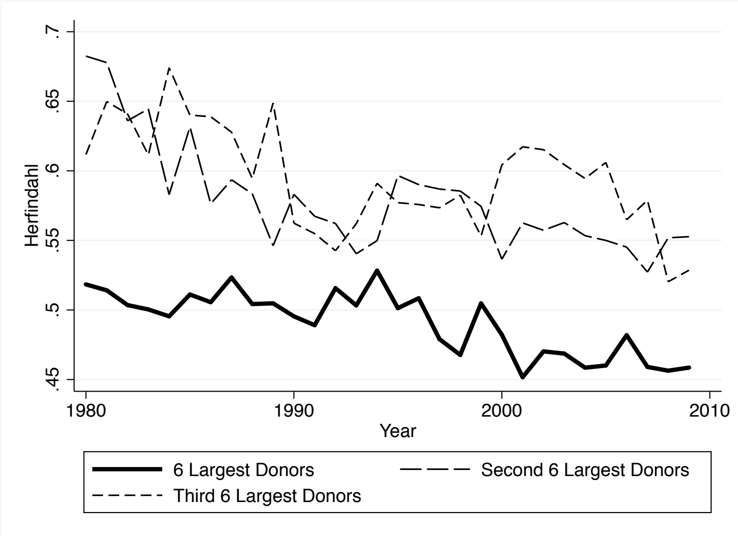

Figure 5: Herfindahl Index and Relative Donor Size

that aid is less fragmented among relatively small donors, and shows that it is unlikely that this is simply driven by budgetary feasibility.

Our model also relates to the debate on "aid selectiveness", which can be seen as having reinforced relativeness. Its basic idea is that donors should allocate their aid towards countries in which it 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 selectiveness have thus become important in donors' aid allocation decisions – at least in their rhetoric. In addition, these two objectives received empirical scrutiny in donor rankings. A higher policy- and poverty selectiveness of aid improves the ranking of donors (see Knack et al., 2011; Easterly and Williamson, 2011, for two recent examples). Donor rankings are clearly a relative measure of impact evaluation. Furthermore, Knack et al. (2011) report that "... there is evidence that donors do in fact pay attention to these rankings and care about public perceptions."

Our model predicts that aid fragmentation (H) is positively (negatively) correlated with policy among policy selective donors, but not among the non policy selective ones. Similarly, aid fragmentation (H) and income per capita should be negatively (positively) correlated among poverty selective donors, but not among non poverty selective ones. To test this, we first produce a

Table 2: Donor Ranking in Aid Selectivity

Policy Selectivity				Poverty Selectivity		
Rank	Estimate	S.E.	Donor	Rank	Estimate	S.E.
1	6.048***	2.193	Belgium	1	-1.965***	0.496
2	5.743	3.838	Austria	16	0.093	0.416
3	5.565	4.669	Denmark	12	-0.199	0.514
4	5.096	3.864	Netherlands	15	0.003	0.554
5	4.448	3.638	Sweden	5	-0.446	0.577
6	2.588*	1.502	United States	10	-0.293	0.294
7	2.430	2.644	Luxembourg	2	-0.678	0.624
8	2.416**	1.162	Japan	19	0.255	0.198
9	2.160*	1.104	Spain	6	-0.440	0.308
10	2.082**	1.003	Germany	11	-0.272	0.207
11	1.679*	0.966	Italy	7	-0.334	0.336
12	1.608	3.495	Ireland	3	-0.506	0.757
13	1.603	1.498	Switzerland	14	-0.109	0.338
14	1.559	1.148	Canada	4	-0.482*	0.270
15	1.508	3.837	United Kingdom	13	-0.142	0.657
16	1.180	1.512	Czech Republic	22	0.703	0.446
17	0.708	1.312	France	8	-0.302	0.332
18	0.647	1.338	Norway	9	-0.298	0.313
19	0.333	1.097	Finland	17	0.141	0.303
20	0.122	0.865	Thailand	21	0.582	0.405
21	0.078	1.149	Slovenia	20	0.528	0.552
22	-0.338	3.421	Portugal	18	0.240	1.027
23	-0.967	1.937	Poland	25	1.000**	0.454
24	-2.585	1.825	Israel	26	1.036***	0.383
25	-2.880	2.379	Greece	23	0.839	0.562
26	-3.993	2.444	Korea	28	1.193*	0.679
27	-4.446***	1.508	New Zealand	27	1.037**	0.408
28	-4.678**	2.386	Turkey	29	1.449***	0.447
29	-4.875***	1.466	Australia	24	0.962	0.629

Significance levels : $*$: 10 percent $**$: 5 percent $***$: 1 percent. Robust standard errors used.

ranking of donors based on the policy and poverty selectiveness of their aid allocations. Each donor is classified as being either policy selective or not, and poverty selective or not. Second, we calculate aid fragmentation levels among different policy/poverty selective and non policy/poverty selective donor groups. We can then assess how the aid fragmentation level is affected by donors being policy/poverty selective or not.

We calculate the policy and poverty selectiveness of donors using a similar approach as Knack et al. (2011). For each donor, we regress the log of gross aid on a one-year lag of the following variables: the log of the World Bank's assessment of policy quality (CPIA), and the log of real GDP per

Table 3: Donor Selectivity and Herfindahl Index

Aid Fragmentation:	Policy Selective		Poverty Selective		All
	Yes	No	Yes	No	
Real GDPpc (log)	0.15***	0.05	0.15***	0.03	0.10***
	(0.03)	(0.03)	(0.03)	(0.04)	(0.02)
CPIA (log)	-0.47***	-0.22	-0.40***	0.05	-0.41**
	(0.16)	(0.14)	(0.13)	(0.14)	(0.16)
Constant	-0.27	0.46**	-0.33*	0.23	-0.03
	(0.18)	(0.23)	(0.18)	(0.24)	(0.18)
R-squared	0.34	0.03	0.34	0.02	0.26
F statistic	15.36	1.53	14.42	0.85	12.63
N	75	74	75	75	75

Dependent variables are aid fragmentation measured by H (higher H, i.e., more concentration meaning less fragmentation) among donor groups that are either policy and/or poverty selective or not. All regressions use OLS using the year 2009. Significance levels : $*$: 10 percent $**$: 5 percent $***$: 1 percent. Robust standard errors are in parenthesis. All independent variables are lagged by 1 year.

capita.[16] Note that the estimated coefficients are elasticities. They measure how responsive the aid of a donor is to a change in the policy quality or poverty level. For each donor, we use the most recent year available, 2009. We drop donors from the analysis if there are less than 15 observations. We define a donor as policy selective if the point estimate on the CPIA is positive. Similarly, a donor is poverty selective if the point estimate on income per capita is negative. The remaining donors are classified as non policy and non poverty selective. The donor rankings on policy selectiveness (the larger the CPIA point estimate, the higher the ranking) and poverty selectiveness (the smaller the income per capita point estimate, the higher the ranking) are shown in Table 2. Note that these donor rankings are sensitive to the specific year chosen, so that care should be taken not to read too much in the specific ranking in Table 2. Apparently, donors are not consistent in their application of policy and poverty selectiveness.

We next calculate the level of aid fragmentation in every recipient country for each donor group for 2009. We can then estimate how the fragmentation

[16]These data were taken from the World Bank's World Development Indicators (http://data.worldbank.org), and the Penn World Tables 7 (http://pwt.econ.upenn.edu/php_site/pwt_index.php), respectively.

level for each group is affected by policy quality and income per capita. Table 3 reports the results. The last column of the table shows that, overall, H significantly decreases in the policy quality, and significantly increases in the per capita income level of recipient countries. However, when considering the aid fragmentation level for the different donor groups, Table 3 reveals that the CPIA has a significantly positive relationship with aid fragmentation among policy selective donors, while it has not among non-policy selective donors. A Hausman test, however, fails to reject the null that the point estimate on the CPIA is identical for policy selective donors than for non-policy selective donors. Similarly, we find that income per capita has a significantly negative relationship with aid fragmentation among poverty selective donors, while it has not among non-poverty selective donors. A Hausman test confirms that the point estimate on income per capita is significantly larger for poverty selective than for non-poverty selective donors (p-value: 0.00). Contrary to the specific donor rankings, these regression results are robust to varying years.

We can conclude that the data are in line with the suggestion of our model that aid fragmentation should be higher for policy/poverty-selective donors. Note that the fact that H is sensitive to the number of donors is a potential problem in our analysis, as forming the subgroups substantially alters the number of donors based on which the fragmentation level is calculated. For that reason, it may be useful to also look at fragmentation measures that do not suffer from this potential problem, such as most inequality measures. As a robustness check, we therefore run the same regressions as reported in Table 3 with such inequality measures instead of H. This does not alter our results.[17]

6 Conclusion

Aid fragmentation remains high, despite increasing rhetoric against it. This fragmentation can be seen as one of the reasons for the ambiguous results in the aid effectiveness literature. The literature on aid allocation and, recently, donor rankings, suggests that donors strive to maximize aid impact in relative terms. Donors can view such impact in the dimension of poverty reduction in the recipient country of course, providing them with "correct" incentives,

[17] See Appendix B for these results.

but also in the dimensions of their own geopolitics, commerce, and/or donor agent satisfaction, providing them with "incorrect" incentives.

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 essentially says that efforts to improve donor coordination are doomed to failure, "cheap talk", 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 the competitive forces pushing towards a fragmented, inefficient equilibrium are strong.

The paper points to the importance of avoiding relativeness in evaluating aid impact. Donor coordination is a feasible equilibrium outcome in our model 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.

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Appendix A

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

$$X(a_1, a_2) = \sum_{j=1}^{r} f_j(a_1^j + a_2^j).$$

Forming a Lagrangian yields

$$L(a_i) = \sum_{j=1}^{r} f(a_1^j + a_2^j) + \lambda_i(t_i - a_i^1 - \ldots - a_i^r).$$

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

$$f_j'(a_1^j + a_2^j) - \lambda_i \leq 0 \quad a_i^j \geq 0, \quad \forall j = 1, \ldots, r, \tag{8}$$

and

$$t_i - a_i^1 - \ldots - a_i^r = 0. \tag{9}$$

Since the aid of each donor enters additively into the impact functions, for any given $a \in A$, f_j' in (8) 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 (8) and (9) 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, (8) must be violated for at least one donor. □

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

$$\frac{\partial a_1}{\partial a_2} = -\frac{(1-2V_1)X'' - \frac{\partial V_1}{\partial a_2}(X_1' + X_2')}{(1-V_1)X'' - V_1 X_2''}. \tag{10}$$

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

$$V_1(f_2'(t_1 - a_1) - f_1'(a_1)) + (1 - V_1)(f_2'(t_2 - a_2) - f_1'(a_2)). \tag{11}$$

This expression (11) equals zero at $(a(t_1), a(t_2))$. We rewrite the first-order conditions in (7) as

$$(1-2V_1)(f_1'(a_1 + a_2) - f_2'(t - a_1 - a_2)) + V_1(f_1'(a_1) - f_2'(t_1 - a_1)) \leq 0. \tag{12}$$

Consider now an allocation $a_2 = 0 < a(t_2)$. Then, $V_1'(a(t_1), a_2) < (>)0$ 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 $V_1(a(t_1), a_2) > (<).5$, 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 j, then $\frac{\partial a_1}{\partial a_2} > 0$. If V_1 is small, then $\frac{\partial a_1}{\partial a_2} < 0$ 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 θ 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.[18] Note that because both f_1 and f_2 are strictly increasing, $a(t)$ and $t - a(t)$

[18] This corresponds to the situation depicted in Figures 3 and 4. In equilibrium, recipient 1 receives less aid than efficient.

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 θ for all $\theta \in [.5,1]$. The fact that $A(\theta)$ is non-increasing in θ for all $\theta \in [.5,1]$ implies that total aid impact $X(a(\theta t), a((1-\theta)t))$ is non-decreasing in θ for all $\theta \in [.5,1]$. Consider now the first-order condition when $\tilde{a} = (a(\theta t), a((1-\theta)t))$. 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 $V_1'(\tilde{a}) < 0$, and $V_2'(\tilde{a}) > 0$. Given $\tilde{a}$, 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 $\tilde{a}$, donor 1 transfers the amount of Δ from recipient 1 to recipient 2 thereby increasing inefficiency, and donor 2 transfers the amount of Δ from donor 2 to donor 1 thereby removing the increased inefficiency created by donor 1. Then, $X_1 = X(\tilde{a}) - f_1(a_2 + \Delta) - f_2((t-\theta)t - a_2 - \Delta) > X_1(\tilde{a})$ and $X_2 = X(\tilde{a}) - f_1(a_1 - \Delta) - f_2(\theta t - a_1 + \Delta) > X_2(\tilde{a})$. 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 $a_1 = a(\theta t)$ 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 $X(a^{**}) > X(\tilde{a})$. Since $X(\tilde{a})$ is (weakly) increasing in $\theta \in [.5,1]$, $X(a^{**})$ must be (weakly) increasing in $\theta \in [.5,1]$. $\square$

Appendix B

We repeat the analysis reported in Table 3 using two different inequality measures as our fragmentation measure, the Mean Log Deviation (MLD) and Theil Index (higher MLD or Theil Index, i.e., more inequality meaning less fragmentation). Table 4 reports the results when using the MLD, and Table 5 reports the results when using the Theil Index. The results show that our analysis is robust to these changes in fragmentation measures.

Table 4: Donor Selectivity and MLD

Aid Fragmentation:	Policy Selective		Poverty Selective		All
	Yes	No	Yes	No	
Real GDPpc (log)	0.22***	0.12	0.21***	-0.29***	0.06
	(0.07)	(0.14)	(0.08)	(0.09)	(0.07)
CPIA (log)	-0.62**	-0.67	-0.35	1.38**	-0.36
	(0.27)	(0.54)	(0.33)	(0.56)	(0.36)
Constant	0.79*	1.25	0.17	2.77***	2.07***
	(0.40)	(0.91)	(0.42)	(0.75)	(0.39)
R-squared	0.12	0.02	0.10	0.09	0.02
F statistic	4.54	0.80	4.26	5.85	0.50
N	75	70	75	74	75

Dependent variable is MLD among donor groups that are either policy and/or poverty selective or not. All regressions use OLS for the year 2009. Significance levels : $*$: 10 percent $**$: 5 percent $***$: 1 percent. Robust standard errors are in parenthesis. All independent variables are lagged by 1 year.

Table 5: Donor Selectivity and Theil Index

Aid Fragmentation:	Policy Selective		Poverty Selective		All
	Yes	No	Yes	No	
Real GDPpc (log)	0.16***	-0.07	0.12**	-0.24***	0.07
	(0.04)	(0.07)	(0.05)	(0.06)	(0.05)
CPIA (log)	-0.53**	-0.06	-0.33	0.91***	-0.50*
	(0.20)	(0.31)	(0.21)	(0.32)	(0.27)
Constant	0.47*	1.29**	0.37	1.98***	1.21***
	(0.28)	(0.50)	(0.27)	(0.47)	(0.31)
R-squared	0.14	0.03	0.07	0.14	0.06
F statistic	6.96	0.69	3.09	8.45	1.68
N	75	70	75	74	75

Dependent variable is the Theil Index among donor groups that are either policy and/or poverty selective or not. All regressions use OLS for the year 2009. Significance levels : $*$: 10 percent $**$: 5 percent $***$: 1 percent. Robust standard errors are in parenthesis. All independent variables are lagged by 1 year.