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Of Donor Coordination, Free-Riding, Darlings, and Orphans: The dependence of bilateral aid on other bilateral giving

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Of Donor Coordination, Free-Riding, Darlings, and Orphans: The dependence of bilateral aid on other bilateral giving

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Abstract

Using data from 1988 to 2007, we examine to what extent bilateral aid flows of an individual donor to a country depend on aid flows from all other bilateral and multilateral donors to that country. We thereby want to assess to what extent donor coordination, free-riding, selectivity, specialization, and common donor motivations drive bilateral aid allocation as these determinants would point to different dependence structures. Using approaches from spatial econometrics and controlling for endogeneity, we find that other bilateral flows lead to a significant increase in aid flows from a particular donor. The effects are particularly pronounced for recipients in Africa and the Middle East and so-called donor 'orphans' who seem to be collectively shunned by bilateral aid donors. The positive dependence also seems be related to donors following the lead of the largest donors. Over time, the positive dependence has become smaller. Overall the results suggest that donor coordination and free-riding are quantitatively less important than common donor interests and selectivity.

Keywords: aid, donor coordination, aid darlings, aid orphans

JEL Codes: F35, F42

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1. Introduction

Foreign aid continues to be the most important form of capital flow to a large number of poor countries, particularly in Africa; for many more, it remains a significant flow, although FDI and debt flows have increased substantially recently. Foreign aid is given by an increasing pool of donors, often allowing countries to choose from (or, as the case may be, be forced to deal with) hundreds of potential donors to fund their budgets, programs, and projects (World Bank, 1998); in fact, the number of donors has dramatically increased in past decades, with new entrants including several new regional development banks, new bilateral donors, global funds, large philanthropic foundations, and a myriad of NGOs of all sizes (Fuchs, Dreher, and Nunnenkamp, forthcoming); as a result, there is increasingly less of a "cartel of good intentions" (Easterly 2002) and instead a highly fragmented aid landscape which is increasingly difficult to negotiate for both donors as well as recipients (Harford, Hadjimichael, and Klein, 2010).

Without effective coordination, such fragmentation can have a range of negative effects. First, it may lead to situations where recipients will be favoured by most donors and become so-called donor "darlings" while others are largely deserted by the international community and are therefore aid "orphans" (Levine and Dollar, 2005, Rogersen and Steenson, 2009; Ansoms, Cassimon, and Marysee, 2007; Utz, 2009). The recent focus on selectivity to improve aid effectiveness could increase this problem of 'darlings' and 'orphans' as some of the findings suggest that for aid to be effective it should be focused on those countries with particular characteristics, such as the combination of high poverty and a good policy environment, better institutions, or poor MDG achievement levels (Burnside and Dollar, 2000; Collier and Dollar 2001, 2002, Wood, 2008).[2] In fact, donors are now being ranked for their policy selectivity (e.g.

[2] Note that there is a large literature suggesting that the findings from Burnside and Dollar are not robust. But several of those papers suggest other ways of how more selective aid could be more effective. For a discussion, see Easterly, Levine and Roodman (2003), Roodman (2007) or Nowak-Lehmann et al. (2012).

Knack et al. 2011), thereby providing explicit incentives to focus aid on 'darlings' with good policies and neglect 'orphans'.

Second, uncoordinated fragmented aid could lead to substantial aid volatility for recipient countries which has been found to be growth-reducing in recipient countries in a number of studies which have carefully investigated the issue and studied various transmission mechanisms through which volatile aid reduces growth in recipient countries (e.g. Bulir and Hamman, 2008; Arrellano et al. 2009; Kathavathe and Mallik, 2012).[3]

Third, fragmented aid can cause massive transactions costs on all sides, tax the capacity of recipient governments, and lead to a loss of qualified staff to donor agencies to manage these many projects. This problem has been described in detail for years (e.g. World Bank 1998). Knack and Rahman (2008) have shown that such fragmentation indeed lowers bureaucratic quality in recipient countries and Kimura et al. (2012) have shown that a proliferation of donors in a country is leading to lower growth.[4]

Of course, all of these problems would be much less severe if this aid coming from so many donors was well-coordinated, predictable, and used joint approaches and country systems to reduce the management burden. Recognizing the potential damage of fragmented and volatile aid flows, the 2005 Paris Declaration on Aid Effectiveness and the 2008 Accra Plan of Action called on donors to better coordinate their aid, make aid flows more predictable, pool aid flows in country-led programs, and use country systems for aid management. To facilitate this process of alignment and harmonization, donors were encouraged to specialize by concentrating their aid on fewer countries, and fewer sectors within countries, in line with their comparative advantage. For example, among bilateral donors organized in the OECD-DAC, lead donors have been

[3] See Chauvet and Guillamont (2008) for a different view that suggests that some aid volatility might actually be desirable and that volatile aid is particularly problematic if it is pro-cyclical with respect to other capital flows.
[4] See also Dreher et al. (2012) on this issue with related findings.

appointed for particular sectors in countries that should coordinate the aid, and the number of actors in each sector should be reduced (OECD, 2009).

Most observers find that these goals still remains largely elusive. Aldasoro, Nunnenkamp, and Thiele (2011) find that, at least up until 2006, there was little progress on donor coordination and specialization (reducing the proliferation of donors at the country level). Bulir and Hamann (2008) find that aid has become more volatile in the late 1990s and early 2000s when the first initiatives to improve donor coordination and increase its predictability were already under-way. Donor rankings based on the 2007 data also suggest that much work remains to be done here (Knack et al. 2011). At the same time, Angeles et al (2008) have found that the direction of change has been in the direction of greater selectivity, certainly with respect to a poverty focus but also with respect to institutional quality.[5]

All of these developments take place against the backdrop of the now well-known findings on aid allocation showing that (bilateral) aid is (and has long been) granted not only for economic and altruistic motives, but that past colonial ties, strategic alliances, and trade relationships affect aid flows (e.g. Alesina and Dollar, 2001; Hoeffler and Outram, 2008).[6] The interaction between donors in their aid allocation decision was not investigated in these studies.

In all these research and policy debates, the question of whether and to what extent aid from a given donor depends on the allocation decisions of other donors is a critical but little researched question. The way donors interact in their aid allocation decision will, however, critically affect aid allocation, the nature and motives behind aid fragmentation, as well as the interest of donors to take donor coordination, alignment, and specialization seriously. If donors

[5] Greater selectivity of course could well go hand in hand with low coordination, fragmentation, little specialization, and high volatility so that these findings do not contradict each other.
[6] See also Martinez-Zarzoso et al (2009) and Nowak-Lehmann et al. (2009) on the impact of bilateral aid on exports from the donor country, showing the relevance of aid to promote a trade relationship.

largely pursue donor-specific interests, we would expect little dependence; if they take coordination and specialization seriously (or want to free ride on other donor giving), we would expect a negative dependence between the given of individual donors. If selectivity is a dominant motivation, there would be a positive dependence leading to the above-described phenomenon of darlings and orphans. Thus the new agenda for aid effectiveness and associated donor rankings, which emphasize selectivity as well as coordination and specialization, would generate opposite effects on the dependence of bilateral giving. But whether these initiatives are successful and will have the desired effects, will depend on a substantial degree on the motives that shape the interaction between the giving of bilateral donors.

Despite the important of this issue for aid effectiveness, there exists remarkably little analysis on how in actual fact aid allocation to particular countries is affected by aid flows from other donors. While there are a large set of studies, following the pioneering work by Alesina and Dollar (2001), examining bilateral aid allocation in general, only a study by Mascarenhas and Sandler (2006) which examines to what extent the total aid flows of a donor and aid flows to regions by a donor depend on giving by other donors, is similar in spirit to what we are doing here. It finds that donors view giving by others largely as complementary which the authors interpret to mean that it follows common underlying motivations (which are not controlled for in the analysis). While the paper sets out a nice theoretical framework and provides an interesting analysis of direct bilateral flows and bilateral contributions to multilateral aid, there are some issues with the empirical analysis. First, it stops at the regional level and does not consider country-level allocations; second, no other covariates from the aid allocation literature are considered so that it is impossible to distinguish between common underlying drivers of aid allocation and pure complementarity effects of giving; third, endogeneity is only cursorily

tackled, and all is estimated using a static model. Our study differs by first looking at country allocations rather than overall or regional aid flows using a spatial econometric framework (modelling the interaction of donors as a 'spatial lag'), by examining a later time period (1988-2007), by specifying a much more complete model of aid allocation using insights from the literature, by using GMM procedures to deal with endogeneity, by also estimating a dynamic model, and by providing a full set of robustness tests.

There is also a more recent study by Frot and Santiso (2011) which use measures from the 'herding' literature in finance to study whether there is herding in aid allocation. Their measure of herding is to simply investigate the proportion of increases or (decreases) in aid allocations to a country in comparison to average increases (decreases) to all countries. Using this approach and only programmable aid (excluding humanitarian aid, debt relief and food aid), they find substantial herding (though smaller than observed in financial markets). They then also control for covariates that might affect increases or decreases in aid (such as conflict onset or end, democratization, growth, foreign intervention, etc.) and find that these matter but do not affect herding much, i.e. that herding remains nearly as strong as in the unconditional model. While these findings are suggestive, there are a range of issues that remain unanswered. First, this analysis only tackles directions of change without considering the magnitude of flows or aid increases and decreases. It does not study how 'herding' changes over time in response to the various policy initiatives discussed above, it does not control for the usual determinants of aid allocation levels, and does not examine in more detail which donors are 'leaders' or 'followers' and how this herding differs among recipients.[7] Our study differs from this paper by explicitly controlling for the usual determinants of aid allocation, by considering different time periods, by

[7] There are some studies that examine whether individual donors tie their allocation, in a form of bandwagon effect, on the giving of others. See Tarp et al. (1998) and Tezanos (2008) for examples. Our study differs by taking a much broader view on studying the dependence of bilateral aid in a much more general framework.

examining different recipient groups (esp. distinguishing between 'darlings' and 'orphans'), and by studying which donors seem to have a particularly strong effect on giving by others.

We find that there is a significant and rather robust (but relatively small) positive effect of giving by others on the giving by bilateral donors. A 1% increase in aid by another donor leads to about 0. 3% increase in own aid. The effect is particularly strong prior to 2000 and has become weaker recently, suggesting some success in specialization and donor coordination. The positive dependence of aid allocation is particularly large in Sub-Saharan Africa and the Middle East, and is actually stronger and significant only for aid 'orphans' suggesting that donors are jointly avoiding them. When using different weighting structures, we find that the positive dependence is comparable with GDP and Population weights (rather than equal weights), with all donors particularly following the allocation decisions of the 5 largest donors.

The paper is organized as follows. The next section discusses a theoretical framework, section 3 presents the estimation strategy and the data, section 4 has the results, and section 5 concludes.

2. Theoretical Framework

In this study we focus on the dependence of *bilateral* aid giving on giving by others. This does not cover the entire spectrum of aid flows, but focuses on one aspect. There are several reasons for this choice. First, bilateral aid continues to be the by far the most important aid flow to developing countries. While multilateral development banks (such as the World Bank and regional development banks) also transfer substantial amounts of resources, much of that is in the form of loans that are granted with near-market terms and conditions and thus do not qualify as aid using the official OECD-DAC definition (where the resource transfer must contain at least

a 25% grant element). Further, country aid allocation using the soft loan windows of these institutions (which does qualify as aid such as World Bank' IDA loans) are driven by allocation formulas (such as World Bank's IDA allocation formula) that leave rather little room for multilateral donor discretion. In contrast, donors have a great deal of discretion over the amount and destination of their bilateral flows.[8] The literature on aid allocation, starting with Alesina and Dollar (2001), shows that the discretion is sizable, and differs among bilateral donors. We will, however, consider whether multilateral aid to a country affects bilateral giving to that country.

When examining the dependence of bilateral flows on other donor flows, one should first distinguish between motivations by donors and motivations by recipients. Actual aid flows are the outcome of a process of interaction between donors and recipients where both donor and recipient interests play a role, with the actual outcome dependent on a range of factors that include the bargaining strength of the two partners and the commonality or divergence of interests.[9]

Starting with recipient interests, recipient governments, on the one hand, want to be as little constrained as possible in their dealing with donors. Thus they would in principle prefer the option to choose from a sizable number of donors to identify those that suit their needs; the larger the potential donor set, the more likely they will be able to negotiate away undesirable and onerous conditions. Thus the optimal number of donors for a recipient is likely to be substantially larger than 1; at the same time, it is likely to be not very large due to the large

[8] Non-governmental donors are generally too small to plausibly affect bilateral flows, although this might be changing currently as some of the large philanthropic funds are now drastically increasing their flows. Interestingly, NGO aid does not greatly differ in the allocation procedures and in fact appears to follow the aid allocation process of the donor country they are located in. See Dreher, Koch, Nunnenkamp, and Thiele (2008) for a discussion.
[9] See Mosley, Harrington and Toye (1995) for a discussion of these issues in the context of structural adjustment policies.

bureaucratic costs of engaging with many donors that administer tiny aid programs in a large number of countries.[10]

Regarding the dependence of bilateral aid flows on other bilateral giving, two potential hypotheses are plausible. To the extent that recipient are interested in maximizing the effectiveness of aid flows on development objectives, they would clearly prefer more donor coordination, specialization, and low volatility of aid flows, i.e. these motivations would imply a negative dependence of bilateral giving on the giving of others. The roles played by recipient governments pushing for the Paris Declaration and the Accra Agenda clearly reflect these interests.

On the other hand, to the extent that corrupt recipient governments are able to benefit from unpredictable and volatile aid flows by diverting larger sums of donor aid to suit their own needs, such governments might prefer more unpredictable aid flows (Kangoye, 2011). In those cases, a positive dependence could be in the interest of such recipient governments.

On the donor side, the dependence on other bilateral giving will greatly depend on the overall motivation of the donor to provide aid in the first place. Different motivations would imply a different dependence structure.

A first approach, also discussed by Mascarenhas and Sandler (2006), is to consider bilateral aid giving as a global public good. If it helps to promote the Millennium Development Goals or raises incomes in recipient countries, all donor countries benefit as they all committed themselves to promoting the MDGs and higher incomes in recipient countries will promote trade, reduce migration flows from these countries, and generate similar desirable effects. In such a setting, free-riding is clearly an issue. In fact, such free-riding would generate suboptimal total aid flows. This is well-recognized and there are several approaches to the problem: the

[10]See also Dreher, Michaelowa, and Spörri (2012) for a related discussion.

multilateral organizations resort to contribution formulas to address the problem[11], and the goal-setting of bilateral flows (aimed to reach 0.7% of GDP of donor countries as reaffirmed in the MDGs) is another (much less successful) attempt to circumvent the problem. Free-riding could not only affect total aid flows, but also affect aid flows to particular recipient countries. The more other donors give, the more one can free-ride on these contributions. One would thus expect that free-riding would cause crowding out, or a negative relation of other donor flows on one's own aid commitment.

Donors may, however, pursue donor-specific motivations that go beyond the provision of a global public good. Colonial ties, strategic and political interests, trade interests, and a donor's domestic political economy all may affect the priorities of aid allocation to particular recipients. To the extent that these motivations vis-à-vis a recipient differ among donors, we would expect then little dependence of aid flows on each other. A clear example would be colonial history where each donor will have different aid allocation priorities with respect to a particular recipient country based on its own history. To the extent the motivations such as strategic, political, and commercial interests are similar across donors, however, and not well captured by our covariates below, we might actually find a positive relationship of each other's giving, or some crowding in.[12]

Such crowing-in could also occur as a result of the increasing selectivity focus of donors on countries with 'good policies' or those in high need. To the extent that these factors are not captured in our covariates, we would expect donors to converge in their selection strategy on the

[11] This is for example how the soft loan window of the World Bank, IDA, raises its funds from bilateral donors.
[12] Of course, even if donor-specific interests predominate, donors might want to partly free ride on other country's flows which would counteract such crowding in. But one might argue that free-riding is much less likely if these motivations dominate. For example, guilt associated with colonial history can hardly be reduced by aid flows from other donors; furthering bilateral trade or strategic interests will likely be jeopardized rather than helped by other bilateral flows (e.g. Martinez-Zarzoso et al. 2009); and even altruistic, humanitarian, or ideological motives cannot depend on other donor flows, particularly if the 'warm glow' of giving is an important aspect of this motivation.

same set of countries. This would, as discussed above, lead to both the phenomenon of "darlings" and "orphans" as well as to a crowding-in of bilateral donors.[13] As selectivity has become an increasing focus of development cooperation in recent years, we would expect a crowding-in to be particularly pronounced in more recent years, compared to earlier periods.

While the need and effectiveness arguments might be important drivers for selectivity, selectivity might also be driven by a desire to associate one's aid flows with positive developments in poor countries. Countries with successful economic policies might attract more aid to associate that success with these aid flows. This could strengthen a crowding-in in 'donor darlings', and a collective flight from 'donor orphans' where difficult aid environments make aid that much harder to achieve (Levine and Dollar, 2005).

Crowding-in could also be the result if donors compete with each other for attention of more successful or politically or economically powerful countries. As other donors increase their allocation, one might want to follow suit to maintain ties to these countries.[14]

Lastly, the Paris and Accra agendas on donor coordination, predictability and specialization, if taken seriously, should affect the dependence of bilateral flows on each other. As donors specialize, coordinate their aid and make it more predictable, higher flows from one donor should lead to reduced flows from others, implying a negative relation between the flows of an individual donor and those of all others.

Thus these theoretical considerations point to different plausible effects. While recipient interests for predictability and the public good argument and the donor coordination argument point to a negative relation between donors' giving, the donor motivation and selectivity

[13] Easterly's (2002) suggestion of a cartel of good intentions would similarly lead to such a positive dependence on aid flows as donors act as a cartel to reward some recipients and shun others.

[14] This might be of particular relevance as it has been shown that aid can promote exports from the donor while bilateral aid from other donors might reduce own exports (see Martinez-Zarzoso et al. 2009 and Nowak-Lehmann et al. forthcoming).

argument might generate a positive relationship. The relative importance of these effects might also vary over time so that it becomes largely an empirical question to inquire which effects dominate for different time periods and regions.

3. Estimation Strategy and Data

In this section, we describe our empirical methodology and our data.

3.1 Estimation Strategy

Our baseline specification estimates total foreign aid (or in some specifications, per-capita aid) from donor *d* to recipient *r* in year *t* as a function of donor characteristics $Donor_{d,t}$, recipient characteristics $Recipient_{r,t}$, donor-recipient variables $Pair_{d,r,t}$ and a time trend:

$$Aid_{d,r,t} = \beta_0 + \beta_1 Donor_{d,t} + \beta_2 Recipient_{r,t} + \beta_3 Pair_{d,r,t} + Trend_t + \varepsilon_{d,r,t} \quad (1)$$

where $\varepsilon_{d,r,t}$ is the error term. Our control variables are drawn from the existing literature and are described below. We then modify this by including the aid from other donors to country *r* in year *t*, a variable known in the spatial econometrics literature as the spatial lag. Specifically, with *N* donors, we estimate:

$$Aid_{d,r,t} = \beta_0 + \rho \sum_{i \neq d} w_{d,i,t} Aid_{i,r,t} + \beta_1 Donor_{d,t} + \beta_2 Recipient_{r,t} + \beta_3 Pair_{d,r,t} + Trend_t + \varepsilon_{d,r,t} \quad (2)$$

where $\sum_{i \neq d} w_{d,i,t} Aid_{i,r,t}$ is a weighted average of ODA by other countries.[15] In the baseline specification, we assume that all donors receive equal weights so that $w_{d,i,t} = 1/20$ for all *i,t*. In robustness checks, we experiment with a range of different weighting structures. Clearly, if aid from *i* impacts country *d* and vice versa, the spatial lag is endogenous. In addition, endogeneity can arise due to an uncontrolled for factor that appears in the error term which affects aid to a recipient by all donors. To deal with this endogeneity, we use two stage least squares

[15] When using equal weights, we could alternatively have used the sum of ODA by other donors, the results of which would be the same as scaling up the coefficient ρ by 20, the number of donors in our sample minus one.

instrumental variables estimation. Following standard spatial econometric procedure, for our instruments we use $\sum_{i \neq d} Donor_{i,t}$ and $\sum_{i \neq d} Pair_{i,r,t}$ that is, the average of the other donor's characteristics and the average of their pair-wise characteristics with the recipient in question. The intuition behind these variables is that for a given donor *i,* donor and pair variables directly impact aid by *i* and are unaffected by aid from *d,* and affect aid allocation of donor i only through the endogenous variable.[16] Therefore they are correlated with the endogenous variable but are themselves exogenous, making them suitable instruments. Note that this instrumentation strategy also has another important advantage for our analysis. It may well be the case that donors respond collectively to unmeasured positive or negative features of a particular recipient country in a given year (e.g. a new political leader, evidence of some corrupt practices, sudden strategic attention or inattention of the recipient country in question) which would lead to a positive dependence of bilateral aid that was driven by these unmeasured factors. By instrumenting the spatial lag, we get rid of the influence of these unmeasured factors that could bias upwards our coefficient on the spatial lag.

A second potential spatial issue is correlation across the error terms for a given recipient-year. To this end, we cluster our error terms by recipient-year. Given our equal weights in the baseline specification, this amounts to correcting for spatially correlated errors.

This baseline specification is modified in several ways, including a dynamic version of the model, alternative weighting schemes in the spatial lag, period dummies, and different donor and recipient categories, to explore the robustness of our findings. The specifics of these modifications are described below.

[16] To take an example, the exclusion restriction implies that the aid allocation of France to country i and period t is only influenced by the amount of funds given by other donors, not the average pair-wise determinants of giving those funds, such as the average distance of all other donors to that country.

2.2 Data

Our data are a panel of 21 donors and 52 recipients that runs from 1988 to 2007.[17] The list of donors and recipients are found in Table A1 of the Appendix.

Our dependent variable $Aid_{d,r,t}$ is the log of bilateral gross Official Development Assistance disbursements from country *d* to *r* in *t*, as reported in the OECD DAC database, using the official DAC definition of aid (i.e. flows that have a grant component of at least 25%).[18] It is measured in millions of constant 2005 US dollars.[19] Figure 1 indicates how total aid flows have varied over time and across regions. As can be seen, the bulk of flows go to Africa followed by Asia. Over time, there was a substantial decline in the real value of bilateral aid flows during the 1990s, a trend which reversed itself during the 2000s. Figure 2 breaks down the average total donations by donor. Japan leads the way with roughly 33% of ODA. This is followed by the US, Germany and France, who jointly make up another 39% of flows. Note that these are only the bilateral ODAs and do not include what donor countries provide to multilateral assistance programs (the lag of which is a control variable).[20]

To control for the size of the donor country $Donor_{d,t}$ includes $GDP_{d,t}$ and $Population_{d,t}$, which are the log of real value of donor GDP and the log of donor population. Note that, as these are logs, one can also interpret one of these as per-capita donor GDP. As with aid flows, GDP is measured in real PPP-adjusted 2005 millions of US dollars. Consistent with the existing

[17] In addition to these 52 recipients, we have data on a further 66 recipient nations. Here, we present results only for the strongly balanced sample where we have full data for each donor-recipient-year combination. One implication is that this eliminates countries which did not exist for the full sample. The cost of this is that we lose 13902 observations. The benefit is that it eliminates concerns that the results are driven by recipients/donors entering or leaving the sample. Nevertheless, the results from the full sample are comparable to those presented here and are available on request.

[18] For values of reported aid that were missing or less than or equal to zero, we added .001 prior to taking the log. This represented 3777 observations of which three were zeros.

[19] We utilized the consumer price deflator from the Economic Report to the President (2009).

[20] In unreported results, we excluded potentially different recipients such as China, India, Mexico, and Saudi Arabia. This did not qualitatively affect the results.

literature (e.g. Fuchs, Dreher, Nunnenkamp, 2012) which finds that larger, wealthier economies donate more, we generally anticipate positive coefficients for these variables. These data (and their recipient counterparts) come from the World Bank's World Development Indicators database.

For the recipient country, we similarly include per capita $GDP_{r,t-1}$ and $Population_{r,t}$, to control for wealth and size. Following previous findings, we expect that more ODA goes to larger but poorer countries; in per-capita terms, we would expect, however, that smaller countries receive more aid/capita (e.g. Alesina and Dollar, 2001). Note that we lag recipient GDP to reduce endogeneity. In addition to recipient size, we include several additional variables.[21] Three of these are intended to control for the nation's political situation. $Freedom_{r,t}$ is the sum of the political liberty and civil liberty scores from the Freedom House Index. $Politics_{r,t}$ is the difference between the democracy and autocracy scores from the Polity 4 Databank. Both $Freedom_{r,t}$ and $Politics_{r,t}$ are coded so that higher values mean less political freedom. $Conflict_{r,t}$ is a dummy variable equal to one if the nation experienced a conflict within its borders that resulted in at least 25 deaths during year *t*. Given that in nations with better institutions less ODA may be diverted due to corruption, increasing the benefit from aid, we expect negative coefficients on these variables. To deal with the likelihood that nations that have experienced a natural disaster may receive more aid, we include a dummy variable $Disaster_{r,t}$ which takes on a value of 1 if the recipient has experienced a disaster during the year that resulted in deaths of at least 100 or of at least 0.1% of the population. These data come from the EMDAT database. In addition, we control for $Openness_{r,t}$ measured as the log of the sum of exports and imports divided by *GDP*, obtained again from the WDI. In order to control for the influence of

[21] When we omit these additional variables but include lagged ODA and recipient dummies, we find results for the spatial lag that are qualitatively comparable to the reported results, although the magnitude of the estimated coefficient varies.

multilateral aid flows to a recipient on its bilateral flows, we include $Multilateral_{r,t-1}$ which is the logged value of the multilateral aid received by recipient *r* in year *t-1*.[22] These data come from the OECD database.

We include several variables specific to a donor-recipient pair, all of which come from the CEPII.[23] $Distance_{d,r}$ is the great circle distance between the two capital cities (measured in kilometres). We expect this to be negatively correlated with aid as donors focus on proximate nations. In a similar vein, $Contiguity_{d,r}$ is a dummy variable equal to one if the two countries are geographically contiguous. $Language_{d,r}$ is a dummy variable equal to one if the two nations share the same official language, a trait we expect to be positively correlated with aid flows. Finally, $Colony_{d,r}$ is a dummy variable equal to one if the two countries were ever part of the same colonial empire. Since we expect donors to be particularly sensitive to the plight of nations with which they share a history, we anticipate a positive coefficient for this variable, as has been found in the literature (e.g. World Bank, 1998; Alesina and Dollar, 2001). Note that as these latter three variables typically equal one for at most one donor for each recipient, we do not use them to construct weighted averages for use as spatial instruments.

Finally, except as noted, we include both donor and recipient dummy variables to control for donor or recipient specific, time-invariant characteristics in all regressions. Summary statistics are found in Table A2 of the Appendix.

4. Results

4.1 Baseline Results

[22] We use the lagged value to deal with potential endogeneity. When using the contemporaneous value of multilateral aid instead, similar results were found.
[23] These data can be found at http://www.cepii.fr/CEPII/en/welcome.asp.

Table 1 presents our baseline results. Column 1 excludes the recipient dummies (but includes donor dummies). Column 2 includes both donor and recipient dummies; the difference should capture a range of unmeasured time-invariant recipient-specific effects that could affect aid allocations. The coefficients suggest that more aid comes from larger donors both in terms of GDP and population, a result very consistent across specifications. When not controlling for recipient-specific fixed effects, more ODA goes to recipients with lower GDP and larger populations (i.e. poorer countries). However, after controlling for recipient specific, time-invariant effects, only the population effect holds. Likewise, although the institutional variables are all matter in column (1), including recipient dummies eliminates their significance. As expected, countries that have experienced a disaster receive more aid. In addition, more ODA goes to recipients with greater multilateral aid flows although this effect becomes much smaller once recipient-specific effects are controlled for. Turning to the pair variables, we find that more aid occurs between donors and recipients that are proximate, share a common official language, and have a common colonial tie. The qualitative nature of these estimates mirror those found elsewhere in the literature (e..g Alesina and Dollar, 2001; Hoeffler and Outram, 2008).

In column 3, we introduce a lagged dependent variable which, unsurprisingly, is significantly positive. Doing so eliminates the significance of some variables, such as recipient population but improves that for others such as *Freedom* (where as in column (1) better institutions are correlated with more aid). As this improves the fit of the model considerably, we use a lagged dependent variable in the rest of the analysis. It is also worth noting that, using the Fisher-type test, we reject the null of unit roots at the 1% level (Choi, 2001).

In column 4, we introduce the spatial lag which we instrument using the average of other donors' GDPs, population, and distance to the recipient. As reported at the bottom of Table 1,

our instruments easily pass the Kleibergen-Paap test for under-identification. Unfortunately, the instruments do not satisfy the Hasen J test for overidentification. This latter problem plagues many of our specifications. Nevertheless, it is worth noting that when we use a single instrument (either the weighted average of other donors' GDPs or their populations), thus exactly identifying our specification, the qualitative results discussed below do not change.

With that caveat in mind, we now consider the changes including the (instrumented) spatial lag causes. First, doing so returns recipient GDP and population to significance where again the coefficients suggest that more aid goes to more populous, poorer countries. In addition, more aid goes to more free countries, those more open to trade, those closer to the donor, and those that share a common language or colonial history with the donor. In addition, when including the spatial lag, the coefficient on multilateral aid becomes significantly negative, suggesting some crowding out between multilateral aid and individual donor aid. Turning to the spatial lag itself, we find a coefficient of 0.362 that is highly significant, suggesting that this interaction is an important factor affecting bilateral aid allocation, a point not considered to date in the standard aid allocation literature. To interpret this, recall that the spatial lag is the average of other donors' ODA to the recipient. Thus, if the average rises by 1%, the predicted ODA by donor *d* would rise by 0.36%, a sizable effect.[24] Alternatively, with 21 donors, this indicates that if a single other nation increases its ODA by 1%, then donor *d* would increase its by .3/(21-1) = .018%.

Finally, column 5 utilizes ODA per-capita rather than total ODA. As can be seen the results are largely comparable with a highly significant spatial lag estimated at .358. This suggests that the finding that aid by donor *d* rises by about .3% when average ODA by others increases holds both in national totals as well as per person.

[24] Note that the spatial lag is the sum of logs, not the log of sums, hence the elasticity interpretation.

Taken as a whole, these estimates reject crowding-out. If anything, they suggest a sizable (but not very large) crowding-in effect.[25] This suggests that, overall, the selectivity, joint interests, or cartel issues are more relevant empirically than free-riding in the provision of a global public good or true donor coordination, predictability, and specialization following the Paris Declaration.

4.2 Alternative Weighting Schemes

In the baseline, we assume equal weights, that is, all donor countries have the same impact on each other. Alternatively, it may be the case that some donors are more influential than others. In Table 2, we explore this by using three alternative weighting schemes. In column (1) we use GDP weights, i.e. $w_{d,i,t} = \frac{GDP_{i,t}}{\sum_{j \neq d} GDP_{j,t}}$. In this case, while the weights a donor *d* assigns to other nations still sum to one, larger nations receive more weight. In column (2), we instead weight by population so that $w_{d,i,t} = \frac{Pop_{i,t}}{\sum_{j \neq d} Pop_{j,t}}$. In column (3), we use "Political Similarity". This is constructed using the 3 category "Affinity of Nations" data with interpolated values for the missing observations.[26] These data attempt to capture the similarity of state preferences based on voting positions of pairs of countries (dyads) in the United Nations General Assembly. We then standardize these so that the two donors with the least similar voting have a "political similarity" of zero and construct weights according to $w_{d,i,t} = \frac{Political\_similarity_{i,t}}{\sum_{j \neq d} Political\_similarity_{j,t}}$ so that more donors

[25] Our findings of positive dependence is also consistent with the findings from Mascarenas and Sandler (2006) and Frot and Santiso (2011) although we want to emphasize that our methods differ substantially and we control for many more factors affecting aid allocation which should therefore have lowered the positive dependence of aid flows. The positive dependence we still find is therefore substantially more robust than the findings in those papers.

[26] Specifically, we use "s3un4608i". These data, along with a full description of their construction is available at http://dss.ucsd.edu/~egartzke/htmlpages/data.html.

with more similar voting patterns receive greater weight. Unfortunately, as discussed by Anselin (1988), there is no test for which is the "correct" weighting matrix. Thus, these alternatives are presented as robustness checks of our results.

As shown in Table 3, when using GDP or population weights, we find results comparable to those with equal weights. In particular, the spatial lag remains significantly positive, with results of .368 and .382 respectively. The baseline finding, however, does not hold when using Political Similarity weights. There, although the coefficient remains positive, it is no longer significant. It should be noted, however, that this insignificance indicates that there is no significant interdependence of *Political Similarity weighted* ODA, not that there no interdependence at all, i.e. that it may be that this weighting scheme is not capturing the relevant factors affecting allocation decisions. To the extent that this weighting scheme is correct, it would suggest that aid from politically similar donors does not have a positive dependence. This could mean that the effects of common donor interests and selectivity (leading to a positive dependence) are in politically similar countries countered by more donor coordination and specialization (leading to a negative dependence), so that the net effect is insignificantly different from zero.

Nevertheless, for these alternative weighting schemes, we still finding no evidence for crowding out. Note that for the GDP and Population weights, we again find a significantly negative coefficient for multilateral aid, again giving rise to some concern for crowding out in that dimension.

We further investigate the dependence issue by considering different donor categories. We examined particular categories (including regional donor categories and splitting out Scandinavian donors plus Holland who are generally seen as generous and particularly poverty-

oriented in their allocations) and find that one particularly strong dependence is that donors particularly follow the lead of the 5 largest donors (Japan, USA, France, Germany, and the UK) in their aid allocation. This is shown in column (4) of Table 2 which shows that the giving by this group matters while the giving by the other groups is unimportant in aid allocation decisions.[27] Whether donors free-ride on the signal provided by the generosity of these top 5 donors to a particular country or whether strategic motives drive this positive dependence (e.g. that other donors compete with the big donors for attention and good-will of these favoured recipients), is an interesting subject of investigation in further research.

To ease discussion, in what follows, we utilized our baseline of equal weights except as noted. Full results with the alternatives are available on request, however here we merely note that, particularly for the GDP and Population weights and the important role of the large donors, these additional results are comparable to those presented.

4.3 Time Issues

In Table 3, we investigate two aspects of the sensitivity of our results to time. First, rather than using a time trend, column 1 includes year dummies. In spatial econometrics, this often results in insignificant spatial lags. This is due to the fact that, when moving between the observations for, say donations from Germany and France to Ghana within a year, the average ODA by other countries differs by 1/20 of the difference in the individual aid levels (recall that with 21 donors, there are 20 other countries used in constructing the average). As a result, the spatial lag does not vary much across donors within a year. With this in mind, it is of little surprise that the estimated coefficient on the spatial lag becomes insignificant. Nevertheless, it remains positive and again argues against crowding-out.[28]

[27] For the other groupings, we did not find significant dependence results.
[28] We also used time and time square which did not materially change the results.

As a partial step towards using year dummies, column 3 utilizes our baseline specification with equal weights but includes 3 period dummies equally splitting the sample and a time trend. This allows for a different average within each three year period as well as a trend between them. As can be seen, this results in a somewhat smaller spatial lag than the baseline's estimate of .301 and one that is slightly less significant.[29] Thus, this provides some reassurance that our results are not entirely driven by spurious time issues.

To test whether the size of the spatial lag varies over time, column 4 introduces a second spatial lag, one that is interacted with a dummy variable $Post2000_t$ which is equal to one for year 2000 and later. Looking at the first row, we find that before 2000, the estimated spatial lag is .766 and significantly positive as before. After 2000, however, the estimated impact falls to .766-.187 = .579 (which is still significantly greater than zero at the 1% level). This suggests that the extent of interrelation in ODA to a given recipient has fallen since 2000. This would be consistent with the claim that donors have actually made some progress in reducing herding and improving specialization, donor coordination and the predictability of aid. But the relationship is significantly positive still after 2000 suggesting that much more needs to be done here. *4.4 Regions*

Table 4 separates our data into five regions.[30] Across regions, the control variables are generally similar in terms of sign although with the drop in the number of observations significance is often lower. Focussing on the spatial lag, excepting the Americas, we find a positive point estimate in each case. However, this is only significant for Africa, and the Middle

[29] When using 2 year periods, we find a positive albeit insignificant spatial lag similar to the results in Table 3, column (1).
[30] Details on which countries are in which category can be found in Table A1 of the appendix.

East. [31] Thus, to the extent that crowding-in occurs, the data indicates that it tends to happen most often in those regions. Relating this to our potential mechanisms described above, it suggests that selectivity issues as well as wanting to be associated with development successes (and avoid development failures) could be the driving force for the positive dependence in those two regions. Conversely, it appears somewhat less likely that competition for commercial or political interests is driving the positive dependence, particularly in Africa (although this might play a role in the Middle East).

Furthermore, in no region do we find evidence indicating crowding-out in bilateral aid. For Africa and Asia, however, note that we find a significantly negative effect on multilateral aid. This suggests that multilateral assistance to those nations may be replacing bilateral aid.

4.5 Time Lags of Bilateral Aid by Others

Table 5 modifies the baseline specification by including time lags of $\sum_{i \neq d} Aid_{i,r,t}$.[32] We do this to investigate whether there is evidence of crowding out over time. In particular, if ODA from the rest of the world were unexpectedly large in year *t-1*, one might be concerned that a given country would revise its ODA in year *t* downwards. Column 1 repeats the preferred specification for ease of comparison. Column 2 adds $\sum_{i \neq d} Aid_{i,r,t-1}$ while column 3 also introduces $\sum_{i \neq d} Aid_{i,r,t-2}$.[33] As can be seen, the past values of ODA by other countries are significantly and negatively correlated with ODA in the current year. This does suggest some downward revision by country *d* in response to past increases by other nations. Nevertheless, the net effect from

[31] The results for Europe also suggest a significant positive dependence but there is only one country (Turkey) in our balanced sample. In results using additional European countries for which data was not available during the entire sample, we found a positive but insignificant spatial lag for Europe. Results are available on request.

[32] As with $Aid_{d,r,t-1}$ we take these as exogenous in year *t*. In unreported results using constructed versions of these, similar results were found.

[33] In unreported results, we extended the time lags of the spatial lag back to *t-5*. These were not significant and did not overly effect the estimates of the reported time lags.

adding the coefficients on the spatial lag are significantly positive as in each case we can firmly reject the null hypothesis that the net effect is less than or equal to zero.[34] However, the estimated response is noticeably smaller. In column 2, the net effect is .196 while in column 3 it is .089. Another notable change is that, when included lagged values of the spatial lag, we no longer find a negative coefficient for multilateral aid. In fact, in column 3 we find a small positive impact for multilateral aid, suggesting there is a rather complex temporal interaction between multilateral and bilateral aid.

In column 4, we instead use the *t-1* and *t-2* spatial lags to consider the possibility that a donor responds only to past donations by others. Here, we find a comparable pattern of coefficients as we do in column 2 where we use *t* and *t-1* spatial lags. However, in column 4 we cannot reject the hypothesis that the net effect is zero.[35]

4.6 Recipient Categories

Finally, Table 6 attempts to examine whether there is a difference between nations that tend to receive higher ODA ('darlings') and those that tend to receive smaller ODA ('orphans'). To categorize countries, we took the estimates from Table 1, column 1 and calculated residuals. Countries where the mean residual was positive, i.e. those which tend to get more ODA than predicted, were then classified as darlings while those with negative mean residuals were classified as orphans.[36] Table A1 of the appendix indicates which nations fell into which categories. Column 1 uses only the orphan countries. As can be seen, the results are largely similar to the preferred specification's pooled results, with the exception that the estimated

[34] The χ^2 for column 2 was 310.27 while that for column 3 was 15.86.
[35] The χ^2 on this test was .21.
[36] In unreported results, we classified darlings as those in the top quartile of mean residuals and orphans as those in the lowest quartile. Qualitatively similar results were found. A second check on our approach utilized column 2 of Table 1 (i.e. also using recipient fixed effects) to construct residuals. A third utilized only the recipient's GDP per capita and population when predicting aid whereas a fourth simply took those with above and below average ODA per capita to define the darlings and orphans. Finally, in a fifth, we utilized the entire sample, not just those for which we had data in all years. In each case, we found qualitatively similar results.

response to an increase in average donations is roughly twice as large. Column 2 uses only the darlings. Here, the point estimate of the spatial lag, although positive, is much smaller in magnitude and insignificant. Thus, once again, we find no evidence of crowding out, even among those countries that tend to receive smaller ODAs that the data would predict. Conversely, it seems more that specifically among orphans, selectivity has some bite, leading donors to collectively abandon them. This is also consistent with our regional story which found the results to be stronger in Africa and the Middle East. It seems to suggest that donors are particularly unwilling to give money to countries that other donors have abandoned, possibly for fear of the reputational effects this might involve. Another notable difference is that it is only within the orphans that we find a significant crowding out effect of multilateral aid.

4. Conclusion

The goal of this paper has been to investigate whether there is evidence of crowding-out or crowding-in in bilateral ODA flows. There are several arguments that point to both effects and their respective strength is an empirical question. Using panel data from 21 donors to 52 recipients over a twenty year period, we find no evidence of crowding-out, that is that increased donations by other countries to a given recipient tends to lower donations by a given donor to that recipient. Instead, we find evidence for crowding in, with a 1% increase in the ODA by all other countries being associated with approximately a .3% increase in ODA by the country in question. It suggests that selectivity and/or donor cartels based on joint interests are more important factors in aid allocation than donor coordination, specialization, or free-riding. The results appear particularly driven by donors following the lead of the largest donors. The falling positive association over time suggests a declining role of cartels and a rising role of aid coordination and specialization, pointing to modest success of the Paris and Accra agenda. For

Africa, and Middle East and aid 'orphans', the dependence of aid flows is particularly strong, making their problem of unpredictable swings in donor flows particularly severe.

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Table 1: Baseline Results

	(1)	(2)	(3)	(4)	(5)
	Total	*Total*	*Total*	*Total*	*Per-Capita*
$\sum_{i \neq d} Aid_{i,r,t}$				0.362***	0.358**
				(0.106)	(0.149)
$GDP_{d,t}$	2.103***	1.996***	0.530***	0.810***	0.634***
	(0.304)	(0.259)	(0.186)	(0.159)	(0.192)
$Population_{d,t}$	8.853***	8.957***	3.004***	2.066***	2.917***
	(0.888)	(0.868)	(0.542)	(0.565)	(0.524)
$GDP_{r,t}$	-0.885***	0.230	-0.130	-0.149*	-0.217**
	(0.066)	(0.162)	(0.109)	(0.078)	(0.106)
$Population_{r,t}$	0.651***	1.281***	0.350	0.167***	-0.032
	(0.034)	(0.464)	(0.398)	(0.057)	(0.336)
$Freedom_{r,t}$	-0.068***	-0.011	-0.033**	-0.026**	-0.025**
	(0.024)	(0.016)	(0.015)	(0.011)	(0.012)
$Politics_{r,t}$	0.036***	0.000	-0.009	-0.008	-0.008
	(0.012)	(0.008)	(0.007)	(0.006)	(0.006)
$Conflict_{r,t}$	-0.140	-0.013	0.023	0.016	0.019
	(0.094)	(0.067)	(0.056)	(0.041)	(0.042)
$Openness_{r,t}$	0.099	0.045	0.106***	0.100***	0.099***
	(0.091)	(0.053)	(0.041)	(0.032)	(0.033)
$Disaster_{r,t}$	0.257***	0.371***	0.050	-0.041	-0.060
	(0.079)	(0.114)	(0.076)	(0.067)	(0.078)
$Multilateral_{r,t-1}$	0.212***	0.093***	0.003	-0.043**	-0.018
	(0.039)	(0.020)	(0.019)	(0.019)	(0.028)
$Distance_{d,r}$	-0.707***	-1.766***	-0.447***	-0.476***	-0.473***
	(0.043)	(0.048)	(0.029)	(0.031)	(0.031)
$Contiguity_{d,r}$	-0.136	-0.933**	-0.117	-0.133	-0.129
	(0.470)	(0.474)	(0.219)	(0.225)	(0.224)
$Colony_{d,r}$	2.450***	1.914***	0.428***	0.455***	0.455***
	(0.082)	(0.078)	(0.049)	(0.050)	(0.050)
$Language_{d,r}$	1.108***	1.864***	0.433***	0.458***	0.460***
	(0.067)	(0.056)	(0.038)	(0.039)	(0.040)
$Aid_{d,r,t-1}$			0.767***	0.771***	0.771***
			(0.007)	(0.007)	(0.007)
$Trend_t$	-0.094***	-0.115***	-0.032***	-0.032***	-0.024**
	(0.009)	(0.013)	(0.010)	(0.005)	(0.010)
Constant	29.148*	58.723***	9.874	19.333***	-5.323
	(17.585)	(16.361)	(13.070)	(7.033)	(15.603)
Recipient Dummies?	No	Yes	Yes	Yes	Yes
Observations	21147	21147	20034	20034	20034
R-squared	0.601	0.679	0.871	0.870	0.860
KP Test P Value					0.0003
Hansen J P Value					0.0000

Robust standard errors clustered by recipient-year in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include donor and recipient dummies.

Table 2: Alternative Weighting Schemes

	(1)	(2)	(3)	(4)
Weighting Scheme	GDP	Population	Political Similarity	Large vs. Small
$\sum_{i \neq d} Aid_{i,r,t}$	0.368***	0.382***	0.141	
	(0.138)	(0.134)	(0.191)	
$\sum_{i \neq d} Aid_{i,r,t}$				-0.049
				(0.176)
$\sum_{i \neq d, large} Aid_{i,r,t}$				0.377***
				(0.137)
Donor Variables				
$GDP_{d,t}$	0.642***	0.628***	0.576***	0.580***
	(0.184)	(0.185)	(0.195)	(0.179)
$Population_{d,t}$	2.785***	3.032***	2.912***	2.706***
	(0.493)	(0.565)	(0.553)	(0.593)
Recipient Variables				
$GDP_{r,t}$	-0.201**	-0.240**	-0.150	-0.599***
	(0.098)	(0.101)	(0.099)	(0.180)
$Population_{r,t}$	-0.124	-0.223	0.122	0.293***
	(0.385)	(0.371)	(0.447)	(0.077)
$Freedom_{r,t}$	-0.027**	-0.027**	-0.031**	-0.030**
	(0.011)	(0.011)	(0.014)	(0.014)
$Politics_{r,t}$	-0.008	-0.008	-0.009	-0.009
	(0.006)	(0.006)	(0.007)	(0.007)
$Conflict_{r,t}$	0.017	0.016	0.020	0.043
	(0.041)	(0.041)	(0.050)	(0.053)
$Disaster_{r,t}$	0.099***	0.099***	0.103***	0.114***
	(0.032)	(0.032)	(0.037)	(0.041)
$Openness_{r,t}$	-0.060	-0.059	0.007	0.068
	(0.074)	(0.071)	(0.093)	(0.096)
$Multilateral_{r,t-1}$	-0.047*	-0.049**	-0.016	-0.027
	(0.025)	(0.024)	(0.031)	(0.024)
Pair Variables				
$Distance_{d,r}$	-0.473***	-0.475***	-0.457***	-0.482***
	(0.031)	(0.031)	(0.032)	(0.032)
$Contiguity_{d,r}$	-0.128	-0.130	-0.122	-0.179
	(0.224)	(0.224)	(0.219)	(0.230)
$Colony_{d,r}$	0.454***	0.459***	0.441***	0.547***
	(0.051)	(0.051)	(0.053)	(0.066)
$Language_{d,r}$	0.460***	0.461***	0.447***	0.453***
	(0.040)	(0.040)	(0.044)	(0.040)
$Aid_{d,r,t-1}$	0.771***	0.771***	0.768***	0.767***
	(0.007)	(0.007)	(0.007)	(0.007)
$Trend_t$	-0.025***	-0.023**	-0.028***	-0.015**
	(0.009)	(0.009)	(0.010)	(0.007)
Constant	-3.122	-8.923	-2.763	-24.562*
	(12.315)	(13.255)	(13.888)	(14.121)
Observations	20034	20034	20034	20034
R-squared	0.870	0.870	0.871	0.868

KP Test P Value	0.0003	0.0002	0.0002	0.0000
Hansen J P Value	0.0000	0.0000	0.0348	0.0000

Robust standard errors clustered by recipient-year in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include donor and recipient dummies.

Table 3: Time

	(1)	(2)	(3)
	Year Dummies	Three Periods	Changing Coefficient
$\sum_{i \neq d} Aid_{i,r,t}$	0.176	0.349***	0.766***
	(0.183)	(0.113)	(0.161)
$\sum_{i \neq d} post2000 * Aid_{i,r,t}$			-0.187***
			(0.056)
Donor Variables			
$GDP_{d,t}$	0.402**	0.669***	0.995***
	(0.191)	(0.195)	(0.220)
$Population_{d,t}$	3.572***	2.467***	1.601
	(0.533)	(0.438)	(1.231)
Recipient Variables			
$GDP_{r,t}$	-0.152*	-0.146*	-0.023
	(0.084)	(0.079)	(0.091)
$Population_{r,t}$	0.214***	0.170***	0.209**
	(0.054)	(0.057)	(0.082)
$Freedom_{r,t}$	-0.022*	-0.024**	-0.036***
	(0.013)	(0.011)	(0.013)
$Politics_{r,t}$	-0.003	-0.007	-0.007
	(0.007)	(0.006)	(0.006)
$Conflict_{r,t}$	0.016	0.012	-0.015
	(0.047)	(0.041)	(0.043)
$Disaster_{r,t}$	0.104***	0.111***	0.081**
	(0.036)	(0.032)	(0.035)
$Openness_{r,t}$	-0.017	-0.042	0.052
	(0.076)	(0.065)	(0.075)
$Multilateral_{r,t-1}$	-0.034	-0.045**	-0.095***
	(0.024)	(0.019)	(0.030)
Pair Variables			
$Distance_{d,r}$	-0.457***	-0.472***	-0.493***
	(0.033)	(0.031)	(0.032)
$Contiguity_{d,r}$	-0.120	-0.129	-0.146
	(0.220)	(0.224)	(0.230)
$Colony_{d,r}$	0.438***	0.453***	0.471***
	(0.052)	(0.051)	(0.052)
$Language_{d,r}$	0.446***	0.457***	0.478***
	(0.040)	(0.039)	(0.040)
$Aid_{d,r,t-1}$	0.770***	0.772***	0.778***
	(0.007)	(0.007)	(0.008)
$Trend_t$		-0.062***	-0.050***
		(0.008)	(0.009)
Constant	-71.133***	73.558***	59.938***
	(9.929)	(16.616)	(19.102)
Observations	20034	20034	20034
R-squared	0.872	0.870	0.865
KP Test P Value	0.0017	0.0000	0.0001
Hansen J P Value	0.0000	0.0000	0.0014

Robust standard errors clustered by recipient-year in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include donor and recipient dummies.

Table 4: Regions

	(1)	(2)	(3)	(4)
	Africa	Asia	Americas	Mideast
$\sum_{i \neq d} Aid_{i,r,t}$	0.721***	0.324	-0.124	0.850**
	(0.119)	(0.222)	(0.475)	(0.343)
Donor Variables				
$GDP_{d,t}$	0.824***	0.502	0.668*	-0.423
	(0.314)	(0.348)	(0.355)	(0.760)
$Population_{d,t}$	2.151**	3.328***	4.312***	4.893**
	(0.940)	(0.882)	(1.062)	(2.322)
Recipient Variables				
$GDP_{r,t}$	0.013	-0.487	-0.213	-3.088**
	(0.142)	(0.394)	(0.337)	(1.223)
$Population_{r,t}$	-1.144**	-0.967	1.171	-0.140
	(0.522)	(0.816)	(1.668)	(1.853)
$Freedom_{r,t}$	-0.032**	-0.048**	0.010	0.126
	(0.014)	(0.019)	(0.046)	(0.081)
$Politics_{r,t}$	-0.026***	-0.012	-0.027	0.022
	(0.006)	(0.008)	(0.024)	(0.016)
$Conflict_{r,t}$	-0.125**	0.121*	-0.200	0.042
	(0.064)	(0.071)	(0.216)	(0.126)
$Disaster_{r,t}$	0.055	-0.006	0.058	0.022
	(0.038)	(0.061)	(0.071)	(0.235)
$Openness_{r,t}$	-0.060	-0.091	-0.046	-0.347
	(0.099)	(0.109)	(0.173)	(0.715)
$Multilateral_{r,t-1}$	-0.162***	-0.138**	0.032	-0.029
	(0.044)	(0.067)	(0.053)	(0.033)
Pair Variables				
$Distance_{d,r}$	-0.616***	-0.310***	-0.411***	-0.680**
	(0.058)	(0.097)	(0.144)	(0.274)
$Contiguity_{d,r}$			0.124	
			(0.216)	
$Colony_{d,r}$	0.596***	0.499***	0.166	0.406
	(0.090)	(0.103)	(0.110)	(0.388)
$Language_{d,r}$	0.493***	0.091	0.726***	0.717***
	(0.058)	(0.078)	(0.117)	(0.205)
$Aid_{d,r,t-1}$	0.763***	0.762***	0.706***	0.726***
	(0.012)	(0.018)	(0.016)	(0.027)
$Trend_t$	0.001	-0.005	-0.054**	0.011
	(0.015)	(0.022)	(0.021)	(0.044)
Constant	-27.367	-34.763	2.439	-69.396
	(21.145)	(29.348)	(27.003)	(65.587)
Observations	7938	4536	5670	1512
R-squared	0.863	0.892	0.873	0.862
KP Test P Value	0.0002	0.0375	0.1944	0.0340
Hansen J P Value	0.0171	0.1284	0.0000	0.3105

Robust standard errors clustered by recipient-year in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include donor and recipient dummies.

Table 5: Time Lags

	(1)	(2)	(3)	(4)
$\sum_{i \neq d} Aid_{i,r,t}$	0.362***	0.925***	0.819***	
	(0.106)	(0.021)	(0.067)	
$\sum_{i \neq d} Aid_{i,r,t-1}$		-0.729***	-0.558***	0.566**
		(0.016)	(0.041)	(0.276)
$\sum_{i \neq d} Aid_{i,r,t-2}$			-0.172***	-0.496***
			(0.018)	(0.162)
Donor Variables				
$GDP_{d,t}$	0.810***	0.412**	0.456***	0.424**
	(0.159)	(0.164)	(0.170)	(0.206)
$Population_{d,t}$	2.066***	4.219***	6.229***	2.846***
	(0.565)	(0.532)	(0.415)	(0.602)
Recipient Variables				
$GDP_{r,t}$	-0.149*	0.015*	0.036	-0.088
	(0.078)	(0.009)	(0.029)	(0.167)
$Population_{r,t}$	0.167***	0.071***	0.122***	0.126
	(0.057)	(0.007)	(0.024)	(0.570)
$Freedom_{r,t}$	-0.026**	-0.001	-0.000	-0.015
	(0.011)	(0.001)	(0.004)	(0.018)
$Politics_{r,t}$	-0.008	0.000	0.003**	0.001
	(0.006)	(0.001)	(0.002)	(0.009)
$Conflict_{r,t}$	0.016	-0.000	-0.004	0.001
	(0.041)	(0.004)	(0.014)	(0.073)
$Disaster_{r,t}$	0.100***	0.007*	-0.002	0.103**
	(0.032)	(0.004)	(0.012)	(0.051)
$Openness_{r,t}$	-0.041	0.003	0.065***	0.021
	(0.067)	(0.006)	(0.022)	(0.105)
$Multilateral_{r,t-1}$	-0.043**	0.001	0.014***	-0.014
	(0.019)	(0.002)	(0.005)	(0.032)
Pair Variables				
$Distance_{d,r}$	-0.476***	-0.455***	-0.456***	-0.461***
	(0.031)	(0.030)	(0.031)	(0.031)
$Contiguity_{d,r}$	-0.133	-0.115	-0.082	-0.089
	(0.225)	(0.227)	(0.231)	(0.224)
$Colony_{d,r}$	0.455***	0.434***	0.426***	0.434***
	(0.050)	(0.051)	(0.053)	(0.051)
$Language_{d,r}$	0.458***	0.440***	0.447***	0.449***
	(0.039)	(0.039)	(0.041)	(0.040)
$Aid_{d,r,t-1}$	0.771***	0.774***	0.768***	0.764***
	(0.007)	(0.007)	(0.007)	(0.007)
$Trend_t$	-0.032***	-0.035***	-0.050***	-0.020
	(0.005)	(0.004)	(0.004)	(0.015)
Constant	19.333***	-12.969**	-24.037***	-16.400
	(7.033)	(6.576)	(5.850)	(20.987)
Observations	20034	20034	18921	18921
R-squared	0.870	0.869	0.869	0.867

KP Test P Value	0.0000	0.0001	0.0007	0.0001
Hansen J P Value	0.0000	0.0000	0.0000	0.6099

Robust standard errors clustered by recipient-year in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include donor and recipient dummies.

Table 6: Darlings and Orphans

	(1)	(2)
	Orphans Only	Darlings Only
$\sum_{i \neq d} Aid_{i,r,t}$	0.575***	0.160
	(0.137)	(0.189)
Donor Variables		
$GDP_{d,t}$	0.398	0.742**
	(0.274)	(0.339)
$Population_{d,t}$	4.040***	2.122***
	(0.791)	(0.599)
Recipient Variables		
$GDP_{r,t}$	-0.267***	-0.076
	(0.095)	(0.193)
$Population_{r,t}$	-1.042***	0.211***
	(0.272)	(0.065)
$Freedom_{r,t}$	-0.021	-0.026
	(0.014)	(0.021)
$Politics_{r,t}$	-0.008	-0.002
	(0.007)	(0.012)
$Conflict_{r,t}$	-0.071	0.096
	(0.059)	(0.064)
$Disaster_{r,t}$	0.142**	0.029
	(0.057)	(0.041)
$Openness_{r,t}$	-0.107	0.081
	(0.083)	(0.163)
$Multilateral_{r,t-1}$	-0.040**	-0.011
	(0.019)	(0.048)
Pair Variables		
$Distance_{d,r}$	-0.542***	-0.431***
	(0.043)	(0.047)
$Contiguity_{d,r}$	-0.213	
	(0.246)	
$Colony_{d,r}$	0.414***	0.477***
	(0.073)	(0.073)
$Language_{d,r}$	0.609***	0.391***
	(0.057)	(0.060)
$Aid_{d,r,t-1}$	0.736***	0.785***
	(0.011)	(0.010)
$Trend_t$	-0.008	-0.034***
	(0.008)	(0.010)
Constant	-38.735***	21.407
	(14.002)	(21.737)
Observations	9828	10206
R-squared	0.857	0.879
KP Test P Value	0.0012	0.0069
Hansen J P Value	0.0009	0.0014

Robust standard errors clustered by recipient-year in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include donor and recipient dummies.

Figure 1: Aid by Region

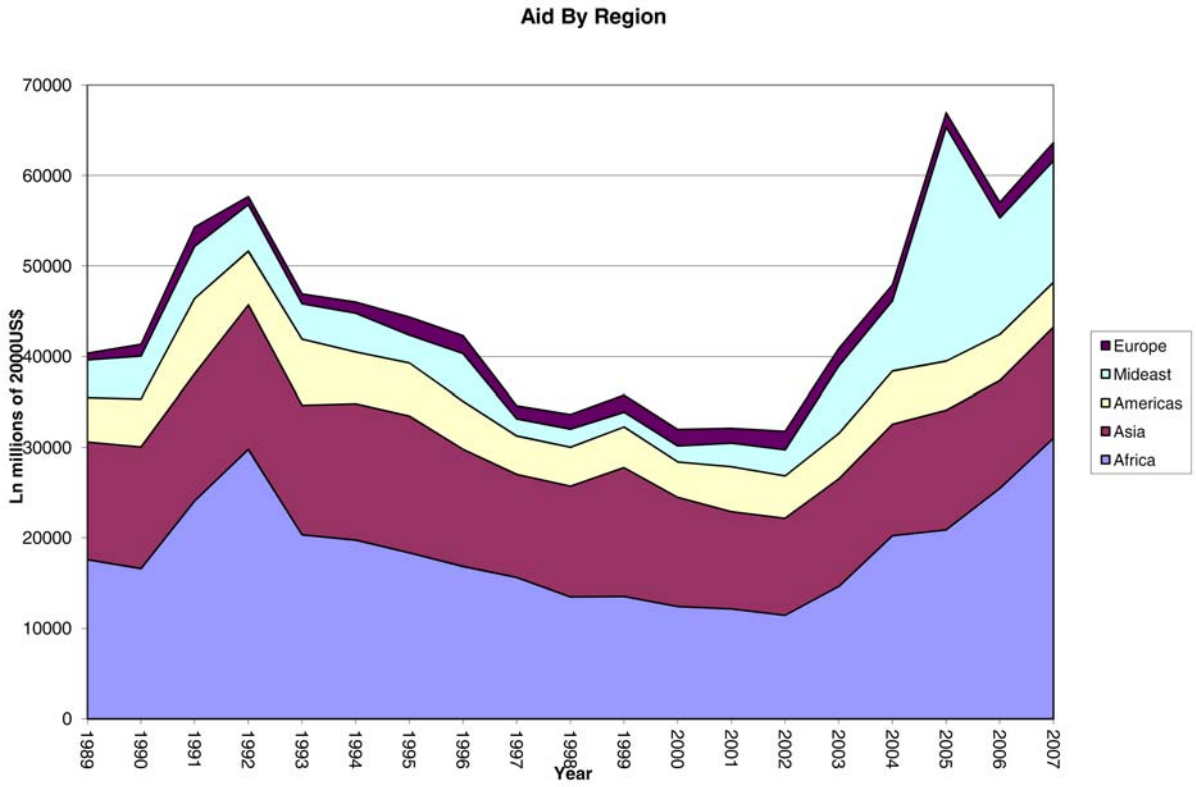
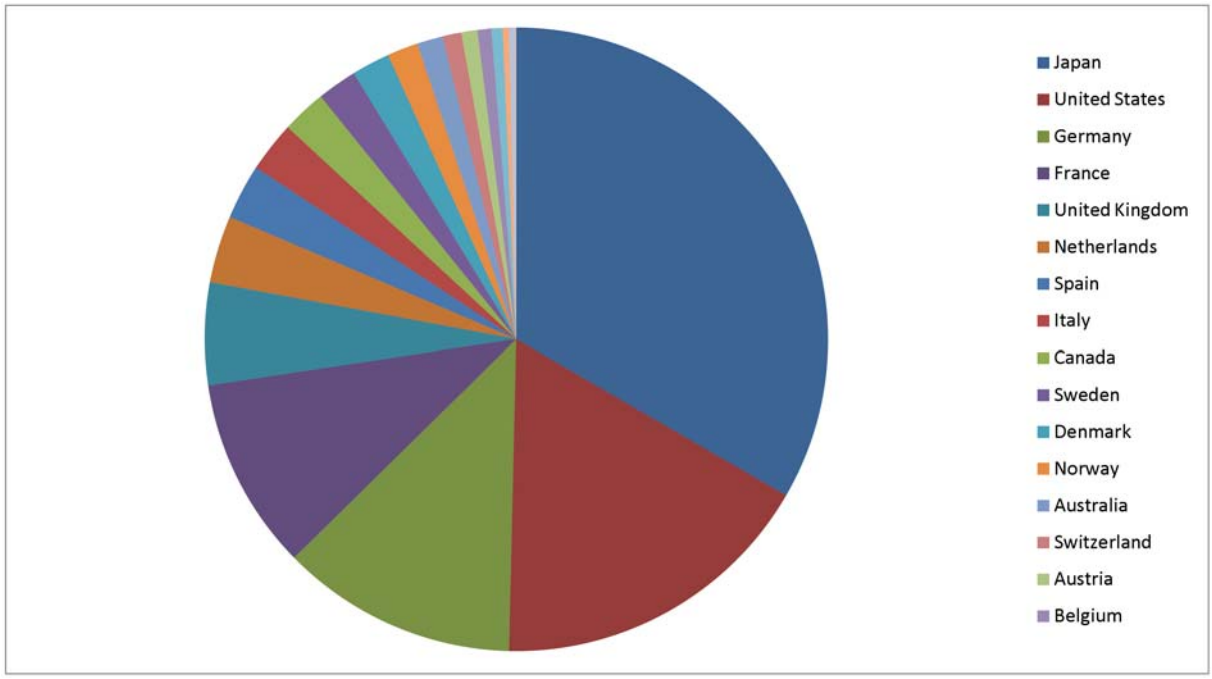


Figure 2: Aid by Donor



Appendix Table A1: List of Countries in the Sample

Donor Countries			
Australia	France	Netherlands	Switzerland
Austria	Germany	New Zealand	United Kingdom
Belgium	Greece	Norway	USA
Canada	Ireland	Portugal	
Denmark	Italy	Spain	
Finland	Japan	Sweden	
Recipient Countries			
Algeria [a]	**Egypt** [a]	Malawi [a]	**Sri Lanka** [b]
Argentina [d]	**El Salvador** [d]	**Malaysia** [b]	**Sudan** [a]
Bangladesh [b]	Gambia [a]	Mauritania [a]	**Swaziland** [a]
Bhutan [b]	**Guatemala** [d]	Mauritius [a]	Syria [a]
Bolivia [d]	Guinea [a]	Mexico [d]	**Thailand** [b]
Botswana [a]	Guyana [a]	Morocco [a]	Trinidad and Tobago [d]
Brazil [d]	**Honduras** [d]	**Mozambique** [a]	Tunisia [a]
Cameroon [a]	India [b]	Nepal [b]	Turkey [e]
Central African Rep. [a]	**Indonesia** [b]	**Nicaragua** [d]	**Uganda** [a]
China [b]	Iran [c]	Paraguay [d]	**Uruguay** [d]
Colombia [d]	**Jordan** [c]	**Philippines** [b]	Venezuela [d]
Costa Rica [d]	**Kenya** [a]	Saudi Arabia [c]	**Vietnam** [b]
Dominican Republic [d]	**Laos** [b]	Senegal [a]	**Zambia** [a]

[a] Africa, [b] Asia, [c] Mideast, [d] Americas, [e] Europe. **Boldface** recipients are darlings, non-bold recipients are orphans.

Table A2: Summary Statistics

Variable	*Obs.*	*Mean*	*Std. Dev.*	*Min*	*Max*
$Aid_{d,r,t}$	20034	-.4168652	3.819831	-6.968033	9.250069
Donor Variables					
$GDP_{d,t}$	20034	10.23964	.2100149	9.644843	10.83027
$Population_{d,t}$	20034	16.70149	1.223302	15.0533	19.52358
Recipient Variables					
$GDP_{r,t-1}$	20034	8.006394	.8907413	5.942288	9.968822
$Population_{r,t}$	20034	16.5423	1.683082	13.13633	20.99962
$Freedom_{r,t}$	20034	8.30608	3.361074	2	14
$Politics_{r,t}$	20034	1.775681	6.708527	-10	10
$Conflict_{r,t}$	20034	.1781971	.3826881	0	1
$Disaster_{r,t}$	20034	.2557652	.4363013	0	1
$Openness_{r,t}$	20034	4.136161	.5337856	2.405812	5.636078
$Multilateral_{r,t-1}$	20034	4.2104	1.368611	-1.033757	7.65074
Pair Variables					
$Distance_{d,r}$	20034	8.873914	.5452234	6.329211	9.84973
$Contiguity_{d,r}$	20034	.0017969	.0423533	0	1
$Language_{d,r}$	20034	.0431267	.2031473	0	1
$Colony_{d,r}$	20034	.115903	.3201165	0	1
$Trend_t$	20034	1998.5	5.188257	1990	2007