A Signal of Altruistic Motivation for Foreign Aid

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Abstract

We develop a stylized theoretical model showing that countercyclical transfers from a wealthy donor to a poorer recipient generate a signal of altruistic donor motivation. Applying the model to OECD foreign aid (ODA) data we find the signal present in approximately one-sixth of a large set of donor-recipient pairs. We then undertake two out-of-model exercises to validate the signal: a logit regression of signal determinants and the growth effects of ODA from signal-positive pairs are compared to non-signal bearers. The logit indicates our signal meaningfully distinguishes donor-recipient pairs by characteristics typically associated with altruism. The growth exercise shows ODA from signal bearers displays stronger reverse causation and more positive long-run effects. Beyond foreign aid, our signal of altruistic motivation may be applicable to a wide range of voluntary transfers.

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1 Introduction

The motives of foreign aid donors, and the effect of foreign aid, have been subjects of intense debate for decades. These subjects may be deeply connected: that is, the effect of aid cannot be accurately measured without considering the donor's motive (Kilby and Dreher, 2010; Dreher, Eichenauer, and Gehring, 2014; Bourguignon and Sundberg, 2007). This paper falls primarily in the lineage of an extensive literature analyzing donor motive. Much of this literature attempts to estimate the relative importance of two broad categories of donor motive: self-interest and altruism (Section 2 reviews the literature). Though progress has been made in motive measurement, no consensus exists on the weighting of these categories or the variables that best represent them. The lack of consensus may be due, in part, to the inconsistent choice of variables to capture self-interest and altruism across studies.

This paper adopts an alternative approach to donor motive identification. We develop a testable theoretical condition that generates a signal of altruistic motive above an identified threshold. The condition is based on a stylized donor optimization model, in which any mixture of weight on self-interest and altruism motives is allowed. The signal is associated with a countercyclical transfer pattern and we find it present empirically in about one-sixth of donor-recipient pairs. Two external validation exercises are undertaken to assess the signal. The results of these exercises support the signal's association with common notions of altruism. Beyond foreign aid, our signal of altruistic motivation may be applicable to a wide range of voluntary transfers.

To understand the intuition for the signal imagine an altruistic father who earns \$10,000 a month and gives his less successful son ten percent of his monthly income to supplement the \$1,000 the son earns. Now an unanticipated income shock reduces both father and son's income by, say, 50%. Will the father transfer a larger or smaller share of his income after the shock? While there is no unconditional answer to this question, we show that in a model allowing transfers for both altruistic and self-interest reasons, a pattern of countercyclical transfers will emerge if a donor is sufficiently altruistic towards the poorer recipient. The explanation is simple. Under the standard assumption of diminishing marginal utility, falling income has a stronger marginal effect on the poorer recipient's utility than the richer donor's utility. If donor's preferences incorporate the recipient's utility with sufficient weight, donor utility maximization will entail offsetting the falling recipient income, at least partially, with increased transfers. To distinguish this altruism signal from alternative conceptualizations we refer to it as "countercyclical-altruism."

The first external validity exercise is estimation of a logit model of the determinants of the *countercyclical-altruistic* pairs. We follow Berthélemy (2006) in the selection of the relevant explanatory variables usually used in literature to study aid allocation. The most significant finding is a powerful and robust inverse relationship between consumption and the likelihood of a significant signal this fits tightly with our theory of *countercyclical-altruism*. Additional results of the logit are that the signal is more likely to be observed in smaller recipients and in those with a colonial link with the donor. The impact of bilateral trade on signal likelihood is mixed, but mostly consistent with expectations that trade (as a self-interest proxy) would be insignificant or negatively related to signal likelihood. The likelihood of the signal is also independent of military relations between donor and recipient, while higher military government spending is negatively associated to our signal. This pattern of significance, and insignificance, is consistent with altruistic donor motivation. These results allow us to distinguish colonial-linkage effects on ODA associated with altruism/post-colonial guilt from those that manifest in trade and military ties, and are more likely to be associated with self-interest. This interpretation aligns closely with our initial father and son story.[1]

The second out-of-model exercise embeds the partition of donors generated by our signal in an adaptation of Burnside and Dollar (2000)) ODA-growth analysis. As noted, understanding ODA motivation may be vital for the correct measurement of the effects of foreign aid on growth. We find that aid from a donor displaying the *countercyclical-altruism* signal has a distinguishable, more positive and significant long-run effect on recipient growth than aid from donors without the signal. This effect becomes particularly strong when early impact aid is considered. Furthermore, the estimates of the contemporaneous effects of the altruistic donors' ODA display clear evidence of reverse causation bias, which is not significantly found for the non-signal-bearing group.

The remainder of the paper is organized as follows: Section 2 provides additional background and a review of the related literature. Section 3 introduces our stylized model and derives the testable condition for altruistic motivation. Section 4 develops the estimation strategy and presents the empirical results. Section 5 contains our external validity exercises. Section 6 summarizes and suggests future extensions. Appendices address details of the theory, the sample and dataset, bias computations, point estimate summaries, and robustness.

2 Additional Background and Literature

A vigorous academic and public debate regarding the motives and efficacy of foreign aid has raged for more than fifty years. The countercyclical altruism signal that is central to this paper falls primarily within the "motives" strand of the literature. In this Section we provide an brief literature review; those desiring a broader introduction are referred to surveys by Temple (2010), Addison and Tarp (2014), and Radelet (2006).

2.1 The Donor Motivation Literature

The literature on donor motivation to allocate foreign aid is large, and the discussion and citations below are by no means complete. Most recent analyses focus on some combination of three stylized donor targets in the distribution of aid: self-interest, recipient need, and recipient merit. The latter two (recipient need and merit) are generally associated with altruistic motivation, with relative donor emphasis on one or the other indicative of donor preferences over altruistic targets. In empirical analyses, recipient need has been captured by per-capita income, infant mortality, and poverty, among others. Recipient merit variables have included measures of democratization, civil rights, low corruption, and "good policies." Common self-interest variables include supportive UN votes and trade benefits. The argument for associating both need and merit with altruistic motivation is straightforward. If aid were a pure donor self-interest transaction (e.g., the purchase of a supportive UN vote),

[1] The "post-colonial guilt" incentive for ODA is technically equivalent to altruism since the guilt is linked to former colonies low utility level relative to former colonizer.

the donor should care only about the supportive vote (or other payoff), and not the effect of aid on the recipient. Therefore, aid flows that are responsive to recipient need or merit are likely indicative of some altruistic motivation. As noted, most donors likely have multiple motivations, and a significant emphasis in the literature is identification of this mixture over specific time periods or for specific types of donors. Most analysis of motive focus on bilateral aid, though comparisons with the determinants of multilateral aid can be found in the literature.

Dudley and Montmarquette (1976) provide one of the first formal theoretical and empirical models of aid supply. The impact of aid upon the recipient's welfare is embedded in the donor objective function, so the theoretical motivation is altruistic by assumption. Their empirical results are among the first to show the correlation of aid with political/economic links and to explicitly address simultaneity bias. A number of papers that followed reflect acknowledgment of multiple donor motives (self-interest and altruism), and an attempt to model them distinctly. McKinley and Little (1979) develop and test models of recipient need versus donor self-interest motives, and conclude the dominance of self-interest motive for the US in the 60s. Similarly, Maizels and Nissanke (1984) develop distinct self-interest and altruistic models to distinguish motivation of both bilateral and multilateral donors. They find the self-interest model yields a better fit with bilateral donors. Trumbull and Wall (1994) undertake a further extension of Dudley and Montmarquette (1976) theoretical model, again embedding the assumption of altruistic donor motivation but with new measures of recipient well-being – such as infant mortality. Using panel data they find the recipient welfare variables significantly associated with aid allocation.

Alesina and Dollar (2000) provide one of the first uses of supportive UN votes in the economics literature to capture the donor self-interest motivation. Their use of democratization and good policy as variables associated with recipient merit is representative of a growing trend in the literature during this period. They also contrast the determinants of aid flows and foreign direct investment, finding the latter more sensitive to good policies of the recipient. Berthélemy and Tichit (2004) use panel data to examine how the fall of European communism affected allocation decisions, finding increased emphasis on trade and governance in aid allocation. Berthélemy (2006) provides another analysis of the relative importance of self-interest and altruism motives. He uses both geo-political dummies and trade to capture self-interest, and liberty and corruption indexes to capture merit. Dreher, Nunnenkamp, and Thiele (2008) show that US foreign aid is strongly associated with supportive UN general assembly votes, in line with self-interest motive. Younas (2008) also presents evidence of large weighting on self-interest motives associated with geo-political and trade considerations. Hoeffler and Outram (2011) explicitly consider self-interest, recipient need, and recipient merit in a model with both donor and recipient specific effects. They find indication of self-interest and recipient-need effects, but merit has very little effect on the bilateral aid flows for most donors. Finally, we should note that the presumption of strong self-interest motives is also the norm in the political science literature (see for example Packenham, 1966; Schraeder, Hook, and Taylor, 1998; de Mesquita and Smith, 2007; Bearce and Tirone, 2010).

In assessing the evolution of the aid motive literature over the past forty years, clear conceptual and technical progress is evident. Nevertheless, it is difficult to compare the results of papers or make general statements about the time-trend or levels of donor weight on self-interest and altruism because of the ad-hoc selection of self-interest and altruism measures across studies. Self-interest variables may include supportive UN votes, various measures of bilateral trade, other geo-political metrics, or any combination of such variables. Similarly for altruistic motives, some studies include only need, others need and merit, and yet others only merit. Moreover, for any choice of these altruism dimensions, there is significant variation across studies in the specific measures chosen. Theoretical motivation for the choice of measure seems a natural next step for the motive literature.

2.2 Other Related Aid Literature

Beyond the strict motive literature, an important strand with relevance to our signal is the aid-growth literature. As noted in the introduction, this literature intersects strongly with that of aid motive since unobserved donor motive is a driver of the endogenous allocation of aid. How to best address this endogeneity is a central theme and important papers in this lineage include Burnside and Dollar (2000), Rajan and Subramanian (2008), and Clemens, Radelet, Bhavnani, and Bazzi (2012).[2] A rigorous and balanced review of aid-growth literature would be lengthy, and the reader is referred to the surveys cited above as literature entry points. We provide brief additional discussion of the aid-growth literature in Section 5.2, which embeds our signal in standard growth models as an external validation exercise.

The literature on ODA and business cycles also warrants note as our signal is generated by cyclical characteristics of aid flows. Arellano, Bulb, Laneb, and Lipschitzb (2009) examine the effects of aid volatility on poor African countries, finding it has significant negative welfare effects on recipients. Bul and Hamann (2008) develop new measures of aid volatility and argue effective procyclical volatility has complicated macro policy for recipients. Pallage and Robe (2001) examine potential recipient welfare gains from temporal reallocation in the face of macroeconomic shocks. Though related, these papers that address the cost of aid volatility on recipient welfare are distinct from our use of countercyclical aid as a signal of motive. Pallage and Robe (2001) look both at the procyclical effect of aid on African recipients and also search for evidence of cyclicity in donor flows, finding little evidence of procyclicality. Dabla-Norris, Minoiu, and Zanna (2010) come closer to our focus, examining cyclicity in bilateral aid in both donor and recipient countries. They find that the general pattern of procyclical aid can reverse in the face of large recipient shocks, which is consistent with the reverse causation mechanism of our signal discussed in Section 4.

Finally, we note that there are various measures of donor motivation designed for public, as well as academic, consumption. Among the best known are the Center for Global Development's (CGD), Commitment to Development Index (CDI) which, in the words of the CDG, is intended to rank "wealthy governments on how well they are living up to their potential to help poor countries."[3] The aid component of the index, which is essentially a ranking of altruistic intent of aid, places weight on aid to lower income recipients, poorly governed recipients, and untied aid.

[2] Werker, Ahmed, and Cohen (2009), find a credible instrument for OPEC donations to other Muslim countries in price of oil fluctuation. However, this instrument is not applicable to most OECD donors.

[3] See http://www.cgdev.org/initiative/commitment-development-index/index.

3 Countercyclical ODA and Altruism Condition

In this section we define a theoretical condition for altruistic donor motivation towards specific recipients. This condition guides the empirical analysis by providing an explicit condition for *countercyclical-altruism* that can be rigorously tested with our data. Our objective is to minimize the gap between theory and empirics. Though the theoretical model is stylized, the mechanism generating the *countercyclical-altruism* signal is quite general. Specifically, diminishing marginal utility of donations and adequate altruism embedded in the utility function of donors are sufficient to generate the signal.

3.1 The Theoretical Condition for Countercyclical-Altruism

The *countercyclical-altruism* signal is derived directly from the donor's optimality conditions. For brevity, we outline the main features of the theoretical framework here, leaving the details to Appendix B.1. We consider the disbursement decision of representative donor, d, to representative recipient, r. Simplifying assumptions that do not undermine the signal's mechanism are employed whenever possible. The unit of analysis for the disbursement decision is the donor-recipient pair and the framework allows for multiple donors and recipients. As is standard in the literature, we abstract from strategic interaction among donors.[4] Donors derive utility from own-consumption and from ODA disbursements. ODA generates donor utility through distinct self-interest and altruism channels.[5] Donor d makes ODA transfer to recipient r by solving a static utility maximization problem subject to the donor's and recipient's resources constraints, linked to each other by the ODA disbursement. Disposable income, defined as income net of investment, and the disbursements to other recipients are taken as given by the donor when the transfer decision to recipient r is made. Finally, consumers' absorption in both countries is assumed to include government expenditure and net exports.

The utility function of the representative donor can be expressed as the sum of three components

$$w\left(a\right) = u\left(c_{d,0} - \sum_{r} a_r\right) + \sum_{r} \rho_r\left(a_r; X_{\rho r}\right) + \sum_{r} \delta_r\left(a_r; X_{\delta r}\right) \tag{1}$$

where $u\left(\cdot\right)$, $\rho_r\left(\cdot\right)$, and $\delta_r\left(\cdot\right)$ respectively indicate the utility from the donor's own-consumption, a direct egoistic return from an ODA transfer to recipient r, and purely altruistic preferences of the donor towards recipient r. Note that this specification allows for any combination of self-interest and pure altruism in the utility.[6] The ODA donation to recipient r is a_r, the vector of donations to the entire set of recipients is a, $c_{d,0}$ is the available donor

[4] Ongoing research examines strategic play among donors separately. Though potentially important for a small number of our 19 donors (the US in particular), there is no inherent contradiction or mutual exclusion with the mechanism we focus on in this paper and strategic disbursement.

[5] See Dudley and Montmarquette (1976); Younas (2008); Chong and Gradstein (2008); Gravier-Rymaszewska (2012) for similar specifications in the ODA literature.

[6] This type of utility decomposition is similar in spirit to that introduced by Andreoni (1989, 1990) in the charitable donations literature and it has also been used in charitable auction theory and in previous work in the ODA literature (as in Chong and Gradstein, 2008).

income when no ODA donations are made, and $X_{\cdot r}$ represent pair-specific shift factors of the two ODA components. All variables are normalized by donor's trend GDP.

The first order condition with respect to a_r is

$$- u_c \left(c_{d,r_0} - a_r\right) + \rho_{r,a}\left(a_r; X_{\rho r}\right) + \delta_{r,a}\left(a_r; X_{\delta r}\right) = 0 \tag{2}$$

where c_{d,r_0} is donor consumption *before* donation to recipient r. We examine equation (2) only in a small positive neighborhood of $a_r = 0$, since empirically the observed bilateral ODA transfers are very small relative to donor income (typically smaller than .01% of GDP). Hence, it is not necessary to globally characterize $\rho_r(\cdot)$ and $\delta_r(\cdot)$ to obtain our theoretical predictions and we impose only a standard set of technical assumptions on these two functions to ensure a solution near zero. Specifically, a non-negative first order derivative and a non-positive second order derivative are required.

Looking forward to the estimation, we take a first order approximation of (2) around $a_r = 0$

$$- \bar{u}_c + \bar{u}_{cc} a_r + \bar{\rho}_{r,a} + \bar{\rho}_{r,aa} a_r + \bar{\delta}_{r,a} + \bar{\delta}_{r,aa} a_r = 0 \tag{3}$$

in which the derivatives of the three components of (2) evaluated at $a_r = 0$ are denoted with over-bars.[7] The corresponding optimal ODA is

$$a_r^* = \frac{\bar{u}_c - \bar{\rho}_{r,a} - \bar{\delta}_{r,a}}{\bar{u}_{cc} + \bar{\rho}_{r,aa} + \bar{\delta}_{r,aa}} \tag{4}$$

Because of diminishing marginal returns to own-consumption as well as ODA returns, the second order derivatives evaluated at zero ODA are all negative, the denominator of (4) is negative. In order to have $a_r^* > 0$ as solution, the numerator of (4) needs to be negative too. The necessary condition for positive ODA is then

$$\bar{u}_c < \bar{\rho}_{r,a} + \bar{\delta}_{r,a} \tag{5}$$

that is, the marginal utility gain of positive ODA must exceed the marginal loss due to the fall in the donor's own consumption. If condition (5) is not satisfied, then $a_r = 0$ and we have a "corner" solution.

We show now that sufficiently strong counter-cyclical ODA can serve as a signal of altruism above a threshold level, which we will call *countercyclical-altruism*.[8] To this end we first postulate the following reduced-form relationship between donor's and recipient's incomes

$$y_r = \beta_0 + \beta_r y_d + \varepsilon \tag{6}$$

where $y_i = Y_i \,/\, \bar{Y}_i$ represents the output gap of country $i = r, d$ defined as the ratio of actual GDP, Y_i, to its trend, $\bar{Y}_i$. On the right-hand-side of equation (6), β_0 is a constant and

[7] That is, we define $\bar{u}_c \equiv u_c\left(c_{d,r_0}\right)$ and $\bar{u}_{cc} \equiv u_{cc}\left(c_{d,r_0}\right)$ and adopt the same convention for ρ and δ.

[8] Non-altruistic mechanisms might also generate countercyclical transfers of the type used in our identification strategy. However, the countercyclical altruism signal requires no stronger assumptions than diminishing marginal utility and some weight on recipient utility. Countercyclical self-interest transfers would require a significantly more complex mechanism, including some enforcement devise for the return. By Occam's Razor we view the simpler altruism story as superior. Additionally, our validation exercises strongly support the altruistic motivation for countercyclical transfers.

ε is an i.i.d. residual with mean zero. It is not necessary to impose any restrictions on the sign of β_r; in general, β_r will vary across donor-recipient pairs and be dictated by the degree of integration of the recipient country with the global economy and its trade mix.

The concept of countercyclical ODA in our model is associated with a negative derivative da_r^* / dy_d. Starting from (4), and using the fact that $\rho_r(\cdot)$ does not depend on donor's income, the definition of y_r in (6), and again the optimal solution for a_r^*, we obtain[9]

$$\frac{da_r^*}{dy_d} = \frac{\bar{u}_{cc} - \beta_r \bar{\delta}_{r,ac} - \left(\bar{u}_{ccc} + \beta_r \bar{\delta}_{r,aac}\right) a_r^*}{\bar{u}_{cc} + \bar{\rho}_{r,aa} + \bar{\delta}_{r,aa}} \tag{7}$$

Since the denominator of this ratio is always negative, the numerator has to be positive in order for $da_r^* \,/\, dy_d$ to be negative. Since our approximation of the solution is for a_r close to 0, the term in a_r^* will be small relative to the other terms in the numerator of (7); for the determination of the sign of the derivative we can therefore focus only on

$$\bar{u}_{cc} - \beta_r \bar{\delta}_{r,ac} > 0 \tag{8}$$

or equivalently, since the second derivative $\bar{u}_{cc}$ is negative, on

$$\frac{\beta_r \bar{\delta}_{r,ac}}{\bar{u}_{cc}} > 1 \tag{9}$$

The sign of the cross-partial $\bar{\delta}_{r,ac}$ will also normally be negative since diminishing marginal utility should ensure that an increase in recipient consumption reduces the altruistic return. In this case, condition (9) can be satisfied only when β_r is positive. For a given $\beta_r > 0$ and $\bar{u}_{cc} < 0$, condition (9) establishes a minimum $\left|\bar{\delta}_{r,ac}\right|$ beyond which a negative $da_r^* \,/\, dy_d$ derivative will be observed. The linkage with β_r in (9) is critical to the intuition. When β_r is positive (as in the father-son income shock story) a large $\left|\bar{\delta}_{r,ac}\right|$ reflects a big increase (decrease) in the altruistic return as consumption falls (rises). When $\beta_r > 0$, this fall (rise) in consumption is occurring simultaneously to both donor and recipient.[10] The condition is more easily satisfied the larger β_r is, the tighter the linkage in the business cycles of the two countries, and the smaller $|\bar{u}_{cc}|$ is, which typically occurs when donor's consumption is high relative to the recipient's. When specific functional forms are chosen in Section 3.2 below, the threshold altruism level of (9) will be embodied in a positive altruism parameter. This parameter threshold (9) becomes the effective *countercyclical-altruism* condition. It is distinct from the case where the donor has a non-zero altruistic return, but it is not large enough to generate countercyclical ODA. In summary, *countercyclical-altruism* occurs when

[9] Our definition of $\rho_r(\cdot)$ makes the return independent from the donor's income. This seems to be a fair assumption, even though it would be possible to write a model in which $\rho_r(\cdot)$ is, for example, proportional to Y_d and this would determine an additional term in (7).

[10] In theory, $\bar{\delta}_{r,a}$ also depends on the shifting variables in $X_{\delta r}$ and those might change in response to y_r in a way that makes the cross-partial non-negative. Therefore, it would be possible to observe $da_r^* \,/\, dy_d < 0$ even when β_r is negative. For example, an increase in the recipient's income could reduce corruption in the recipient country increasing the effectiveness of ODA. From the donor's perspective this would shift the altruistic return component upward. A negative β_r, however, is inconsistent with the idea of altruistic donor presented in the introduction of this paper. In the empirical section, we show that such occurrences are relatively infrequent in the data.

voluntary transfers from a richer to a poorer agent move inversely with changes in both agents' income.

3.2 Empirical Strategy

Empirical evaluation of condition (8), requires specification of functional forms for $u(\cdot)$, $\rho_r(\cdot)$, and $\delta_r(\cdot)$. As illustrated in Appendix B.1, equation (1) is the log-additive version of the donor's utility. Therefore, as a baseline case, we simply choose a log-linear specification for these components, corresponding to very general power functions for the original utility. We check the robustness of our results for other functional forms by considering constant absolute and relative risk aversion (CARA and CRRA) functions, as explained in Appendix B.

The power function is a natural functional form for own-consumption utility in our context; it is both simple and flexible and it allows us to locally characterize a wide set of preferences with a single parameter in a neighborhood of $a_r = 0$, the region in which we are mostly interested. The own-consumption component is then $u(c_d) = \sigma \log(c_{d,r_0} - a_r)$.

On the other hand, aside from the natural concavity property in return functions, there is little precedent for selecting specific functional forms for the ODA components. We adopt a power function for these two components as well. Specifically, $\rho_r(a_r; X_{\rho r}) = \rho_{r,0} \log(1 + a_r)$ where $\rho_{r,0}$ can be interpreted as the direct return rate on the ODA "investment". For the altruism function we think a natural first-case is to let the altruism "return" be proportional to the change in the recipient's utility from the ODA donation a_r. For example, $\delta_r(a_r; X_{\delta r}) = \delta_{r,0}[\log(c_{r,0} + a_r) - \log c_{r,0}]$ where $\delta_{r,0}$ expresses the degree of altruism of the donor toward recipient r, and $c_{r,0}$ is the income available to recipient r for consumption before receiving any ODA donation.[11,12]

Adopting these functional forms, the first order condition (3) yields the following regression equation that allows us to estimate the return parameters $\rho_{r,0}$ and $\delta_{r,0}$ and then test for the *countercyclical-altruism* condition

$$\sigma c_{d,r_0}^{-1}\left(1 + c_{d,r_0}^{-1} a_r^*\right) = \rho_{r,0}(1 - a_r^*) + \delta_{r,0} c_{r,0}^{-1}\left(1 - c_{r,0}^{-1} a_r^*\right) \tag{10}$$

Estimation and testing of this condition requires consideration of potential biases. Specifically, regression coefficients could be affected by an omitted variable bias due to the dependence of $\rho_{r,0}$ and $\delta_{r,0}$ on the shifting factors and the bias could also affect the *countercyclical-altruism* test. However, in our model these concerns are in part attenuated. In the estimation

[11] The parameter $\delta_{r,0}$ also contains curvature information for the recipient's utility function. As discussed later, it is not necessary to disentangle the two effects to implement our altruism test under this functional form representation.

[12] The equivalent non-linear utility components are:

$$\begin{aligned}
\mathbb{U}(c_d) &= (c_{d,r_0} - a_r)^{\sigma} \\
\mathbb{R}_r(a_r; X_{\rho r}) &= (1 + a_r)^{\rho_{r,0}} \\
\mathbb{D}_r(a_r; X_{\delta r}) &= \left(\frac{c_{r,0} + a_r}{c_{r,0}}\right)^{\delta_{r,0}}
\end{aligned}$$

For notational simplicity, the set of "shifter" variables are omitted from the expressions above. In this respect, a more complete notation for $\rho_{r,0}$ and $\delta_{r,0}$ would be $\rho_{r,0}(X_{\alpha r})$ and $\delta_{r,0}(X_{\delta r})$.

Section 4.1 and in the online Appendix S3, we show that the final altruism test developed in this section is invariant to shifting variables that represent time-fixed characteristics of the donor-recipient pair. Time-varying shifters are also addressed in the estimation section.[13]

Under the assumed functional forms, condition (9) becomes

$$\frac{\beta_r \delta_{r,0} c_{r,0}^{-2}}{\sigma c_{d,r_0}^{-2}} > 1 \tag{11}$$

In general, we would expect a non-negative direct return ($\rho_{r,0} \geq 0$) and altruism parameter ($\delta_{r,0} \geq 0$). If also β_r is positive, then (11) can be reduced to the following condition on $\delta_{r,0}$:

$$\delta_{r,0} > \frac{\sigma c_{r,0}^{2}}{\beta_r c_{d,r_0}^{2}} \tag{12}$$

That is, the altruism parameter must exceed a threshold level to satisfy the *countercyclical-altruism* condition. Inequality (12) is the function specific analog to the theoretical condition (9). The *countercyclical-altruism* signal is more likely the smaller is the curvature parameter of the donor's own-consumption utility function; the smaller is the recipient's consumption net of the ODA relative to donor income, $c_{r,0}$; and the larger is the initial donor's consumption, c_{d,r_0}. This makes sense since donor altruism towards a recipient has greater affect when $c_{r,0}$ is small and it is less costly (in utils) when its consumption is higher.

From condition (11), it is clear that a pair of negative estimates for β_r and $\delta_{r,0}$ could potentially satisfy the condition without actually identifying a *countercyclical-altruistic* donor-recipient relationship. While a negative β_r is theoretical and empirically legitimate, a negative $\delta_{r,0}$ estimate indicates a gap between theory and empirics for this functional form. However, since our goal is to identify and assess the set of donor-recipient pairs displaying the *countercyclical-altruism* signal the estimates of $\rho_{r,0}$ and $\delta_{r,0}$ are not of stand-alone interest. Therefore, we adopt an identification strategy based on the donor's decision between a zero and a positive a_r, which is made before the decision of how much ODA to donate to recipient r. Applying the baseline functional forms to condition (5), the donor sets a positive ODA only if $\sigma c_{d,r_0}^{-1} - \rho_{r,0} - \delta_{r,0} c_{r,0}^{-1} < 0$.

Let $(\rho_{r,0^*},\ \delta_{r,0^*})$ be the pair of coefficients such that the optimal ODA choice would be $a_r^* = 0$. These coefficients satisfy the condition

$$\sigma c_{d,r_0}^{-1} = \rho_{r,0^*} + \delta_{r,0^*} c_{r,0}^{-1} \tag{13}$$

Taking the differential of (13) with respect to y_d and combining it with (11), we obtain the condition for a negative $da_r^* \,/\, dy_d$

$$\beta_r \left(\delta_{r,0} - \delta_{r,0^*}\right) > 0 \tag{14}$$

[13]Additional estimation issues concern the specific functional forms chosen. The left hand side of condition (9) depends on these choices and it could be quite sensitive to them. As noted above, to address these concerns we perform a series of robustness checks by re-estimating the alternative models with CARA and CRRA functional forms. These results are quite similar to the baseline estimation.

We can estimate $\delta_{r,0^*}$ (along with $\rho_{r,0^*}$) from (13) and compare it to the estimate of $\delta_{r,0}$ from (10) in order to evaluate condition (14). The threat of potential bias in the estimates of $\delta_{r,0}$ and $\delta_{r,0^*}$ is reduced in evaluating (14), since both $\delta_{r,0}$ and $\delta_{r,0^*}$ would be affected by the bias in the same way when a shifting variable is not time-varying. Note also that, for the same reason, the risk aversion parameter σ drops out of (14).

Condition (14) is satisfied when

$$\beta_r \left(\delta_{r,0} - \delta_{r,0^*}\right) > 0 \text{ and } \beta_r > 0, \left(\delta_{r,0} - \delta_{r,0^*}\right) > 0 \tag{15}$$

as well as in a second case when

$$\beta_r \left(\delta_{r,0} - \delta_{r,0^*}\right) > 0 \text{ and } \beta_r < 0, \left(\delta_{r,0} - \delta_{r,0^*}\right) < 0 \tag{16}$$

The actual *countercyclical-altruism* donor-recipients pairs are identified only by the conditions in (15) because it corresponds to the case in which the altruism parameter $\delta_{r,0}$ is bigger than the minimum degree of altruism found in (13) necessary to have $a_r^* \geq 0$. Figure 1 provides a graphical representation of the full mechanism supporting the *countercyclical-altruism* condition and the ODA decision. For given σ, c_{d,r_0}, and $c_{r,0}$, equation (13) defines the set of all $(\rho_r \ \ \delta_r)$ parameter pairs for which $a_r^* = 0$. Since c_{d,r_0}^{-1} and $c_{r,0}^{-1}$ are positive, equation (13) represents a downward sloping line in the $(\rho_r \ \ \delta_r)$ plane with a positive intercept. On the right hand side of this line we have the region of $(\rho_r, \ \delta_r)$ pairs such that $a_r^* > 0$, while on the left hand side we would have negative ODA. Suppose $\beta_r > 0$ and that the estimates of $(\rho_{r,0^*} \ \ \delta_{r,0^*})$ from (13) are $(\rho_B \ \ \delta_B)$. As we move to the left of δ_B, to point 1 for example, the *countercyclical-altruism* condition is not satisfied because $(\delta_{r,0} - \delta_{r,0^*}) < 0$ but a_r^* can still be made positive by a high direct return $\rho_{r,0}$. On the other side, moving just a little towards the right would be enough to get $a_r^* > 0$; however, if $\rho_{r,0}$ is small we would need a larger altruism parameter $\delta_{r,0}$ in order for the *countercyclical-altruism* condition to hold, as for example in point 2 in Figure 1.

4 Empirical Estimation

This section presents the main empirical results for the *countercyclical-altruism* test. A description of the data sources and the dataset characteristics is given in Appendix C.

4.1 Estimation

We now test whether the *countercyclical-altruism* signal from the theoretical model, inequality (14), is satisfied significantly by some donor-recipient pairs. The empirical framework used to evaluate the *countercyclical-altruism* condition is given by three equations: the reduced form relationship between recipient and donor business cycles (6); the first order condition of the donor's optimization problem (10); and the condition for zero ODA (13). We modify these equations slightly from the theoretical versions to make them more suitable for estimation. The estimation model for each donor-recipient pair is

$$y_{r,t} = \beta_0 + \beta_r y_{d,t} + \varepsilon_{1,t} \tag{17}$$

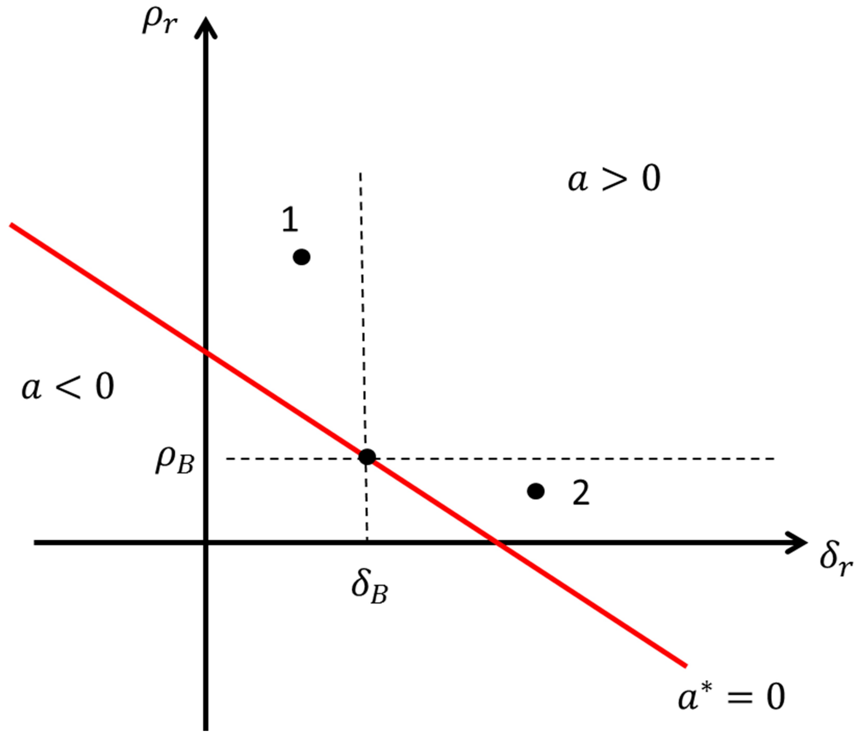

Figure 1: ODA decision and the *countercyclical-altruism* condition. Graphical interpretation of the ODA decision and of the *countercyclical-altruism* condition. The estimates of $(\rho_{r,0^*} \;\; \delta_{r,0^*})$ from (13) are $(\rho_B, \;\delta_B)$. The *countercyclical-altruism* condition could be satisfied at point 2 but not point 1 when $\beta_r > 0$.

$$\underbrace{c_{d,r_0}^{-1}\left(1 + c_{d,r_0}^{-1} a_r^*\right)}_{y_{1,t}} = \rho_{r,0}\underbrace{(1 - a_r^*)}_{x_{1,t}} + \delta_{r,0}\underbrace{c_{r,0}^{-1}\left(1 - c_{r,0}^{-1} a_r^*\right)}_{x_{2,t}} + \gamma_0' Z_t + \varepsilon_{2,t} \tag{18}$$

$$\underbrace{c_{d,r_0}^{-1}}_{y_{2,t}} = \rho_{r,0^*} + \delta_{r,0^*}\underbrace{c_{r,0}^{-1}}_{x_{3,t}} + \gamma_{0^*}' Z_t + \varepsilon_{3,t} \tag{19}$$

where $\varepsilon_{i,t}$ for $i = 1, 2, 3$ are standard residual terms. Equation (17) reflects (6), and we do not introduce specific controls in it. This is a simple way to allow the coefficient β_r to measure the degree to which the donor and recipient economies are linked – regardless of what third factor drives this link. Equations (10) and (13) are normalized by σ in equations (18) and (19). This normalization makes the estimation independent of the curvature of $u(\cdot)$ without affecting the significance of the altruism signal. Moreover, the four parameters $[\rho_{r,0} \; \delta_{r,0} \; \rho_{r,0^*} \; \delta_{r,0^*}]$ in (18) and (19) absorb this normalization and the effects of any time-invariant shifting variable. In a minor abuse of notation, we maintain the original notation for the adjusted coefficients. The online Appendix S3 shows that, for fairly general representations of the effects of time-invariant shifters, the altruism signal in (14) remains valid. Finally, we introduce an identical vector of (time-varying) control variables, Z_t, in both (18) and (19). As noted earlier, many factors may influence the ODA allocation decision and, like most of the prior literature, our theory does not indicate which of the large set of potential control variables to include. We therefore select four common controls from the literature that have the advantage of homogenous definition across countries for our large set of recipients: population growth rate, inflation, trade openness, and life expectancy at birth.

Equations (17)-(19) are estimated by GMM. The standard orhogonality conditions between regressors and the error terms of the equations provide the necessary conditions to estimate the coefficients of the model. The full vector of estimated parameters is $\theta = [\beta_0\ \beta_r\ \rho_{r,0}\ \delta_{r,0}\ \rho_{r,0^*}\ \delta_{r,0^*}\ \gamma_0'\ \gamma_{0^*}']'$. We rely on the asymptotic properties of the GMM estimator to conduct the *countercyclical-altruism* test on inequality (14). The vector of estimates $\hat{\theta}$ has a normal asymptotic distribution; the distribution of $\hat{\beta}_r\left(\hat{\delta}_{r,0} - \hat{\delta}_{r,0^*}\right)$ can be derived from that of $\hat{\theta}$ applying the delta method. Under the null hypothesis $H_0 : \hat{\beta}_r\left(\hat{\delta}_{r,0} - \hat{\delta}_{r,0^*}\right) \leq 0$, the asymptotic distribution of $\hat{\beta}_r\left(\hat{\delta}_{r,0} - \hat{\delta}_{r,0^*}\right)$ is approximately normal too and a donor-recipient pair satisfies the *countercyclical-altruism* condition if the null is rejected at 5% level of confidence.[14,15]

4.2 Summary of the Baseline Estimation Results

Since we estimate the parameter vector $\hat{\theta}$ for all 2603 donor-recipient pairs it is infeasible to report the entire set of point estimates of the model parameters. In any case, the objective of this research is not to explain idiosyncratic altruistic motivation among specific donor-recipient pairs, but to identify a signal of donor altruism that can be applied to wide range of ODA analyses. Therefore, in this section we report some broad characteristics of the set of donor-recipient pairs displaying the *countercyclical-altruism* signal and the complement of that set of countries. The first observation is that in the baseline 16.3% of the pairs satisfy the *countercyclical-altruism* condition at the five percent confidence level with positive β_r. Hence, although the altruism signal is not present in the large majority of ODA transfers, neither is it insignificant. Figure 2 provides a compact summary of the number of donor-recipients pairs (by donor) that significantly display the *countercyclical-altruism* signal for the baseline case; the average number of pairs is 22.3 per donor. The complete list of specific pairs in Figure 2 is reported in Table S1 of Appendix S1 in the online Supplementary Material.[16]

An interesting interpretation of Figure 2 is as the extensive margin of donor altruism. In this Figure, we are counting the number of recipients that cross the threshold for each

[14] See Appendix C for further details about the computation of the distribution of $\hat{\beta}_r\left(\hat{\delta}_{r,0} - \hat{\delta}_{r,0^*}\right)$.

[15] The criterion corresponding to this null hypothesis can be considered "conservative", in the sense of avoiding misclassifying "regular" donor-recipient pairs as *countercyclical-altruism*, but at the same time it could misclassify some *countercyclical-altruism* cases as "regular." We could, for instance, base our identification of the *countercyclical-altruism* signal only on the significance of the two terms $\hat{\beta}_r > 0$ and $\left(\hat{\delta}_{r,0} - \hat{\delta}_{r,0^*}\right) > 0$ separately, which would guarantee the positivity of the product in condition (14). We check for the implication of this alternative type of condition, and we find that our results are not particularly affected by a this different approach. The set of *countercyclical-altruism* pairs using the two alternative types of conditions differ only by 7 pairs out of 424. These pairs are listed in Table S1 of the online Appendix S1.

[16] There are an additional 6.8% of the pairs that pass condition (16) with a negative β_r. The total share displaying a negative derivative da_r^* / dy_d is then 24%, although only two thirds of it identify *countercyclical-altruism* pairs.

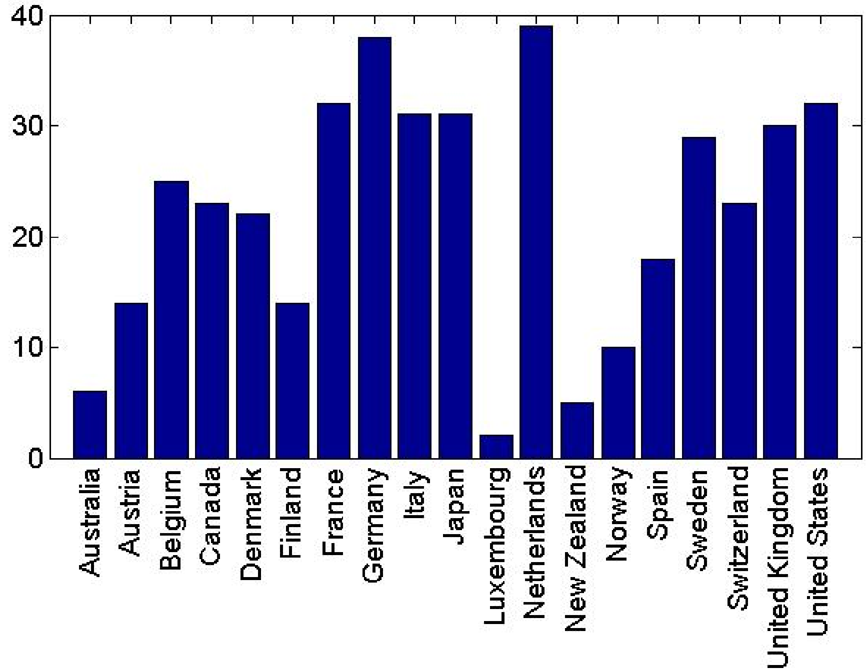

Figure 2: Number of significant pairs that satisfy the *countercyclica-altruism* condition by donor.

donor, but not the extent to which they cross the threshold. This distinction, between the extensive and intensive margins of donor altruism, has received little discussion in the donor motive literature. Cognizance of this distinction is important in comparing our results to measures of donor altruism such as the Commitment to Development Index (CDI), discussed the literature review. For instance, Sweden and Netherlands are ranked as top-five donors (among 27) in both the Overall and Aid dimensions of CDI. Similarly, these countries rank in the top eight among 19 in our donor ranking by signal frequency. On the other hand, France and Germany are middle of the pack donors based on CDI ranking, but they display significantly more *countercyclical-altruistic* signals than the mean in our 19 donor sample. Contrarily, Luxembourg and Norway, who rank highly in most CDI dimensions, display a relatively small numbers of *countercyclical-altruistic* relationships in our model.[17] Larger economies, such as Germany, France, and the US, tend to have rank higher in counter-cyclical incidence (extensive margin) than their CDI ranking. Detailed analysis of these similarities and discrepancies from the perspective of extensive and intensive margins is outside the central objective of the current paper, but is the subject of ongoing research.

Figure 3 illustrates the estimated $(\delta_{r,0} - \delta_{r,0^*})$ with this difference plotted against its standard deviation and the level of significance being represented by the straight, blue-dotted lines (5% for the external lines, 10% the internal lines). If a point lies outside the two most external lines, it is significant at the 5% level; if it lies inside the two narrower cones, it is significant at 10% level. The red dots correspond to the *countercyclical-altruism* pairs which satisfy condition (15) and these are compared to the other pairs in black. Figures S1-S3 in the online Appendix provide the same information for β_r, $\delta_{r,0}$, and $\rho_{r,0}$.

[17] In the robustness checks we see that, in the "no controls" model, Luxembourg has significant movement at the extensive margin. Luxembourg is also affected by its shorter available ODA series compared to the other donors.

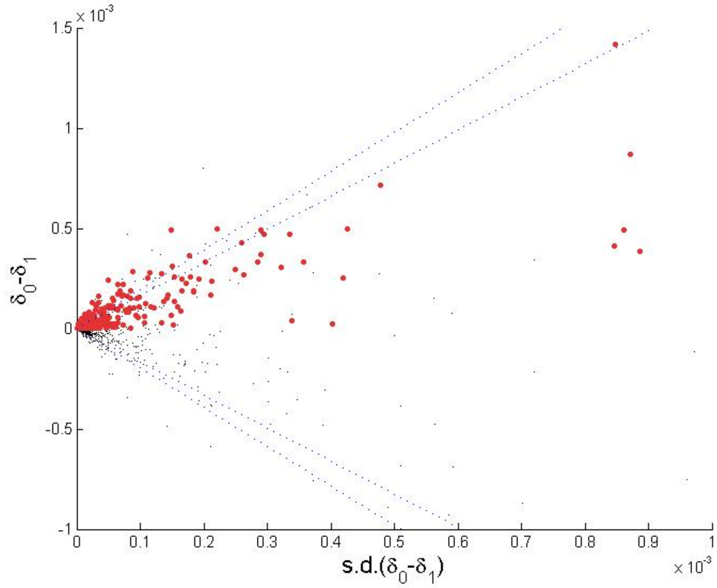

Figure 3: Point estimates of the difference $\delta_{r,0} - \delta_{r,0^*}$. Red dots identify pairs that satisfy the *countercyclical-altruism* condition (15). In black is the complement set of country pairs. Parameters significance is indicated by blue dotted lines. External lines are the 5% significance thresholds; internal lines are the 10% level.

As expected, significant *countercyclical-altruistic* relationships are often associated with large differences between $\delta_{r,0}$ and $\delta_{r,0^*}$. However, we also observe many instances of smaller $\delta_{r,0} - \delta_{r,0^*}$ that satisfy the *countercyclical-altruism* condition. To understand this recall that the condition in (15) also involves β_r and that pairs satisfying the condition for smaller $\delta_{r,0} - \delta_{r,0^*}$ must be compensated by larger β_r. Figure 4 provides an empirical replication of the theoretical diagram in Figure 1 and assists in juxtaposition of the theoretical intuition and empirical results. In this figure, we plot $(\delta_{r,0} - \delta_{r,0^*})$ versus $(\rho_{r,0} - \rho_{r,0^*})$ for all donor-recipient pairs. This is analogous to drawing Figure 1 after re-centering the axes on $(\rho_B \quad \delta_B)$ for each pair of countries. The theoretical intuition represented in Figure 1 is that the majority of the *countercyclical-altruism* pairs should be found in the south-east quadrant of Figure 4 and this is indeed the case below. Figure 4 also illustrates that counter-cyclical ODA can occur when $(\rho_{r,0} - \rho_{r,0^*})$ is positive. We see some such pairs in Figure 4 but it is far less common for these cases to satisfy the *countercyclical-altruism* condition.

Finally, the *countercyclical-altruism* condition is more likely to hold the smaller $\delta_{r,0^*}$ is. Taking the differential of (13) with respect to y_d, it is easy to see that $\delta_{r,0^*}$ is directly proportional to σ and $c_{r,0}$ and inversely proportional to c_{d,r_0} for a given β_r. This means that the smaller is the curvature of the donor's own-consumption utility function relative to the recipient's utility function curvature (implicitly captured by $\delta_{r,0^*}$), the more likely the condition is satisfied. A more concave recipient utility function implies a higher net marginal utility payoff in transfers from a rich altruistic donor to a poor recipient. Similarly, the lower the recipient's consumption relative to the donor's GDP trend and the higher the donor's consumption is, the more likely the *countercyclical-altruism* condition is satisfied. Also this effect reflects the incentive to transfer from low to high marginal utility agents. Additional

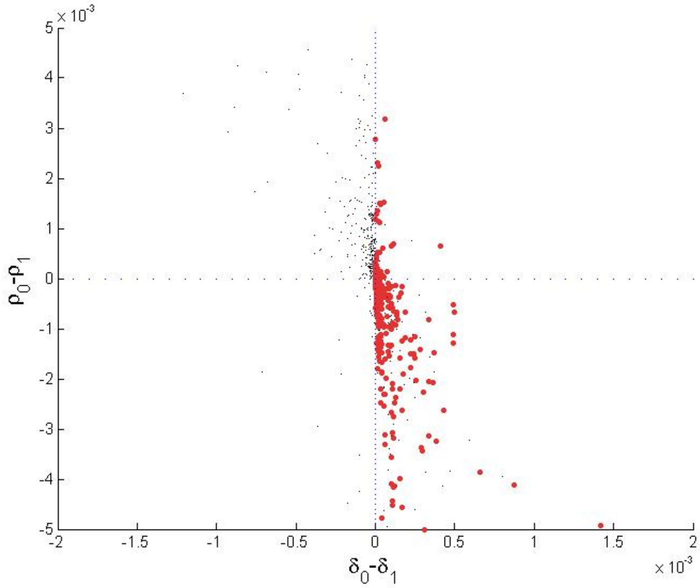

Figure 4: Bridging empirical results and the model - empirical counterpart of Figure 1. Plot of $(\delta_{r,0} - \delta_{r,0^*})$ versus $(\rho_{r,0} - \rho_{r,0^*})$. Red dots identify pairs that satisfy the *countercyclical-altruism* condition (15). All others in black.

insights on this mechanism can be seen in Figure 5. This scatter plot displays the average recipient's consumption $c_{r,0}$ (vertical axis) against the average donor's consumption c_{d,r_0} (on the horizontal axis). Note that the mass of pairs satisfying the *countercyclical-altruism* condition (red dots) typically correspond to relatively small recipient consumption level.

5 Out of Model Characterization of the Altruism Signal

In this Section we undertake two out-of-model exercises to illuminate the relationship between the *countercyclical-altruism* signal we identify and other perspectives on altruism/self-interest in the literature. In the first exercise, we use a logit to estimate the probability of obtaining the signal as a function of specific donor-recipient pair characteristics. Second, we embed our *countercyclical-altruism* signal in a seminal ODA-growth regression to see if ODA among pairs displaying the signal has distinguishable effects on growth when compared to donor-recipient pairs not displaying the signal.

Taken together, these out of model exercises support the conclusion that the signal identifies bi-lateral pairs with coherent distinguishable characteristics from those that do not display the signal. These characteristics have a large intersection with popular concepts of altruism. As in popular notions of altruism, *countercyclical-altruists* focus on the most indigent recipients, respond contemporaneously to changing recipient need (reverse causation), are not associated with positive military or trade ties, and care more about the long run

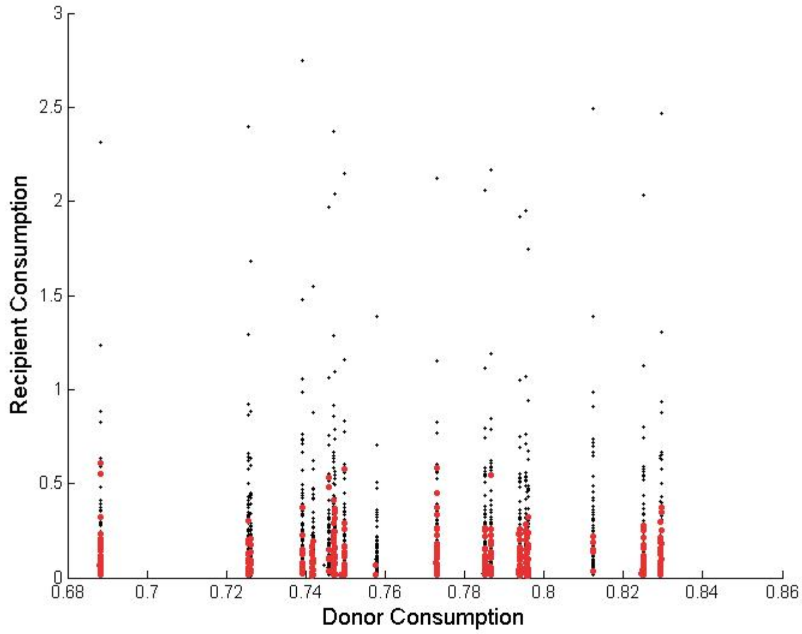

Figure 5: Donor-recipient relative consumption levels and the *countercyclical-altruism* decision. Recipient's consumption $c_{r,0}$ versus donor's consumption c_{d,r_0} (both pre-ODA donations). Red points correspond to the pairs significantly satisfying the *countercyclical-altruism* condition (15).

effectiveness of their aid relative to non-countercyclical altruists. All else equal, colonial linkage is important, and this effect is separable from contemporary trade and military ties.

5.1 Logit Analysis of the Countercyclical-Altruism Signal

Employing common explanatory variables for the determinants of ODA allocation (see Berthélemy, 2006, for a review of this literature), we use a logit model to explore how these determinants are related to the incidence of *countercyclical-altruism*. Specifically, the significance of the signal generates a binary variable for each donor-recipient pair that we use as the dependent variable in a cross section logit regression. The direct link between our theory and signal significance among the explanatory variables is consumption (or income), which should be negatively related to our signal under the *countercyclical-altruism* hypothesis. The other explanatory variables common in the literature are often associated with either altruistic or self-interest (commercial or geopolitical) motivations. Though not explicitly in our theoretical model, we expect the altruistic related variables to be positively associated with *countercyclical-altruism* signal significance. On the other hand, to the extent commercial and military ties are related (independently) to "self-interest," we expect them to be negatively associated with signal-significance. Note that as we estimate odds ratios, coefficient estimates less than one indicate a negative relationship and greater than one a positive relationship.

We follow Berthélemy (2006) in the selection of most of the explanatory variables and in estimating the model in both level and logged regressor forms as a robustness check. Given the absence of a theoretical reason to prefer log-transformed regressors in our context, our discussion focuses on the results for both level and logged variables. A full description of the data sources, samples, descriptive statistics, and manipulations can be found in Appendix S2.[18] Our estimation is based on the cross-section of the donor-recipient pair only, since we derive the *countercyclical-altruism* signal as a time invariant characteristic of a pair. The explanatory variables are then transformed to capture the average attributes of a donor-recipient pair over the sample of the signal estimation. The estimated coefficients of this exercise (odds ratios) in both level and log models, in which all variables with the exception of dummies are transformed in logs, are reported in Table 1.

Variables associated with humanitarian/altruistic motivations include per-capita consumption (per-capita income would yield similar conclusions), a dummy for the overall recipient's democracy quality, and two dummy variables indicating whether a recipient country was involved in a significant internal or external conflict.[19] The conflict variables may be associated with altruistic motivation for aid in complex ways. An altruist might respond to conflict (either external or internal) with humanitarian relief. On the other hand, she might consider conflict an indicator of poor governance. These two narratives have opposite implications on the effects of conflict on altruistic donations. At the same time, a strategic donor may use ODA to support an ally during conflict with geo-political objectives, which could be consistent with countercyclical flows. As such, it will be important to assess the role of these determinants jointly with other factors, such as military trade and military expenditure.

The mortality rate is another indicator traditionally of concern to altruistic donors. Also potentially associated with altruistic motivation is population size. One simple channel is that the cost of impactful countercyclical altruism is inversely related to country size, though other arguments could also be made. The clear commercial/self-interest variables are bilateral trade and bilateral military trade (e.g. Berthélemy, 2006, proxies selfish ODA motivations by trade). Recipient military expenditure might fit in either (or neither) category, but in many low-income countries lower military spending would be associated with better policy and democracy. We also considered total ODA received by a recipient from all other donors and multilateral ODA to a recipient in order to control for complementarity and/or substitutability effects in the ODA donations from different sources. However, the coefficient of the total ODA from other donors is never significant and the estimates are very erratic in sign across specifications, hence we do not include it in the results presented below.

Again following Berthelémy, we use a set of dummy variables to indicate former colonial relationships between a donor and recipient, special historical US ties (Israel and Egypt in the Middle East and some Latin American countries), the closer links between Japan and Asian recipients, and the preferential treatment of European countries to ACP recipients (Associated states of Africa, Caribbean, and Pacific Ocean). The European-ACP variable

[18] We replicate the large majority of the variables used by Berthélemy (2006), with the exception of the present value of debt to export ratio due to the lack of consistent debt data across our recipients set.

[19] We also included the inflation rate in some specifications of the model as a second indicator of policy and institution quality; this variable is sometimes used in the ODA literature, although it was not included originally by Berthelémy. As for the democracy dummy, the effects of inflation are irregularly signed and not significant. We, hence, keep only democracy in our estimates.

has a large overlap with former colonial ties. Since the colonial effect is found to be largely independent of all other determinants (whether altruistic or commercial), very long-run characteristics such as cultural affinity and post-colonial guilt are likely important. The relationship between these dummy variables and standard notions of altruism is debatable. However, since commercial and military trade are controlled for separately, the argument for an altruism interpretation is strengthened. A positive association between colonial linkage and signal significance seems more naturally interpreted as evidence of a correspondence between the signal and generic altruism, given the set of controls.

We first focus on the effect on signal-significance of the variables traditionally associated with humanitarian/altruistic motivations. The specification in column (a) of Table 1 isolates these variables, the following columns then control for the other explanatory variables. The specifications that use log-transformed variables are indicated by the symbol †.

The effects of consumption per-capita are very stable across the various specifications: consumption is always powerful and negatively related to signal significance (p-values are reported in parentheses), as our theory predicts. Again recall that since these are odds ratios, estimates greater than 1 indicate that signal-significance is more likely when the explanatory variable increases while an odds ratio less than 1 indicates less likely signal-significance as the variable increases. For example, the .934 estimate for consumption in column (a) indicates that if the level per-capita consumption increases by one unit (i.e. if per-capita income increases by 100 PPP-dollars in our case), the pair is about 7% less likely to have a significant *countercyclical-altruistic* signal. The coefficient drops to the range ($.6 - .7$) for the log-specifications, with a comparable economic magnitude of the estimated effect at the mean level of consumption of 500 PPP-dollars. For instance, the point estimate of .643 in model ($c^{\dagger}$) implies that doubling the per-capita consumption of a recipient (i.e. adding 500 dollars to the mean consumption) makes the *countercyclical-altruistic* signal about $25 - 30\%$ less likely to occur, which is roughly four times the effect of 100 dollars in the levels models. These effects are then very consistent across level and logged specifications.

This negative effect is significant, at the 1% or 5% confidence level, in all but two of the log-specifications (columns $f^{\dagger}$ and $g^{\dagger}$). When consumption is not significant, however, multilateral ODA displays a positive and highly significant effect, which indicates strong complementarity between it and donations under our altruistic signal. In the regressions in levels, the sign of the coefficients of multilateral ODA is still positive, but never significant. Since multilateral ODA is generally believed to likely be more associated with altruistic motivations than bi-lateral aid, these results are consistent with our interpretation of the signal. Overall, this result provides strong support for a significant intersection of *countercyclical-altruism* and concepts of altruism prevalent in the literature.

	a	b	c	$c^\dagger$	d	$d^\dagger$	e	$e^\dagger$	f	$f^\dagger$	g	$g^\dagger$
consump.	0.934	0.938	0.932	0.643	0.928	0.640	0.905	0.706	0.936	0.752	0.912	0.867
	(0.003)***	(0.004)***	(0.009)***	(0.005)***	(0.025)**	(0.007)***	(0.005)***	(0.034)**	(0.045)**	(0.118)	(0.009)***	(0.432)
pop.	0.982	0.982	0.978	0.870	0.976	0.777	0.979	0.847	0.965	0.670	0.970	0.727
	(0.039)**	(0.042)**	(0.042)**	(0.066)*	(0.064)*	(0.005)***	(0.082)*	(0.034)**	(0.019)**	(0.000)***	(0.052)*	(0.001)***
democr.	0.841	0.798	1.209	1.216	0.828	0.734	0.842	0.712	0.822	0.704	0.831	0.662
	(0.632)	(0.556)	(0.644)	(0.689)	(0.610)	(0.490)	(0.654)	(0.425)	(0.588)	(0.394)	(0.623)	(0.288)
int. conflict	1.554	1.570	1.589	1.547	1.608	1.714	1.450	1.530	1.600	1.733	1.443	1.549
	(0.017)**	(0.019)**	(0.019)**	(0.070)*	(0.026)**	(0.040)**	(0.069)*	(0.074)*	(0.029)**	(0.032)**	(0.075)*	(0.060)*
ext. conflict.	1.435	1.499	1.524	1.033	1.499	1.040	1.275	0.934	1.421	1.105	1.223	1.017
	(0.443)	(0.410)	(0.393)	(0.945)	(0.502)	(0.944)	(0.655)	(0.880)	(0.585)	(0.863)	(0.724)	(0.971)
mortality	1.003	1.003	1.004	1.004	1.003	1.381	1.002	1.263	1.002	1.341	1.001	1.214
	(0.328)	(0.301)	(0.187)	(0.353)	(0.405)	(0.199)	(0.610)	(0.360)	(0.543)	(0.238)	(0.738)	(0.452)
colony		2.706	2.255	1.752	1.902	1.433	1.882	1.642	1.892	1.400	1.877	1.657
		(0.000)***	(0.000)***	(0.006)***	(0.005)***	(0.096)*	(0.004)***	(0.020)**	(0.005)***	(0.119)	(0.004)***	(0.019)**
US influence		1.571	1.463	1.290	1.490	1.269	1.463	1.445	1.438	1.173	1.436	1.358
		(0.281)	(0.364)	(0.520)	(0.412)	(0.610)	(0.404)	(0.427)	(0.461)	(0.730)	(0.428)	(0.509)
JP influence		3.058	3.298	2.783	3.596	3.104	3.117	2.817	3.418	3.276	3.027	3.069
		(0.007)***	(0.010)**	(0.024)**	(0.021)**	(0.032)**	(0.040)**	(0.050)*	(0.024)**	(0.030)**	(0.041)**	(0.038)**
EU influence		1.389	1.368	1.289	1.361	1.228	1.350	1.253	1.359	1.214	1.350	1.246
		(0.051)*	(0.048)**	(0.042)**	(0.046)**	(0.012)**	(0.067)*	(0.007)***	(0.047)**	(0.010)**	(0.068)*	(0.006)***
trade			1.265	1.254	1.244	1.317			1.311	1.338		
			(0.148)	(0.000)***	(0.214)	(0.000)***			(0.183)	(0.000)***		
milit. G					0.895	0.862	0.918	0.934	0.888	0.863	0.912	0.939
					(0.070)*	(0.196)	(0.146)	(0.534)	(0.061)*	(0.184)	(0.131)	(0.551)
milit. trade					1.005		1.002		1.004		1.001	
					(0.682)		(0.878)		(0.735)		(0.927)	
trade h1							2.558	1.450			2.619	1.475
							(0.033)**	(0.002)***			(0.026)**	(0.002)***
trade h2							0.626	0.821			0.626	0.805
							(0.078)*	(0.104)			(0.076)*	(0.082)*
mult. ODA									1.160	1.363	1.124	1.404
									(0.352)	(0.038)**	(0.438)	(0.012)**
Obs.	2527	2527	2318	2318	1800	1800	1874	1874	1800	1800	1874	1874
Pseudo R^2	.04	.07	.06	.07	.07	.07	.07	.07	.07	.07	.07	.08

Table 1: Logit model for the altruism signal - Odds Ratios. The dependent variable is our *countercyclical-altruism* binary signal from the baseline estimation model. Independent variables are: population size (pop.), per-capita consumption (consump.), institution quality dummy (democr.), involvement in internal (int.) and external (ext.) conflict, mortality rate, former colonial status (colony), regional influence dummies for US/Japan/Europe (US/JP/EU influence), bilateral trade (trade), trade first/second half of sample (trade h1/h2), bilateral military (milit.) trade, government military expenditure (milit. G), multilateral aid (mult. ODA). † indicates specifications with logged regressors. More details about the definition and the sources of the variables are provided in the online Appendix S2. Standard errors clustered at recipient level; p-values are reported in parentheses with 1, 5, and 10% significance levels indicated by ***, **, and * respectively.

Population has an inverse association with our signal, and is statistically significant in most specifications, with an increase in population by ten million people reducing the probability of the signal by about 2-3%. The theory does not predict a specific relationship between population and signal significance, and various arguments can be made. As noted, the simplest explanation is that the cost of impactful countercyclical altruism is inversely related to country size. The dummy that indicates strong democratic institutions is never significant and has an unstable "sign". Similarly, the coefficients of mortality is always correctly signed, but is not statistically insignificant. A significant internal military conflict increases the probability of signal significance in our sample, making the *countercyclical-altruism* signal 1.5 times more likely. An effect of similar magnitude, but never significant, is found for the military involvement of a recipient outside their domestic territory. These positive effects might be associated with altruistic donors if altruists respond countercyclically to conflict with humanitarian relief and the humanitarian assistance component of the conflict variables is predominant. That is, since internal conflict should reduce a recipient's income, humanitarian relief would increase during these periods of contraction. Alternatively, internal conflict could be viewed as evidence of weak governance, discouraging aid from altruists (a pro-cyclical relationship). Given the limited responsiveness of the *countercyclical-altruism* signal to the democracy indicators, the humanitarian channel seems to be a more plausible interpretation of these effects.

Moving to the colonial linkage (starting from column b), the coefficient of the colonial dummy indicates a powerful and robust effect across the board. Having a former colonial relationship makes a donor-recipient pair about 1.5 to 2 times more likely to bear a significant *countercyclical-altruistic* signal than a recipient without a former colonial link. Importantly, introducing the colonial dummy does not affect the significance of the humanitarian factors found in the first specification of the logit model. At the same time, the colonial effect is quite robust to the introduction of the self-interest variables, which only marginally affects the incidence of the colony variable on signal significance. These patterns are difficult to reconcile with the hypothesis that post-colonial ODA reflects the commercial self-interest of the colonizers. Likewise, there is little reason to suspect that political support (e.g. quid-pro-quo payments for supportive U.N. votes) links so powerfully to business cycles. Furthermore, the colonial indicator is found in less than ten percent of the *countercyclical-altruistic* pairs, and is therefore unlikely to be driving the signal. Hence, the colonial effect is more likely related to cultural and institutional affinities between donors and recipients which is, in turn, associated with common notions of altruism. This interpretation is supported by the significance (or lack thereof) of the three influence dummies. The dummies are significant for Japan and the European donors, but not for the US. The US case is arguably distinct given its unique geo-political standing and interests in some regions of the world (e.g., the Middle East). As noted, the European dummy overlaps significantly with the colonial definition itself, while the Japanese signal significance is associated with regional and cultural ties.

Turning to the commercial/self-interest variables, columns (c) to ($g^{\dagger}$) introduce three variables typically associated with self-interest: bilateral trade, military trade, and military expenditure. Bilateral trade is defined as the share of the trade between the donor-recipient pair (sum of imports and exports) in the total trade of the donor. In levels, bilateral trade is never statistically significant. In the log-regressors model bilateral trade is positive and becomes significant.[20] This is the most significant difference between the level and log specifications of the model. Columns (e)-($e^\dagger$) and (g)-($g^\dagger$) illuminate the source of this distinction by partitioning the trade variable during the first and second half of the sample ($trade\ h1$ and $trade\ h2$ respectively in Table 1).[21] The partitioning allows us to make a couple of interesting observations. First, the only actual difference in significance of the coefficients across the two specifications is found for aggregate trade and not for trade in the two sub-periods. Second, the estimated positive coefficient of total trade on the signal incidence is attributable to the effect of earlier trade, and not to more recent trade. More importantly, more recent trade actually has a negative relationship with signal significance, significant at 10% level of confidence, on the odds of the signal. This last result suggests growing altruistic motivations over time, though in-depth exploration of this is beyond the scope of the current paper. Linking this evidence to the discussion for the colony dummy above, another interpretation of this result is that it might reflect a shift in the composition of trade away from former colonies towards new markets. This decoupling of the colonial and trade effects is consistent with persistent post-colonial affinities, independent from commercial interests.

The military variables, which we expect to have less direct linkage to altruistic motivations, are also generally consistent with a meaningful altruistic signal. For instance, the volume of military trade (obtained from the SIPRI Arms Transfers Database) has no effect on the likelihood of the *countercyclical-altruism* signal. We restrict the use of the military trade variable to the models in levels (columns d, e, f, and g) because it is zero for about 80% of our observations, which would be lost when the log-transformation is applied. Such an extreme reduction in sample size makes the results of doubtful comparability to the levels version for robustness purposes. Hence, we exclude this variable from the log-specifications in columns $d^\dagger$, $e^\dagger$, $f^\dagger$, and $g^\dagger$, and prefer to preserve sample size comparability by harmonizing the estimation samples of pairing regressions.[22] Additionally, government military expenditure exhibits a negative relationship, marginally significant in some cases, with the altruism signal. Arguably, this variable reflects non-altruistic motives since higher military expenditure would be likely correlated with imports of military equipment. At the same time, high government spending in a poor recipient country could be considered a poor use of public resources by an altruistic donor.

Finally, the standard view in the literature (with which we concur) is that multilateral aid is more likely associated with altruistic motivation than bilateral ODA. This is consistent with the coefficient in Table 1 where multilateral aid is positively related to the likelihood of signal significance – that is, *countercyclical-altruistic* donors see their aid as complementary to multilateral ODA. As noted above, the estimate lacks statistical significance for the models in levels, while they are largely significant for the logged specifications in columns ($f^\dagger$) and

[20] We check for the robustness of this result defining, as in Berthélemy (2006), bilateral trade in ratio to donor's GDP instead of total trade. The estimated odds ratio usually increases to 2, but the significance patterns remain the same. Similar conclusions are obtained when considering only exports shares rather than total bilateral trade.

[21] In Table 1 the partitioning year is 1990, but the results are robust to alternative partitions.. Alternative partitions explored for robustness include the first and last decade of the sample.

[22] In any case, the estimated coefficients remain quite similar even with the reduced sample, especially the effects of consumption and trade (results not reported here)

($g^{\dagger}$), both for the total trade and partitioned trade models.

Surveying the full sequence of specifications in Table 1 some significant regularities emerge. First, and most importantly, *countercyclical-altruism* is powerfully related to low recipient consumption. This relationship fits tightly with both our theory and general notions of altruism, and is extremely robust across specifications. Second, bilateral trade, which is often associated with self-interest in the literature, has no significant effect on signal likelihood in any specification in levels. With logged regressors, the overall effect of trade is significantly positive; however, a partition of trade between first and second half of the sample shows that it has a marginally significant negative impact on the odds of the signal for the second part, and a significant positive impact only for the first half of the sample. The jointly positive effect is then driven by the first half of the trade partition. Third, higher government military spending is negatively associated with our signal, though statistically not particularly significant, while military trade is not significant. Together, these results suggest the signal to be disassociated from direct military interests. Fourth, colonial links increase the likelihood of the signal but appear unrelated to commercial or military trade between the countries. Cultural affinity and post-colonial guilt, which are theoretically equivalent to altruism, are reasonable explanations. This interpretation aligns with our initial father and son story.

We provide some robustness checks for the results in Table 1 in Appendix D.2 for two alternative specifications: the baseline model with no controls and the main CARA functional specification. The results of this Section are broadly confirmed by these alternative specifications, with the exception of a few specific differences discussed in the Appendix.

5.2 Growth Regressions and the Countercyclical-Altruism Signal

We first reemphasize that this sub-section provides a second exploration of the external validity of our signal and is not intended as a direct contribution to resolution of the ODA-growth debate. Rather, the exercise is to evaluate signal significance within two of the most highly cited competing ODA-growth models: Burnside and Dollar (2000) (hereafter BD) and Clemens, Radelet, Bhavnani, and Bazzi (2012) (hereafter CL). Our hypothesis is that, all else equal, the donors who have stronger altruistic motivation would choose ODA with more positive effects on recipient growth than donors with more self-interest motivation, at the margin. This would manifest in a more positive ODA-growth relationship among signal bearers, than among non-signal bears.

A second important caveat to this exercise is that our signal identification relies on consumption patterns, but a more standard channel from aid to growth would be via investment. Explicitly modeling firms and investment would complicate and obfuscate the very simple underlying mechanism of counter-cyclical altruism conveyed by the father-son allegory. Nevertheless, we believe there are a number of reasonable transmission mechanisms from aid to growth, through consumption, especially in poor countries – although testing them is beyond the scope of the current paper. For example, aid targeting poverty, health, or education should relax the household budget constraint and increase savings/investment, at the margin. Similarly, if poverty-reducing aid improves health, it should also increase labor productivity and again affect growth through a consumption channel, at least initially. Finally, aid that induces improved governance (through better policy or reduced corruption) could spur growth outside a direct investment channel as well. Of course, these mechanisms are speculative and it is an empirical question as to whether such spillovers would be significant; however, they seem to have some plausibility given the results of our growth regressions.

In the BD model our results show generally positive differences in the growth effects of ODA from signal bearers and non-signal bearers. These differences become larger and more significant when non-linear effects of aid on growth and the CL definition of early impact aid are introduced. We present the BD results in Table 2 below.[23] As to the mechanism for differential effects of ODA from signal and non-signal bearers, there are many dimensions of donor choice that could serve as channels. These include sector and structure (including time) of disbursement and/or repayment. For example, CL disaggregate ODA into "early-impact" and other aid in searching for growth-effects. Though our model is not specifically designed to generate a signal of donors' intent to spur recipient growth, the debate in this literature provides an interesting external validation opportunity.

We adopt a three-fold indirect validation strategy based on the distinguishing qualitative characteristics our signal should display in ODA-growth regressions. As a first step, we look for systematic differences in the behavior of the donor groups our signal distinguishes. The second step is to search for a downward bias among the signal-bearing group in the contemporaneous growth effects of ODA due to reverse causation, as predicted by our model. Recall that our model identified a mechanism derived from an explicit donor optimization problem by which lower recipient income should induce higher contemporaneous ODA from a more altruistic donor due to the increased marginal utility of transfers (i.e., countercyclical-altruism/reverse-causation). Following the approach of CL, we use lagged ODA regressors to disentangle the effects and the magnitude of contemporaneous reverse causation from longer-term growth effects. As a third step, we search for differing long-run growth effects of ODA from donors bearing our counter-cyclical altruism signal vis-à-vis donors without the signal. Recall that by "long-run" in this context, we do not mean a cardinal time designation greater than some threshold. Rather we mean the ODA/growth mapping that is largely independent of contemporaneous reverse-causation.

We begin the exercise by modifying the BD growth equation to reflect our partitioned donor set. This can be done compactly with the regression model:

$$g_{i,t} = c + f\left(A^{a}, A^{na}\right) + \mathbf{Z}_{i,t}\beta + \varepsilon_{i,t} \tag{20}$$

where the dependent variable is the GDP growth rate $g_{i,t}$ of recipient i in period t. The function $f\left(A^{a}, A^{na}\right)$ allows various partitions of the donor set for each recipient into those with the *countercyclical-altruism* signal, A^{a}, and those without, A^{na}, while $\mathbf{Z}_{i,t}$ is the set of control variables. In the baseline regressions presented below, the dependent and independent variables in equation (20) are defined as in BD and the time subscript indicates

[23]We try the same exercise with the specification by Rajan and Subramanian (2008) (hereafter RS), another highly relevant paper for the analysis of ODA effectiveness. The estimates for the RS model are generally of the correct signs, but largely insignificant. They become more ambiguous when non-linear effects of ODA are added to the model. The strength of the BD aid-growth relationship, compared to RS, is not surprising since the BD model generally yielded larger and more significant ODA-growth linkages in both the original papers and the CL replications. CL, for instance, finds significant effects of ODA on recipients' growth only for early impact aid in the RS model. In our case, not even the early impact category provides particularly positive estimates. The RS results are illustrated in Appendix D.2 and Table A2.

a four-year average.[24] Now incorporating elements of CL we focus on three specification for $f(A^a, A^{na})$, in which either contemporaneous or one-period lagged ODA are included:

$$f(A^a, A^{na}) = \begin{cases} \beta_a A^a_{i,t} + \beta_{na} A^{na}_{i,t} \\ \theta_a A^a_{i,t-1} + \theta_{na} A^{na}_{i,t-1} \\ \theta_a A^a_{i,t-1} + \theta_{na} A^{na}_{i,t-1} + \gamma_a (A^a_{i,t-1})^2 + \gamma_{na} (A^{na}_{i,t-1})^2 \end{cases}$$

The partition of donors allows us to look for distinguishing characteristics of the donor sets, to directly compare the size and direction of the endogeneity bias in contemporaneous effects, and to assess the growth effects of aid received from the two types of donors. Models are estimated either using recipient and period fixed-effects or in differences; reported standard errors are clustered by recipient country.[25] Estimation results of these models are reported in Table 2 for the un-partitioned model and the baseline specification of our altruism signaling model. A further robustness check with CARA utility in the signaling model is reported in Appendix .[26]

With respect to the first validation step, a cursory comparison of the pooled and baseline partitioned models (top panel in comparison to the bottom panel of the table respectively) in the various forms, reveals striking differences. The pooled donor results are qualitatively similar to those in many traditional growth regressions – small and largely insignificant effects of ODA on growth. The partitioned donor group regressions, on the other hand, exhibit a clear split of the coefficients around the midpoint represented by the pool regression, with larger and significant effects for the altruistic set that (versus never significant effects of the non-altruistic one). In sum, the first validation step yields strong evidence of significant differences in the two groups of donors our signal distinguishes.

Moving to the second validation step, first note that in the *pooled* models none of the estimated contemporaneous coefficients are significant. That is, the contemporaneous coefficient are very similar and insignificant in both the pooled and partitioned donor sets (compare columns (a) in the top and lower panels). We next introduce lagged ODA, as suggested by CL, to illuminate reverse causation (negative endogeneity bias) in the contemporaneous coefficients.[27] Comparing columns (a) and (b), we see that in the *pooled model* lagging increases the coefficient by almost half, even though the long run effects of ODA on growth remain non-significant. As we move from pooled to partitioned models with lags, however, the coefficient changes are consistent with the expected reverse causation bias only for the *countercyclical-altruists*. Specifically, contemporaneous reverse causation between ODA and

[24] This data was provided by CL. The CL identification strategy does not rely on the use of instrumental variables. Hence, our regressions use the framework of BD without adopting the full specifications of their econometric model, exactly following the spirit of CL exercise. It should also be noted that, in this literature, robust coefficient movements are often deemed to convey valuable information, even if the individual coefficients themselves fall outside conventional statistical significance thresholds (see for example CL Section 4.2).

[25] The fixed effects make any time-invariant regressors in the original BD specification redundant.

[26] Recall that the baseline signal identification model utilized a general power function for all utility components.

[27] These results compare with the first two columns of Table 7 of CL. The ODA series is somewhat different in that we sum the ODA only from the nineteen donors in our sample while they consider a series that includes disbursements from any donor to a recipient. These differences seem to matter mostly for the estimate of the effect in columns (a) and (b).

income growth for signal-bearers implies an increase in the estimate of θ_a with respect to β_a going from column (a) to column (b), while θ_{na} slightly drops relative to β_{na}. A similar relative shift in the coefficients estimate, though smaller, is observed for the model in column (c).[28]

Turning to the third step of this validation exercise, recall that if our signal is identifying donors with greater altruistic motivation it is reasonable to expect their ODA to show greater long-term effects on income growth. Donor's with more weight on the self-interest return, should be less concerned, all else equal, with the growth effects of their ODA. In Table 2 indications of the different "long-run" growth effects of ODA from *countercyclical-altruists* can already be observed in column (b), but they are even clearer in the results in columns (d)-(g).

Controlling for squared ODA in the specifications in columns (d) and (e) amplifies the difference between θ_a and θ_{na}, with very large and strongly significant estimates for θ_a in both cases and non-significant θ_{na} in either specification. Furthermore, by juxtaposition with the corresponding pooled models in columns (d) and (e) of the top panel, we can see that the significance of the pooled effects is attributable to the *countercyclical-altruist* group of donors. As suggested by CL, we repeat the same analysis using categories of aid with more rapid impact on growth, indicated as "early impact" in columns (f) and (g) of Table 2. This exercise strongly confirms the difference between the two groups of donors - with the use of early impact aid the gap between signal bearers and non signal bearers becomes larger due in particular to the strong increase of θ_a.

Assessment of full long-run impact of aid in models (d)-(g) requires joint consideration of the effects of the quadratic and linear terms. First notice that the coefficients of the quadratic terms are significant only for the altruistic group, in line with the distinct behavior of our two donor sets. The negative estimates of γ's, which are smaller than the corresponding θ's, indicate diminishing marginal returns to aid. We compare returns to aid by evaluating the marginal return of ODA at the mean aid level for the four quadratic specifications. This average return and its significance are reported in the last two rows of the bottom panel of Table 2, labeled $\overline{MR}_a$ and $\overline{MR}_{na}$. $\overline{MR}$ is generally positive for both partitions, with the exception of model (g) for which the marginal returns are always negative for the non-altruist group; however, $\overline{MR}$ is much larger and statistically significantly positive only for the *countercyclical-altruistic* group as we would expect if our signal were valid.

In summary, this external validation exercise embeds the donor partition generated by our signal into highly cited growth/ODA frameworks. Our three-step assessment revealed the following: i. systematic differences in the effects of ODA on growth across the donor groups our signal identifies; ii. the expected downward bias among the signal-bearing group in the contemporaneous effect due to reverse causation, as predicted by our theoretical model; iii. more positive long-run growth effects of ODA from donors bearing our counter-cyclical altruism signal vis-à-vis donors without the signal. The robustness of the signal for all three steps of the validation exercise is supported by the qualitative similar estimation results

[28] One interesting attempt to address endogeneity that can be related to these results is found in Werker, Ahmed, and Cohen (2009). They use exogenous variation in oil prices as an instrument to test for the impact on growth of donations from rich middle-eastern OPEC nations to poorer Islamic country allies. Their finding of positive but only weakly significant effects on growth is supportive of our signal in that their local average treatment effect is upon non-altruistic donors only.

	All Donors					Early Impact	
	(a)	(b)	(c)	(d)	(e)	(f)	(g)
A_t	0.106						
	(0.072)						
A_{t-1}		0.147	0.102	0.425	0.571	0.483	0.429
		(0.088)	(0.106)	(0.180)**	(0.246)**	(0.196)**	(0.237)*
$(A_{t-1})^2$				-0.013	-0.018	-0.034	-0.033
				(0.006)**	(0.006)***	(0.014)**	(0.017)*
Model	F.E.	F.E.	Diff.	F.E.	Diff.	F.E.	Diff.
Obs	414	414	357	414	357	368	312
$\overline{MR}$				.35**	.47**	.37**	.32

	Partitioned					Early Impact	
	(a)	(b)	(c)	(d)	(e)	(f)	(g)
A_t^a	0.113						
	(0.110)						
A_t^{na}	0.100						
	(0.117)						
A_{t-1}^a		0.209	0.121	0.468	0.809	1.137	1.386
		(0.114)*	(0.144)	(0.233)**	(0.304)**	(0.253)***	(0.409)***
A_{t-1}^{na}		0.094	0.077	0.358	0.293	0.253	-0.527
		(0.163)	(0.247)	(0.300)	(0.473)	(0.421)	(0.638)
$(A_{t-1}^a)^2$				-0.022	-0.043	-0.179	-0.173
				(0.012)*	(0.014)***	(0.026)***	(0.044)***
$(A_{t-1}^{na})^2$				-0.015	-0.013	-0.055	-0.009
				(0.010)	(0.015)	(0.041)	(0.050)
Model	F.E.	F.E.	Diff.	F.E.	Diff.	F.E.	Diff.
Obs	414	414	357	414	357	368	312
$\overline{MR}_a$				.42**	.70**	.90***	1.44***
$\overline{MR}_{na}$				.31	.25	.16	$-.54$

Table 2: Estimation of the growth regressions for the Burnside and Dollar (2000) (BD) model. Data cover the period 1971-2005 and is provided by Clemens et al. The dependent variable is GDP per capita growth rate as defined in BD. ODA disbursements are in ratio to the recipients' GDP. Top panel: results without donor partition by *countercyclical-altruism* signal; Bottom panel: the model with ODA donor partition between A^a and A^{na}, and considering early impact aid as defined by Clemens et al. Donor partition is based on our baseline model specification. The regression models are estimated either by including fixed effects (F.E.) or in first difference (Diff.). Standard errors clustered at recipient level reported in parentheses. 1, 5, and 10% significance levels are indicated by ***, **, and * respectively. $\overline{MR}$ indicates the overall marginal return of ODA evaluated at the mean aid level for the quadratic specifications.

with the baseline without controls model and the CARA utility function signaling model presented in the Table A1 of the Appendix.

6 Conclusions

Over forty years of vigorous research has yielded few consensus conclusions regarding the motives of donors, and the impact of foreign aid on recipient countries. However, there is consensus that these questions are connected and that understanding, measuring, and accounting for donor motive is necessary to measure the causal effect of aid. Though significant empirical progress has been made, general conclusions are sparse concerning the importance of the three main factors assumed to motivate donor aid allocation: self-interest, recipient need, and recipient merit. The wide range of explanatory variables used in aid allocation regressions have yielded many conflicting conclusions.

We employ an alternative strategy for motive identification. We develop an integrated theoretical-empirical framework for the identification of altruistic motivation in ODA donations at the donor-recipient level. We show theoretically that altruism above an explicitly identified threshold generates countercyclical donations. The theoretical mechanism for this result is straightforward – with standard diminishing marginal utility, falling income has a stronger marginal effect on the poorer recipient's utility than the richer donor. If a donor places sufficient weight on recipient utility, donor utility maximization will entail some compensation for falling recipient income with increased transfers. This mechanism is perhaps the simplest that can generate a pattern of countercyclical transfers and we refer to this as a signal of "countercyclical-altruism." The presence of this signal does not exclude a mixture of self-interest and altruistic motivation.

We test for signal incidence using OECD aid disbursements for 2603 donor-recipient pairs and find that around 16% of the pairs satisfy the theoretical *countercyclical-altruism* criteria at the 5% confidence level. The *countercyclical-altruism* threshold test results are quite robust to changes in the utility functional forms. The share of donor-recipient relationships displaying the *countercyclical-altruism* signal varies significantly across donors – from a high of about 28% for the Netherlands to a low of 1.5% for Luxembourg.

We undertake two out-of-model exercises to illuminate the characteristics of the pairs exhibiting the *countercyclical-altruism* signal, and whether donations from *countercyclical-altruists* have distinguishable effects from those without the signal. Our first exercise is to estimate a logit model of the determinants of the *countercyclical-altruistic* pairs. All else equal, we find the signal is more likely if the recipient is poorer, smaller, has a colonial link with the donor, and has low military spending. The likelihood of the signal is independent of trade or military relations between donor and recipient, but is positively related to the involvement of the recipient in an internal conflict. This independence distinguishes colonial-linkage effects on ODA associated with contemporary commercial linkages (i.e. self-interest) from those associated with altruism/post-colonial guilt.

The second out-of-model exercise embeds the signal in an adaptation of Clemens, Radelet, Bhavnani, and Bazzi (2012) highly cited ODA-growth regression model. We find convincing evidence of the negative contemporary relationship between ODA and growth due to reverse causation among signal bearers. That is, negative growth is associated with higher contemporaneous ODA from an altruistic donor than from a donor without the signal. This is precisely the *countercyclical-altruism* signal. We also find that aid from a signal bearing donor has a distinguishable, more positive long-run effect on recipient growth than aid from donors without the signal. This effect is also reinforced by the use of early impact aid. Though identifying donor motivation is an important step in understanding ODA causality, much additional work is required in ODA-growth modeling before we can confidently establish causation between ODA and long-run growth.

Taken together, we believe the out-of-model exercises provide strong indication that the *countercyclical-altruism* signal is capturing a donor-recipient pair characteristic that intersects significantly with general notions of altruism. We also note that our theoretical framework, and the countercyclical donation signal we identify, may be applicable to broader questions regarding altruism. The Giving USA Foundation estimates charitable flows in the US to be over $290 billion in 2010. Globally, altruistic transfers occur in many dimensions not captured by our traditional data sources – but they are likely very large. Though presenting extraordinarily difficult measure challenges, we believe the empirical identification of altruistic motivation to be an important research area in general, and in understanding the effect of foreign aid in particular.

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Appendices

A Donor and Recipient Countries in Sample

The 19 OECD-DAC countries donor list: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, UK, US.

The 137 recipients countries list: Afghanistan, Albania, Algeria, Angola, Antigua and Barbuda, Argentina, Bahamas, Bahrain, Bangladesh, Barbados, Belize, Benin, Bermuda, Bhutan, Bolivia, Botswana, Brazil, Brunei, Burkina Faso, Burundi, Cambodia, Cameroon, Cape Verde, Central African Republic, Chad, Chile, China, China Taipei, Colombia, Comoros, Congo (Dem. Rep.), Congo (Republic of), Costa Rica, Cote d'Ivoire, Cuba, Cyprus, Djibouti, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Ethiopia, Fiji, Gabon, Gambia, Ghana, Grenada, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hong Kong, India, Indonesia, Iran, Iraq, Israel, Jamaica, Jordan, Kenya, Kiribati, Korea (Republic of), Kuwait, Laos, Lebanon, Lesotho, Liberia, Libya, Macao, Madagascar, Malawi, Malaysia, Maldives, Mali, Malta, Marshall Islands, Mauritania, Mauritius, Mexico, Micronesia, Mongolia, Morocco, Mozambique, Namibia, Nepal, Nicaragua, Niger, Nigeria, Oman, Pakistan, Palau, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Qatar, Rwanda, Samoa, Sao Tome and Principe, Saudi Arabia, Senegal, Seychelles, Sierra Leone, Singapore, Solomon Islands, Somalia, South Africa, Sri Lanka, St. Kitts and Nevis, St. Lucia, St.Vincent and Grenadines, Sudan, Suriname, Swaziland, Syria, Tanzania, Thailand, Togo, Tonga, Trinidad and Tobago, Tunisia, Turkey, Uganda, United Arab Emirates, Uruguay, Uzbekistan, Vanuatu, Venezuela, Vietnam, Yemen, Zambia, Zimbabwe.

B Theoretical Elements

B.1 The model

In each period, the donor country planner solves a static utility maximization problem to determine how much ODA to transfer to each of the N_R potential recipient countries. ODA disbursements need not be equal across the N_R recipients. The donor derives utility from own-consumption and from ODA disbursements in a manner to be described precisely below. The baseline donor's consumption is defined as income net of investment and it is assumed to be taken as given by the planner when the ODA decision is made. Government expenditures and net exports are assumed to be fully absorbed by consumers. Each dollar disbursed has an equal direct opportunity cost in donor own-consumption. To keep the analysis tractable we abstract from strategic interaction among donors. We first solve the problem of disbursement to a single representative recipient and then generalize this solution to the full disbursement problem.

Let N_D be the total number of donors and d a representative donor. Denote the vector of ODA disbursements by donor d as $A = [A_1, A_2, ...A_{N_R}]$. In what follows, variables are time series but the time indices are omitted for ease of notation; we will explicitly reintroduce time indices only when necessary.

The donor resource constraint links total absorption, C_d, to the ODA donations through the standard accounting relation

$$C_d + \sum_{r=1}^{N_R} A_r = Y_d - I_d \tag{A1}$$

where $Y_d - I_d$ is the donor's income net of private investment. For later reference, we define $C_{d,0} = Y_d - I_d$ as donor income when no ODA donations are made. Consistent with our discussion above, we will refer to this total absorption term as simply "consumption." Finally, ODA disbursements must be non-negative $A_r \geqslant 0$ for all $r = 1, 2, ..N_R$ and cannot exceed $C_{d,0}$. This generates the second constraint of the optimization problem

$$\sum_{r=1}^{N_R} A_s \leqslant C_{d,0} \tag{A2}$$

In the baseline model we adopt a log-additive utility function

$$\mathbb{W}(A) = \mathbb{U}(C_d)\, \mathbb{G}(A) \tag{A3}$$

in which total utility $\mathbb{W}(\cdot)$ includes the standard own-consumption component, $\mathbb{U}(C_d)$, and a second component, $\mathbb{G}(\cdot)$, that represents the donor's total gain from the full vector of ODA disbursements. We disaggregate the self-interest and altruism components of $\mathbb{G}(\cdot)$ below. This type of specification is not new to the ODA literature. Dudley and Montmarquette (1976) use a utility function component equivalent to $\mathbb{G}(\cdot)$ representing direct and subjective altruistic returns of ODA in a seminal early work. More recent work with similar modeling includes Younas (2008), Chong and Gradstein (2008), and Gravier-Rymaszewska (2012).

We assume that the total gain function $\mathbb{G}(\cdot)$ can be expressed as the product of individual gain functions associated with the disbursements to each of the N_R recipients

$$\mathbb{G}(A) = \prod_{r=1}^{N_R} \mathbb{G}_r(A_r)$$

The gain from each individual transfer, $\mathbb{G}_r(\cdot)$, is decomposed in two distinct components

$$\mathbb{G}_r(A_r) = \mathbb{R}_r(A_r)\, \mathbb{D}_r(A_r)$$

The first component, $\mathbb{R}_r(A_r)$, is a direct egoistic return from an ODA transfer to recipient r (e.g., the supportive UN vote). The second term, $\mathbb{D}_r(A_r)$, reflects purely altruistic preferences of the donor towards recipient r and it can be thought of as a mapping from the recipients own-consumption utility function that preserves the marginal utility properties of the recipient's utility.[29] It is reasonable to assume that there is no gain from either component if no ODA donation is made to a recipient. Therefore $\mathbb{G}_r(0) = \mathbb{R}_r(0) = \mathbb{D}_r(0) = 1$. This specification allows a donor to be motivated by pure self-interest, pure altruism, or any

[29] Let $\mathbb{U}_r(C_r)$ indicate the recipient's own-consumption utility with C_r a function of A_r (see A4). In a simple case, $\mathbb{D}_r$ can be represented as a functional composition of $\mathbb{U}_r$ such that $\mathbb{D}'_r \propto \mathbb{U}'_r$ and $\mathbb{D}''_r \propto \mathbb{U}''_r$.

combination of the two. A similar type of utility decomposition has been largely used in the charitable donations literature and charitable auction theory (see, for instance, Andreoni, 1989 and 1990, and Engers and McManus, 2001).[30]

As implied above, we assume $\mathbb{R}_r'$, $\mathbb{D}_r' \geq 0$, and $\mathbb{R}_r'', \mathbb{D}_r'' \leq 0$ for all r. In fact, it is only necessary to make this assumption in a small positive neighborhood of $A_r = 0$, not for its entire dominion $(0, C_{d,0})$. Since all observed bilateral ODA transfers are very small relative to $C_{d,0}$ (typically smaller than .01% of GDP), it is not necessary to fully characterize the gain function to obtain our theoretical predictions. Hence, we impose only a minimal set of assumptions on $\mathbb{G}_r(A_r)$ for A_r close enough to 0 to ensure a solution near $A_r = 0$. That is, we approximate the solution around $(C_d, A_r) = (C_{d,0}, 0)$.

Empirically, we will also allow the gain functions components to be affected by pair-specific shift factors, $X_{\rho r}$ and $X_{\delta r}$. Hence, $\mathbb{R}_r(A_r; X_{\rho r})$ and $\mathbb{D}_r(A_r; X_{\delta r})$ are more complete expressions of the gain components suitable for estimation. Examples of shifters for $\mathbb{R}_r$ (the egoistic "return" component) in the literature are the tightness of the trade relationship between donor and recipient, geopolitical factors, and colonial relationships. Potentially important shifters for $\mathbb{D}_r$ (the "altruism" component) are the recipient's level of consumption without ODA, cultural and religious factors, the recipient's population size, political efficiency, and corruption. In our estimation, we explicitly incorporate the recipient's initial level of consumption in the altruistic component by making $\mathbb{D}_r(\cdot)$ proportional to the change in the recipient's utility due to the ODA donation, while the other shifters are introduced as control variables at the estimation stage.

The donor's maximization problem is completed with the budget constraint of the recipient as seen from the donor's perspective:

$$C_r = C_{r,0} + A_r \tag{A4}$$

Equation (A4) makes explicit the relationship between $\mathbb{D}_r(A_r; X_{\delta r})$ and recipient consumption, C_r, for given $C_{r,0}$, since $A_r = C_r - C_{r,0}$. An implicit assumption here is that altruistic donors care about recipient country consumers, but do not explicitly consider firms in their altruistic decisions. The recipient constraint also implies that ODA is consumed instantaneously by the recipient government and/or consumers – that is, we maintain the full absorption assumption for recipient government expenditures as we did for donors.

Consistent with clear empirical reality, we assume that constraint (A2) is never binding for any donor. Therefore, the local interior first-order necessary conditions of the donors problem are satisfied where the marginal utility of donor "own-consumption" is equal to the marginal gain (from the total gain function) for each of the recipients. Indirect effects of transfers across recipients that would be conveyed by the shadow price of constraint (A2), were it binding, are absent. Hence, we can obtain the local qualitative theoretical signal of altruism utilizing the ODA decision to a single representative recipient, r, taking the donor's ODA to the other $N_R - 1$ potential recipients as already optimally determined. Note that the predetermined ODA to any (or all) of the other $N_R - 1$ recipients may also be zero.

[30]In the charitable donations literature, the donor's utility function includes an altruistic component derived from the provision of the public good to the community and a second private component derived from the individual contribution to the public good, which is directly comparable to the consumption of a private good. Our decomposition of $\mathbb{G}_r(\cdot)$ into altruistic and egoistic components is analogous.

Finally, we modify the utility function with two simplifications that do not affect the results. First, we explicitly account for a reference level by normalizing the arguments of the utility function by the donor's trend income $\bar{Y}$. Second, we take a log-transformation of the total utility $\mathbb{W}(\cdot)$ which is now additive in the logs of the three components. This transformation imposes a restriction on the sign of the three components of total utility, which must be strictly positive.[31] We can now re-write the utility function (A3) after substituting for constraint (A1) as

$$w(a) = u\left(c_{d,0} - \sum_r a_r\right) + \sum_r \rho_r(a_r; X_{\rho r}) + \sum_r \delta_r(a_r; X_{\delta r}) \tag{A5}$$

where, in order to simplify notation, let $z = Z / \bar{Y}$ be variable Z normalized by donor trend GDP and let $w(\cdot)$, $u(\cdot)$, $\rho_r(\cdot)$, and $\delta_r(\cdot)$ respectively indicate the log of $\mathbb{W}(\cdot)$, $\mathbb{U}(\cdot)$, $\mathbb{R}_r(\cdot)$, and $\mathbb{D}_r(\cdot)$.

The first order condition with respect to the generic donation a_r to recipient r is

$$-u_c(c_{d,r_0} - a_r) + \rho_{r,a}(a_r; X_{\rho r}) + \delta_{r,a}(a_r; X_{\delta r}) = 0 \tag{A6}$$

which is equation (2) in the main text.

B.2 Alternative utility functional forms

This section describes more in detail the CARA version of the model used for the robustness exercise in Section D.1 and the results for the CRRA version. The basic assumptions and results of the paper hold for these two versions too with the only exception that we start directly from the additive functional form in (A5) instead of the log-additive function in (A3). In particular, the *countercyclical-altruism* condition (9) is not affected by the choice of the functional form. In equation (A5), it is reasonable to assume in this case that $\rho_r(0) = \delta_r(0) = 0$ and ρ_r', $\delta_r' \geq 0$ and ρ_r'', $\delta_r'' \leq 0$ for any r in a positive neighborhood of $a_r = 0$.

In the CARA version of the econometric model, we assume negative exponential functional forms for the own-consumption utilities

$$\begin{aligned} u_d(c_d) &= 1 - e^{-\sigma_d c_d} \\ u_r(c_r) &= 1 - e^{-\sigma_r c_r} \end{aligned}$$

where σ_d and σ_r are donors' and recipients' risk aversion parameters. This choice corresponds to constant absolute risk aversion in the preferences for own-consumption. This type of functional form is fairly common in literature because preferences are easily characterized by the curvature parameter only. We adopt the same type of negative exponential function for $\rho_r(\cdot)$ as we used for $u_r(\cdot)$

$$\rho_r(a_r; X_{\rho r}) = \rho_{r,0}\left(1 - e^{-\sigma_\rho a_r}\right)$$

[31] This property will be important only in the selection of the functional forms in the empirical exercise.

where $\rho_{r,0}$ and σ_ρ are the parameters representing a scale factor and the riskiness of the direct return to ODA respectively. Finally, the altruism function is

$$\delta_r\left(a_r; X_{\delta r}\right) = \delta_{r,0}\left(-e^{-\sigma_r\left(c_{r,0}+a_r\right)} + e^{-\sigma_r c_{r,0}}\right)$$

where $\delta_{r,0}$ expresses the degree of altruism of the donor toward recipient r. Under these functional forms, the second and third regression equations of the model for a given calibration of the risk aversion, σ_d and σ_r, and return, σ_ρ, parameters are (omitting the controls)

$$\sigma_d e^{-\sigma_d c_{d,r_0}}\left(1+\sigma_d a_r^*\right) = \rho_{r,0}\sigma_\rho\left(1-\sigma_\rho a_r^*\right) + \delta_{r,0}\sigma_r e^{-\sigma_{\overline{r}} c_{r,0}}\left(1-\sigma_r a_r^*\right)$$

and

$$\sigma_d e^{-\sigma_d c_{d,r_0}} = \rho_{r,0^*}\sigma_\rho + \delta_{r,0^*}\sigma_r e^{-\sigma_r c_{r,0}}$$

The CRRA version of the econometric model can be derived starting from constant relative risk aversion own-consumption utility functions

$$u_d\left(c_d\right) = \frac{c_d^{1-\sigma_d}}{1-\sigma_d} \qquad u_r\left(c_r\right) = \frac{{c_r}^{1-\sigma_r}}{1-\sigma_r}$$

and following similar steps. As mentioned below, the CRRA specification is more troublesome than the CARA in the sense that the estimation of the model is more sensitive to the small variability of the ODA flows, especially when multiple controls are included in the regression equations. In particular, the number of pairs that empirically satisfy the *countercyclical-altruism* test drops to $3-4\%$ when controls are added, making a comparison with the other two specifications improper. Without controls, the results from this specification are perfectly consistent with those from the baseline and the CARA model. However, as two control variables are added, the number of cases for which the last two equations of the model are indistinguishable increases to about 60% of the total pairs leaving very little to the analysis. The CRRA specification is unsuitable for the estimation exercise we conduct because it is incompatible with the small variability of the ODA series; this case definitely calls for some caution in the choice of the functional forms.

C ODA Accounting, Data, and Econometric Details

C.1 Dataset

Letting A be total ODA donations, the donor's resource constraint (A1) can be written as $Y_d = C_d + I_d + A$. In national accounting, ODA disbursements are included in donors' GDP as exports that generate a trade flow without the corresponding income flow. The actual income available to a donor for consumption and investment must be adjusted for those items. We measure income as GDP and take investment from national accounting. Our framework implies a definition of consumption corresponding to absorption by the private and public sectors, and also assumes government expenditure and net exports are, ultimately, fully absorbed by consumers. Symmetrically for recipient countries, ODA transfers increase the resources available for consumption. Hence, we construct total recipient consumption by adding the ODA disbursements from donors to the recipient's GDP, net of investment.

National account data is drawn from the Penn World Tables dataset PWT 7.1 while ODA data is from the OECD DAC Aid Statistics dataset; PPP per-capita GDP is drawn from rgdpl in PWT. We use net ODA disbursements for 19 OECD donors and 137 recipients for the period 1970 to 2010.[32] Appendix A lists the 156 countries in our sample. All analysis utilizes 2005 International Dollars per person – the reporting basis in the Penn World Tables and the data taken from OECD was mapped to PWT data. Therefore, all the variables used in our analysis are expressed in equivalent PPP per-capita terms. Since the ODA flows from donor d to recipient r reported by the OECD are in current USD, these are adjusted by multiplying the flows by the ratio between PWT GDP and the current USD GDP from the OECD. Figure A1 below illustrates total net ODA disbursements for the 19 donors in our sample as a share of donor GDP. The majority fall between $.1 - .5\%$ and, interestingly, the stated OECD-DAC target of .7% of GDP is rarely achieved. Finally, we use four variables as controls in the empirical assessment of the model. These controls are transformations of population, price index, degree of openness (from PWT 7.1) and of life expectancy from the World Bank online dataset World Development Indicators (WDI).[33] The population growth rate seems appropriate for our analysis since we focus on business cycle variations over a long time series. Inflation is used to control for the quality of monetary policy; other papers use money supply but the two variables normally overlap. The degree of openness is the ratio to GDP of the sum of imports and exports. The change in life expectancy at birth captures generic development. The trend GDP, $\bar{Y}_d$, necessary to compute the ratio variables is constructed by applying the HP filter to the GDP series with the smoothing parameter set to 100.

Figure A2 shows ODA relative to GDP for all 137 recipient countries – again each line represents a specific country. Note that ODA receipts range from very little to over 20% of GDP for some recipients. The darker line in Figure A2 represents the average amount of aid received by the 137 recipient countries in our sample, which is between 2% and 4%. Both Figures illustrate that there is considerable variance of ODA as a share of GDP for some donors and recipients while others are relatively stable. As noted previously, each donor disburses ODA to a large set of recipients. However, most donors have a stronger systematic ODA relationship, in terms of GDP share, with a relatively small subset of total recipients. The remaining recipient countries receive aid in smaller amounts, and some only on an occasional basis. This characteristic will play an important role in our results. The US is an extreme example of this pattern, disbursing ODA to 130 out of 137 countries with half of the countries receiving on average less than .5% of the total US ODA, while the 10 largest US recipients together receive on average 53% of total US ODA disbursements. US

[32]Regarding the donor sample we include the 15 largest the DAC donors countries over our time-period and all Scandinavian countries (since they are often pointed to as altruists in the literature). For Spain, Luxembourg, New Zealand, and Finland the ODA series are shorter since they joined the DAC after 1970. Regarding the choice of net disbursements, various ODA measures have been used in the literature. Net disbursements have been employed in many analyses and we believe this measure to be most appropriate in this context. Clemens et al. discuss the alternative measures.

[33]The PWT series kc, kg, and ki are used to construct the other accounting definitions starting from rgdpl. The control variables are obtained from POP, p, openk. The code for the WDI series is SP.DYN.LE00.IN.

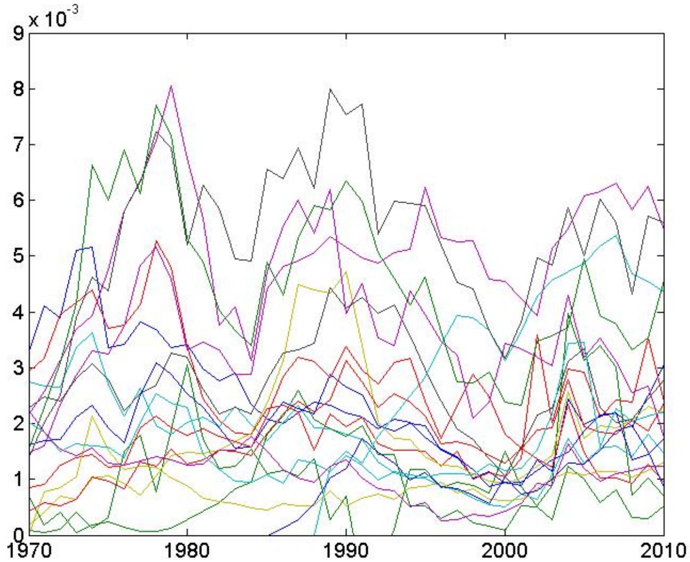

Figure A1: Total ODA Disbursements as a ratio of GDP for the 19 DAC Donors - Sample $1970 - 2010$. Each color represents a unique donor.

ODA disbursements are presented in Figure A3.

C.2 Estimation Details

In the GMM estimation, the optimal weighting matrix is computed using a Bartlett kernel with a Newey-West fixed bandwidth. The model is estimated in Matlab, using a modification of the toolbox developed by Cliff (2003) which accommodates equation specific orthogonality conditions. One estimation issue is that, for some pairs, it may be difficult to distinguish equation (18) and (19) when a_r^* does not exhibit sufficient time variation. This could be the case, for example, when a recipient receives only sporadic ODA donations from a particular donor. Such a pattern may not be compatible with the altruism signal identified in this paper since continuity in the donor-recipient relation is assumed in the theory. Therefore, we apply a weak pre-selection criterion to each pair before the estimation stage and classify those pairs where the recipient received a disbursement during less than 10% of the time periods and the standard deviation of a_r^* was less than 10^{-6} as not displaying the *countercyclical-altruism* signal. This criterion affects about 17% of the pairs, leaving the large majority of pairs to be classified as satisfying the *countercyclical-altruism* condition, or not. In addition to these two criteria, a further pre-selection criterion was used when ODA variability was insufficient to distinguish the two equations up to machine computational precision. This propensity increased with the number of control variables. Control variables magnify the problem since their variability could mask the very small variability in ODA in some cases. We prefer to adopt a conservative approach and classify these pairs as non-altruistic as well. With no controls this situation virtually never occurs; with one or two controls about 20% of the pairs approach computational precision; and with four controls another 20% approach the limit. This constraint reduces the number of pairs that pass the *countercyclical-altruism*

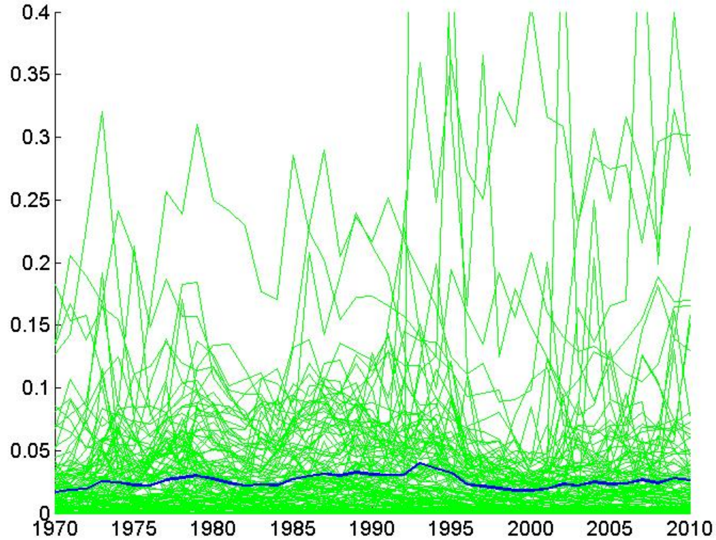

Figure A2: Total ODA Disbursements as a ratio of GDP for all recipients - Sample 1970 – 2010. Each green line represents one of the recipients. The dark line is the mean ODA across recipients

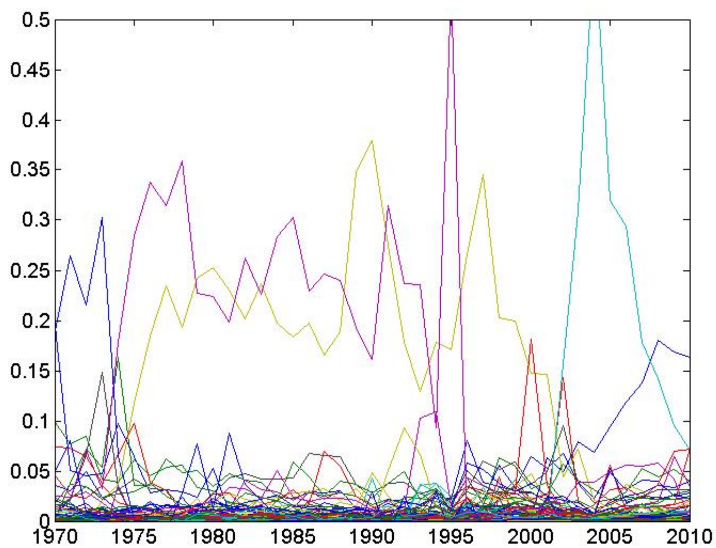

Figure A3: Shares of US ODA disbursements by recipient from 1970 to 2010. Each line represents a unique recipient.

test, though the number never drops below 10% of the total pairs. We pick a middle ground for addressing this issue and we adopt a baseline with the two controls most linked to our context: population growth and inflation. We discuss the other specifications in the robustness section of the Appendix. Finally, the sample used for estimation includes 35 observations from 1975 to 2010 for our 2603 pairs.

In the GMM, the asymptotic distribution of $\hat{\theta}$ is $\sqrt{T}\left(\hat{\theta}-\theta\right) \to N\left(0,V\right)$, where T is the length of the sample and V is the covariance matrix of $\hat{\theta}$ obtained from the inverse of the optimal weighting matrix obtained in the GMM procedure. Under the null hypothesis of the *countercyclical-altruism* test, the asymptotic distribution of $\hat{\beta}_r\left(\hat{\delta}_{r,0}-\hat{\delta}_{r,0^*}\right)$ is approximated by

$$\sqrt{T}\hat{\beta}_r\left(\hat{\delta}_{r,0}-\hat{\delta}_{r,1}\right) \to N\left(0, L_{\hat{\theta}} V L'_{\hat{\theta}}\right)$$

where $L_{\hat{\theta}}$ is the gradient of $\beta_r\left(\delta_{r,0}-\delta_{r,0^*}\right)$ with respect to the components of θ evaluated at the estimated coefficient vector $\hat{\theta}$

$$L_{\hat{\theta}} = \left[0 \ \left(\hat{\delta}_{r,0}-\hat{\delta}_{r,0^*}\right) \ 0 \ \hat{\beta}_r \ 0 \ -\hat{\beta}_r \ 0_z\right]$$

in which 0_z is a row vector with length equal to twice the number of controls included in the regression equations (18) and (19).

D Robustness Checks

The assumptions made in the empirical implementation of the model warrant additional attention since the results of the paper could have been driven by implausible fortunate coincidences. We therefore conduct a series of robustness checks to address two main concerns. The first checks are sensitivity analyses of the role of the controls at the estimation stage in light of the small variability in ODA that, in some cases, affects equations (18) and (19). The second set of robustness checks explore how the parameter estimates and the set of pairs displaying the *countercyclical-altruism* signal change with alternative utility functional forms.

D.1 Robustness to the Model Specification

Regarding the control variables we find that increasing the number of controls reduces the number of pairs displaying the *countercyclical-altruism* signal for all specifications explored. For instance, going from zero controls to two controls in our baseline specification reduces the altruistic pairs from 23.1% to 16.3%. Changing the set of control variables might also affect the parameter estimates and the composition of the *countercyclical-altruistic* donor-recipient set; however, this did not occur in our robustness checks. Rather, the contraction of the set of altruistic pairs is mostly due to an increase in the number of cases for which equations (18) and (19) become statistically indistinguishable and the small variability of ODA is absorbed by the controls.[34] Fortunately, even though the selection of the controls clearly matters for the numerical relevance of the altruism signal, the number of controls in the model does not seem to be that crucial for the determination of the intrinsic characteristics of the signal, as we see in the growth and logit regressions.

We now turn to the choice of the functional forms. As an alternative to our baseline model of equation (A5) we consider constant absolute risk aversion (CARA) own-consumption utility functions. The full description of the model under this different set of assumptions is given in Appendix B.[35] In order to avoid non-linear restrictions on the coefficients of the model, we keep the curvature parameters of the three functions separate from $\rho_{r,0}$ and $\delta_{r,0}$, which requires a calibration of the risk aversion coefficients of the two countries, σ_d and σ_r, and of the riskiness parameter of the return function, σ_ρ. The combination of the log-additivity property and power functions in (A5) is particularly convenient in this respect because it allows us to estimate the model independently of the calibration of any parameter of the functional forms. We estimate the alternative models for parameter calibrations ranging from $[\sigma_d \ \sigma_r \ \sigma_\rho] = [2\ 2\ 2]$ to $[8\ 8\ 8]$ and including different combinations of the controls in the regressions.[36] We find that the CARA model generates results very similar to the baseline specification. The CARA model with $\sigma_d = \sigma_r = \sigma_\rho = 2$ and two controls, which we take as main alternative specification, returns 20.6% donor-recipient altruistic pairs (it is 16.3% the baseline); about 80.9% of the pairs identified by the baseline model are also included in this CARA specification. Increasing the number of controls reduces the number of altruistic pairs in the CARA model as in the baseline. For example, the altruistic share with CARA goes from 23.2% with no controls to 20.6% with two controls. The results for the basic CARA specification are very robust to the changes in the calibration vector and, in general, we find the intersection of the set of altruistic pairs greater than 80% between the basic CARA and the other calibrations with two controls.

The most interesting difference between the baseline model and the CARA specification is the higher number of *countercyclical-altruistic* pairs relative to the other countries for Luxembourg, Norway, and in part Finland as well. Our baseline specification reduces the Scandinavian countries' signals and, in this sense, can be considered a more conservative choice. However, although the composition of the altruistic group changes somewhat with

[34] In fact, 86% of the pairs classified as altruistic in our baseline scenario with two controls satisfy the test in the specification with no controls too; only a 14% of new pairs are identified as a consequence of the introduction of the controls. Using four available controls, the *countercyclical-altruism* pairs drop to 10% but 85% of them were already included in the altruistic pairs of the model with two controls.

[35] We also consider a second case based on constant relative risk aversion (CRRA) functions for u, ρ, and δ. Also the CRRA model gives us results in line with those of the baseline and the CARA models when no controls are included in the estimation of the model. However, this specification is more sensitive to the small ODA variability issue than the other two when more controls are added to the regression equations of the model.

[36] Even though it might be reasonable to assume the same coefficient of risk aversion for donors and recipients, empirical evidence have suggested that low development countries can display higher levels of risk aversion. Yesuf and Bluffstone (2009) and Wik, Kebede, Bergland, and Holden (2004) show that poor people in low development countries display high levels of risk aversion. Under some assumptions this may translate to greater risk aversion at the country level too, see Blackburn and Ukhov (2008) for discussion. Since the relative risk aversion in the donor-recipient pair may affect the results of the test, also calibrations with $\sigma_r > \sigma_d$ are considered. There is no much guidance in the choice of σ_ρ instead, so we try a few combinations of values between 2 and 8 as we change the risk aversion coefficients.

CARA, the output of the growth regressions for the basic CARA case reported in Table A1 and of the logit regressions reported in Table A3 does not differ from our baseline model. The fact that the quality of the signal is preserved across specifications provides further evidence that the theoretical model identifies a robust signal.

A final robustness feature worth noting concerns the theoretical model. In earlier stages of this work other versions of the theoretical model were explored. For instance, we developed models with linear direct returns from ODA in the donor's budget constraint or returns proportional to the loss in utility of the donors. The basic countercyclical signal emerges from these formulations as well. The theoretical model presented herein is more general and more tightly linked to the estimation.

D.2 Robustness of the Results in Section 5

In this Appendix, we provide some robustness check of the two out of model exercises discussed in Section 5. We start estimating the growth regressions for two other specifications of our empirical altruism model, namely the baseline model with no controls and the CARA (with parameterization $\sigma_d = \sigma_r = \sigma_\rho = 2$) functional form. The results, illustrated in the two panels of Table A1, are broadly consistent with the baseline evidence discussed in Section 5.2. We then discuss the results of the growth validation exercise with the RS specification, reported in Table A2 for the models with only linear effects. In this case the partition between altruistic and non-altruistic donor sets does not provide clearcut evidence in support of our *countercyclical-altruism* signal. The estimates of the ODA effects on growth are generally positive, but never statistically significant. The coefficients of the altruistic set are bigger in some of the specifications, as for example in column (1), (2), (4), or (6); however, the results are not always consistent across models as columns (3) and (5) show, and we don't find a clear endogeneity bias in the contemporaneous regressions. Using early impact aid widen the gap between the estimates of the two donor sets, yet significance at conventional confidence levels is not achieved.

The strength of the BD aid-growth relationship, compared to RS, is not surprising since the BD model generally yielded larger and more significant ODA-growth linkages. CL, for instance, can find significant effects of ODA on recipients' growth only for early impact for the RS model. In our case, not even the early impact category provides particularly positive estimates. Finally, using quadratic ODA terms in the non-linear specification of the regression model does not improve the overall outlook of the results in Table A2. The coefficients change often sign across specifications with no particular regularity and the growth-ODA relation becomes convex with early impact aid. These results suggest that our signal effectively identify aid with more positive impact on growth only in the BD specification, which as we know estimates the effects of ODA conditional on the quality of the institutions of the recipient country.

In Table A3 we present some robustness checks for the logit regression discussed in Section 5.1. We consider two alternative specifications: the baseline model with no controls and the main CARA functional specification (with parameterization $\sigma_d = \sigma_r = \sigma_\rho = 2$). The overall outlook of effects estimated in Table 1 is fairly confirmed by these alternative specifications, with the exception of a few specific differences. The first is that the effect of the population size, which was small but significant, is now non-significant in the specifications for the

	Baseline - no controls: Partitioned					Early Impact	
	(a)	(b)	(c)	(d)	(e)	(f)	(g)
A_t^a	0.111						
	(0.121)						
A_t^{na}	0.102						
	(0.119)						
A_{t-1}^a		0.223	0.161	0.243	0.775	1.315	1.440
		(0.125)*	(0.159)	(0.264)	(0.324)**	(0.318)***	(0.479)***
A_{t-1}^{na}		0.085	0.027	0.429	0.249	0.073	-0.776
		(0.171)	(0.254)	(0.325)	(0.502)	(0.437)	(0.664)
$(A_{t-1}^a)^2$				-0.006	-0.038	-0.232	-0.198
				(0.015)	(0.015)**	(0.038)***	(0.062)***
$(A_{t-1}^{na})^2$				-0.020	-0.013	-0.034	0.025
				(0.012)*	(0.017)	(0.041)	(0.051)
Model	F.E.	F.E.	Diff.	F.E.	Diff.	F.E.	Diff.
Obs	414	414	357	414	357	368	312
$\overline{MR}_a$				.23	.68**	1.01***	1.17***
$\overline{MR}_{na}$				.37	.21	.01	$-.73$

	CARA specification: Partitioned					Early Impact	
	(a)	(b)	(c)	(d)	(e)	(f)	(g)
A_t^a	0.074						
	(0.097)						
A_t^{na}	0.132						
	(0.121)						
A_{t-1}^a		0.190	0.093	0.365	0.639	1.031	1.216
		(0.109)*	(0.129)	(0.249)	(0.302)**	(0.383)***	(0.481)**
A_{t-1}^{na}		0.110	0.113	0.408	0.348	0.373	-0.495
		(0.164)	(0.237)	(0.287)	(0.454)	(0.393)	(0.739)
$(A_{t-1}^a)^2$				-0.014	-0.030	-0.179	-0.176
				(0.011)	(0.012)**	(0.053)***	(0.058)***
$(A_{t-1}^{na})^2$				-0.018	-0.016	-0.059	0.023
				(0.010)*	(0.016)	(0.044)	(0.080)
Model	F.E.	F.E.	Diff.	F.E.	Diff.	F.E.	Diff.
Obs	414	414	357	414	357	368	312
$\overline{MR}_a$				.33	.57**	.81**	.99**
$\overline{MR}_{na}$				.35	.29	.27	$-.45$

Table A1: Estimation of the growth regressions for the Burnside and Dollar (2000) (BD) model. The top panel reports the results with ODA donor partition between A^a and A^{na} based on our baseline model specification with no controls; the bottom panel for the partition based on the CARA $\sigma_d = \sigma_r = \sigma_\rho = 2$ functional forms. The regression models are estimated either by including fixed effects (F.E.) or in first difference (Diff.); standard errors clustered at recipient level are reported in parentheses. 1, 5, and 10% significance levels are indicated by ***, **, and * respectively. $\overline{MR}$ indicates the overall marginal return of ODA evaluated at the mean aid level for the quadratic specifications. See the notes of Table 2 for further details.

	Partitioned			Early Impact		
	(1)	(2)	(3)	(4)	(5)	(6)
A_t^a	0.057			0.212		
	(0.135)			(0.165)		
A_t^{na}	-0.032			0.021		
	(0.109)			(0.154)		
A_{t-1}^a		0.079	0.116		0.002	0.209
		(0.084)	(0.107)		(0.159)	(0.238)
A_{t-1}^{na}		0.011	0.145		0.142	0.118
		(0.127)	(0.203)		(0.092)	(0.147)
Model	F.E.	F.E.	Diff.	F.E.	F.E.	Diff.
Obs	384	387	310	383	335	270

Table A2: Estimation of the growth regressions for the Rajan and Subramanian (2008) (RS) model. ODA donor partition between A^a and A^{na} based on our baseline model specification. The regression models are estimated either by including fixed effects (F.E.) or in first difference (Diff.); standard errors clustered at recipient level are reported in parentheses. 1, 5, and 10% significance levels are indicated by ***, **, and * respectively. See the notes of Table 2 for further details.

baseline with no controls. However, consumption is now significant for the baseline with no controls even when multilateral ODA is significant in the level models. The second is that the formal colonial status dummy is less significant in Table A3 for the CARA model, while it survives in the baseline with no controls. Among the three ties dummies, then, only the EU dummy preserves its original significance, reinforcing our interpretation of the results for the colonial variable. Looking at the humanitarian variables, while the significance of the internal conflict dummy drastically drops, the mortality rate seems to replace it in the identification of the *countercyclical-altruism* pairs, especially for the specifications in columns f and $f^{\dagger}$. Recipients with higher mortality rates are now more likely to receive altruistic aid. Bilateral trade follows the same pattern, except for model (f) under the CARA case where it is significant now, and military expenditure preserves its negative and marginally significant effects. Finally, it is worth noticing that multilateral ODA is positively related to the *countercyclical-altruism* signal in a significant way, which indicates a complementarity of bilateral altruistic ODA with other forms of aid that are usually believed to reflect more altruistic donors' motivations.

	Baseline - no controls				CARA			
	f	$f^\dagger$	g	$g^\dagger$	f	$f^\dagger$	g	$g^\dagger$
consump.	0.949 (0.050)*	0.913 (0.616)	0.926 (0.004)***	1.006 (0.975)	0.926 (0.013)**	0.951 (0.773)	0.900 (0.001)***	1.066 (0.711)
pop.	0.983 (0.121)	0.825 (0.066)*	0.988 (0.247)	0.884 (0.251)	0.971 (0.016)**	0.772 (0.031)**	0.976 (0.030)**	0.828 (0.112)
democr.	0.793 (0.615)	1.028 (0.956)	0.819 (0.661)	0.977 (0.965)	0.890 (0.738)	1.034 (0.938)	0.894 (0.753)	0.937 (0.875)
int. conflict	1.170 (0.464)	1.210 (0.379)	1.073 (0.733)	1.091 (0.675)	1.354 (0.130)	1.402 (0.127)	1.203 (0.340)	1.239 (0.296)
ext. conflict.	1.278 (0.577)	1.204 (0.636)	1.144 (0.731)	1.145 (0.693)	1.745 (0.330)	1.289 (0.614)	1.557 (0.380)	1.223 (0.632)
mortality	1.005 (0.076)*	1.719 (0.032)**	1.005 (0.131)	1.510 (0.105)	1.005 (0.112)	1.866 (0.012)**	1.004 (0.193)	1.679 (0.042)**
colony	1.600 (0.021)**	1.302 (0.212)	1.577 (0.030)**	1.515 (0.045)**	1.097 (0.722)	0.917 (0.750)	1.045 (0.862)	1.040 (0.885)
US influence	0.837 (0.718)	0.671 (0.418)	0.808 (0.661)	0.778 (0.615)	0.733 (0.588)	0.628 (0.380)	0.688 (0.504)	0.719 (0.536)
JP influence	1.651 (0.353)	1.757 (0.321)	1.370 (0.563)	1.597 (0.422)	2.513 (0.073)*	2.949 (0.068)*	2.122 (0.139)	2.739 (0.090)*
EU influence	1.162 (0.041)**	1.091 (0.093)*	1.152 (0.075)*	1.116 (0.044)**	1.183 (0.029)**	1.110 (0.056)*	1.163 (0.055)*	1.130 (0.022)**
trade	1.112 (0.472)	1.177 (0.002)***			1.345 (0.037)**	1.213 (0.002)***		
milit. G	0.917 (0.135)	0.869 (0.190)	0.939 (0.267)	0.946 (0.612)	0.885 (0.058)*	0.839 (0.074)*	0.911 (0.130)	0.916 (0.353)
milit. trade	0.992 (0.463)		0.987 (0.308)		1.003 (0.777)		1.000 (0.984)	
trade h1			2.279 (0.017)**	1.336 (0.002)***			2.317 (0.020)**	1.356 (0.003)***
trade h2			0.628 (0.016)**	0.795 (0.022)**			0.751 (0.181)	0.803 (0.026)**
mult. ODA	1.353 (0.028)**	1.461 (0.011)**	1.310 (0.037)**	1.514 (0.004)***	1.244 (0.182)	1.521 (0.009)***	1.186 (0.240)	1.544 (0.004)***
Obs.	1800	1800	1874	1874	1800	1800	1874	1874
Pseudo R^2	.07	.07	.07	.08	.07	.07	.07	.08

Table A3: Logit model for alternative specification of the altruism model – Odds Ratios. The dependent variable is our *countercyclical-altruism* binary signal from the baseline model estimated with no control variables and the CARA $\sigma_d = \sigma_r = \sigma_\rho = 2$ functional specifications. Columns headers and variables definitions reflect those in Table 1. P-values reported in parenthesis.

Supplementary Material (for online publication)

S1 Baseline Point Estimates

Figures S1-S3 shows the estimates of β_r, $\delta_{r,0}$, and $\rho_{r,0}$ analogous to Figure 3 for $\delta_{r,0} - \delta_{r,0^*}$. As explained in the theoretical section of the paper, our estimates of $\delta_{r,0}$ and $\rho_{r,0}$ provide an ordinal rather than cardinal measure of the degree of altruism and the direct return parameter of the donor countries. For this reason, it may be possible to observe pairs also in the negative quadrant of Figures S2 and S3 . Finally, in Table S1 we list the names of the recipient countries that satisfy the *countercyclical-altruism* condition as reported by Figure 2.

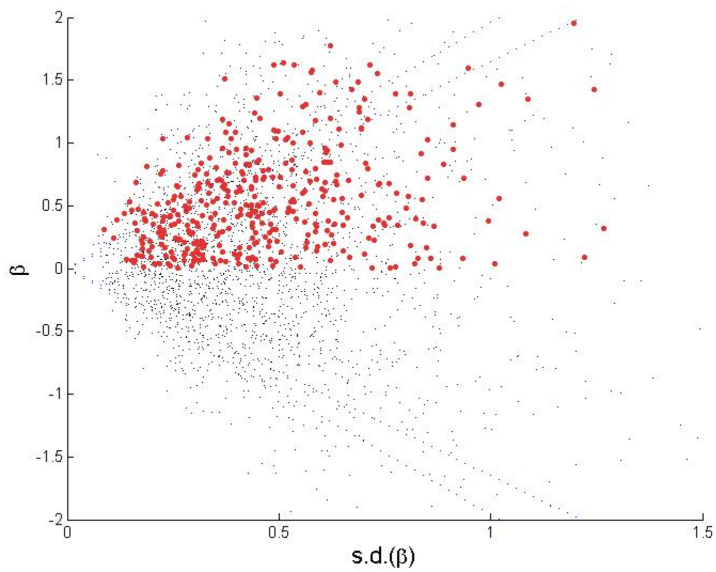

Figure S1: Point estimates of β_r. Red dots identify pairs that satisfy the *countercyclical-altruism* condition. In black all the others. The significance of the parameters is shown by the blue, dotted lines. The external lines show the 5% significance thresholds. The internal lines the 10% level.

S2 Dataset for the Logit Regressions

In this Appendix, we provide a description of the sources of the variables used in the logit regression in Tables 1 and A3 and of the transformations applied to them. The key feature of the dataset is that the explanatory variables in the regression must express average effects over time in order to match the binary nature of the *countercyclical-altruism* signal. The log-specifications of the logit regression in the paper are obtained applying the natural logs to the variables in levels, after the transformations described here. Table S2 reports the summary statistics of these variables.

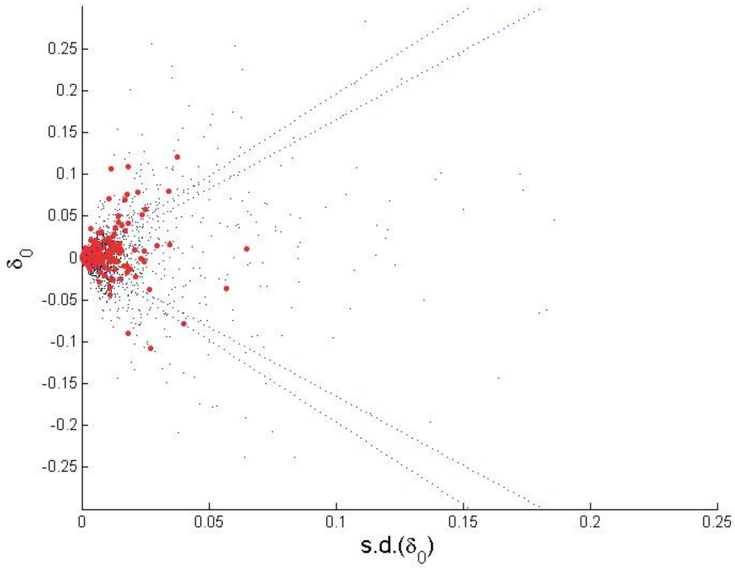

Figure S2: Point estimates of $\delta_{r,0}$. Red dots identify pairs that satisfy the *countercyclical-altruism* condition (15). In black all the others. The significance of the parameters is shown by the blue, dotted lines. The external lines show the 5% significance thresholds. The internal lines the 10% level.

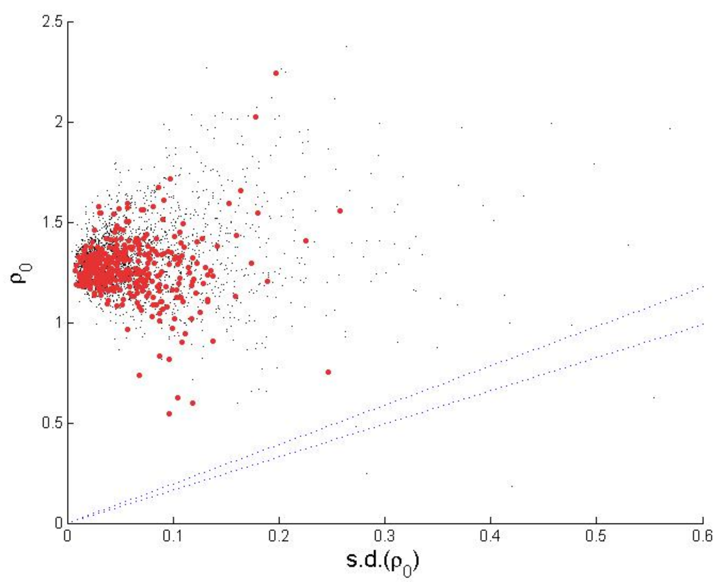

Figure S3: Point estimates of $\rho_{r,0}$. Red dots identify pairs that satisfy the *countercyclical-altruism* condition. In black all the others. The significance of the parameters is shown by the blue, dotted lines. The top (bottom) blue line show the 5% (10%) significance threshold.

Donor	Recipients
Australia	Fiji, Hong Kong, Kenya, Namibia, Seychelles, Tonga.
Austria	Algeria, Angola, Bolivia, China Taipei, Costa Rica, Cyprus, Egypt, El Salvador, Guatemala, Iraq, Malaysia, Malta, Mozambique, Tanzania.
Belgium	Angola, Bolivia, **Dem. Rep. Congo**, Costa Rica, Ecuador, El Salvador, Gabon, Guatemala, Guinea, Haiti, Iraq, Jamaica, Liberia, Malawi, Malaysia, Morocco, Namibia, Pakistan, Philippines, Senegal, Seychelles, Suriname, Tanzania, Togo, Zimbabwe.
Canada	Algeria, Antigua Barbuda, Bangladesh, Botswana, Burkina Faso, Cameroon, Costa Rica, Cote d'Ivoire, Cuba, El Salvador, Haiti, Iraq, Kenya, Liberia, Mauritania, Nicaragua, Niger, Sierra Leone, St.Kitts&Nevis, Tanzania, Togo, Turkey, Zambia.
Denmark	Afghanistan, Algeria, Argentina, Benin, Central Africa Rep, Dem. Rep. Congo, Costa Rica, Cote d'Ivoire, Cuba, El Salvador, Honduras, Iran, Iraq, Jordan, Kenya, Maldives, Mongolia, Nicaragua, Pakistan, Peru, Samoa, Zambia.
Finland	Afghanistan, Angola, Bhutan, Botswana, Cambodia, Cape Verde, Cuba, Ethiopia, Fiji, Iraq, Kenya, Nicaragua, Peru, South Africa.
France	Bolivia, Botswana, Burkina Faso, Cambodia, Cameroon, Central Africa Rep, Dem. Rep. Congo, Cote d'Ivoire, Dominica, Ecuador, Fiji, Guatemala, **Guinea**, Hong Kong, Iraq, Kenya, Mauritania, Morocco, Nepal, Niger, Paraguay, Rwanda, Sao Tome, Senegal, Somalia, St. Lucia, Sudan, Suriname, Tanzania, Togo, Uruguay, Zimbabwe.
Germany	Angola, Argentina, Botswana, Burkina Faso, Burundi, Cambodia, Cyprus, Egypt, El Salvador, Guinea-Bissau, Indonesia, Iran, Iraq, Jamaica, Kenya, Lesotho, Liberia, Malawi, Malaysia, Malta, Mauritius, Morocco, Mozambique, Nepal, Niger, Pakistan, Philippines, Samoa, Singapore, Somalia, South Africa, Tanzania, Thailand, Togo, Trinidad, Tunisia, Arab Emirates, Uzbekistan.
Italy	Albania, Algeria, Bolivia, Brazil, Burkina Faso, Burundi, Cape Verde, Chile, Colombia, Costa Rica, Ecuador, Ethiopia, Ghana, Guatemala, Guinea, Iraq, **Jordan**, Kenya, Liberia, Libya, Madagascar, Malta, Morocco, Niger, Paraguay, Rwanda, Sudan, Tanzania, Tunisia, Turkey, Uruguay.
Japan	Angola, Brazil, Burkina Faso, Burundi, Chad, Egypt, Honduras, Hong Kong, India, Indonesia, Lesotho, Malaysia, Mali, Marshall Isl., Mauritius, Mexico, Morocco, Mozambique, Namibia, Nepal, Pakistan, Philippines, Samoa, Sierra Leone, Singapore, Somalia, South Africa, Tanzania, Thailand, Turkey, Uzbekistan.
Luxembourg	Namibia, Rwanda.
Netherlands	Angola, Bolivia, Botswana, Burkina Faso, Burundi, Cambodia, **Dem. Rep. Congo**, Costa Rica, Cote d'Ivoire, Dominican Rep, El Salvador, Ethiopia, Fiji, Gabon, Ghana, Guatemala, Guinea-Bissau, India, Iran, Iraq, Lesotho, Liberia, Malawi, Mauritania, Mozambique, Paraguay, Philippines, Rwanda, Samoa, Senegal, Somalia, South Africa, St.Kitts&Nevis, Suriname, Swaziland, Tanzania, Togo, Yemen.
New Zealand	Afghanistan, Iraq, Kiribati, South Africa, Vanuatu.
Norway	Cape Verde, Cuba, Guyana, Iran, Iraq, Laos, Maldives, Mongolia, South Africa, Sri Lanka.
Spain	Belize, Dem. Rep. Congo, Congo, Gambia, Honduras, Iraq, Kenya, Mauritania, Morocco, Niger, Paraguay, Rwanda, Senegal, Somalia, Togo, Tunisia, **Venezuela**, Zimbabwe.
Sweden	Afghanistan, Angola, Botswana, Cape Verde, Dem. Rep. Congo, Costa Rica, Cuba, El Salvador, Ghana, Honduras, India, Iran, Iraq, Kenya, Korea, Liberia, Mongolia, Mozambique, Namibia, Nicaragua, Pakistan, Peru, Rwanda, Sierra Leone, Somalia, South Africa, Swaziland, Tanzania, Zambia.
Switzerland	Angola, Bangladesh, Bolivia, Burkina Faso, Cambodia, Cape Verde, Costa Rica, Dominica, El Salvador, Eq Guinea, Guatemala, Iraq, Lebanon, Lesotho, Liberia, Mongolia, Mozambique, Paraguay, Rwanda, Somalia, South Africa, Togo, Turkey.
UK	Afghanistan, Angola, Antigua Barbuda, Botswana, Burundi, Cameroon, Dem. Rep. Congo, Costa Rica, Cyprus, Dominica, El Salvador, Ghana, Grenada, Iraq, Kenya, Kiribati, Lesotho, Liberia, Mozambique, Nicaragua, Peru, Sierra Leone, Somalia, South Africa, St. Lucia, St.Vincent, Sudan, Swaziland, Tanzania, Zambia.
US	**Afghanistan**, Bangladesh, Botswana, Brazil, Burkina Faso, Burundi, Cameroon, China Taipei, Dem. Rep. Congo, Costa Rica, Cote d'Ivoire, El Salvador, Guinea, Haiti, Honduras, Kenya, Lebanon, Liberia, Malawi, Mali, Mauritania, Mongolia, Morocco, Mozambique, Nicaragua, Niger, Pakistan, **Sierra Leone**, Somalia, Venezuela, Yemen, Zambia.

Table S1: Recipient countries that satisfy the *countercyclical-altruism* condition. This table lists the countries that satisfy the condition for *countercyclical-altruism* equation (15) in the main text and summarized in Figure 2. Blue recipients are found for the full *countercyclical-altruism* condition but not for the split condition as described in Footnote 15 of the paper.

Population: Population series are from Penn World Tables dataset (PWT 7.1) for both donors and recipients (identifier POP). The same series are also used as controls in the estimation stage of the signaling model. The average over the sample $1975 - 2010$ is taken to obtain the final transformation. The variable is expressed in 10 million units.

Consumption: The consumption variable is expressed in consumption per capita terms in thousands of PPP-dollars. The consumption series are from PWT 7.1 for both donors and recipients (identifier kc). The variable is computed as the average over time of the recipient's consumption per capita series. The variable is expressed in 100 PPP-dollars units.

Democracy Quality: We start from the two indicators of governance quality published by Freedom House, about political rights and civil liberties which fully cover the sample of our analysis ($1975-2010$). We obtain a single democracy index by averaging the two indicators together for each recipient and, then, taking the average over time of the aggregate index. This index would go from 1 (highest quality) to 7 (lowest quality). The democracy quality variable is constructed as a dummy that takes value 1 for very high quality democracies with average index of 1 or 2, and 0 for the others.

Internal and External Conflict: These two dummy variables are constructed with the information from the UCDP (Uppsala Conflict Data Program)/PRIO (International Peace Research Institute of Oslo) Armed Conflicts Version 4-2009 dataset, available at https://www.prio.org. We distinguish between interstate and internal conflicts (classification Type=2 and Type=3 or 4 in the database). The dummy takes value 1 to indicate severe conflicts over the sample $1975-2009$, based on the cumulative intensity index of a multi-year conflict which indicates as severe conflicts that since the onset exceeded 1,000 battle-related deaths.

Mortality: Mortality rate at birth is originally obtained from the World Development Indicators (WDI) provided by the World Bank (identifier SP.DYN.IMRT.IN). The average over the sample $1970 - 2010$ is taken to obtain the final transformations. This variable is a proxy for general health conditions and returns similar effects as life expectancy in the logit regressions (not reported in the main table). The variable is expressed in number of deaths per $1,000$ live births.

Former Colonial Status: This is a dummy variable that takes value one if a recipient is a former colony of a donor and zero otherwise. Information about the past colonial status of recipient countries is drawn from the Colonial/Dependency Contiguity (v3.0) dataset – Entities List, provided by The Correlates of War Project available online at http://correlatesofwar.org/. This variable is clearly defined at the donor-recipient level.

Geo-political and Regional Influence: These three dummies are defined following Berthélemy (2006) in order to capture the closer ties and geo-political influence at regional level of US, Japan, and European donors. For the US the dummy catches the ties between US and Latin American countries and the geo-political interests of the US in the Middle East through Israel and Egypt. For Japan the variable indicates the closer ties between Japan and the countries in Asian region. Finally for the European countries the dummy captures the bias of the European Union towards the so called ACP recipients (Associated states of Africa, Caribbean, and Pacific Ocean).

Bilateral Trade: This is the main variable representing self-interest motivations in the logit regression. A publicly available source that fully covers our sample is the IMF-DOTs Database (Direction of Trade Statistics), available online at http://http://data.imf.org. We construct the bilateral trade variable as the sum of imports and exports between a donor

Variable	N	Mean	sd	Min.	p(.25)	Med.	p(.75)	Max.
consump.	2603	5.24	8.22	0.35	1.12	2.51	5.45	50.09
pop.	2603	2.94	12.07	0.00	0.08	0.50	1.69	111.99
democr.	2603	0.12	0.33	0.00	0.00	0.00	0.00	1.00
int. conflict	2603	0.33	0.47	0.00	0.00	0.00	1.00	1.00
ext. conflict	2603	0.08	0.27	0.00	0.00	0.00	0.00	1.00
mortality	2527	62.19	36.80	7.89	29.22	54.79	93.33	154.34
colony	2603	0.05	0.21	0.00	0.00	0.00	0.00	1.00
US influence	2603	0.01	0.12	0.00	0.00	0.00	0.00	1.00
JP influence	2603	0.01	0.11	0.00	0.00	0.00	0.00	1.00
EU influence	2603	0.21	0.65	0.00	0.00	0.00	0.00	11.00
trade	2375	0.14	0.43	0.00	0.00	0.02	0.09	8.39
milit. G	2033	2.55	2.24	0.00	1.18	1.95	3.18	13.64
milit. trade	2412	0.75	3.59	0.00	0.00	0.00	0.01	92.86
mult. ODA	2603	0.62	0.99	0.00	0.07	0.32	0.84	8.46

Table S2: Summary statistics of the variables (in levels) used in the logit regression models. See Appendix S2 for the definition of the variables. The variables are: population size (pop.), per-capita consumption (consump.), institution quality dummy (democr.), involvement in internal (int.) and external (ext.) conflict, mortality rate, former colonial status (colony), regional influence dummies for US/Japan/Europe (US/JP/EU influence), bilateral trade (trade), bilateral military trade (milit. trade), government military expenditure (milit. G), multilateral aid (mult. ODA).

and a recipient divided by the sum of total imports and exports of the donor in each period of the sample. The final transformation is the average over the sample of this ratio variable. As a second version of this variable, we construct the ratio of bilateral trade to donors' GDP, where the GDP series are obtained from the OECD online Database (http://stats.oecd.org/ with identifier B1_GE). These are bilateral variables and they are defined only at the donor-recipient pair level. The two versions of the trade variable perform almost equivalently in the logit regression, so we keep the first definition in the baseline specifications of the model. The partitioned version of this variable for first and second half of the time sample is constructed as the average of the ratio before and after 1990 respectively. The variable is expressed in percentage terms.

Military Expenditure: We obtain data about military expenditure from The Stockholm International Peace Research Institute (SIPRI) Military Expenditure Database 2014, available at http://milexdata.sipri.org. Data is provided in constant 2011 US dollars for the sample $1988-2013$; this sample and the main sample of our estimates, which ends in 2010, do not perfectly overlap, but this is the best source available for this variable. However, we include only the observations until 2010. The variable is computed as the average over time of the recipient's expenditure series.

Military Trade: We obtain data about the volume of arms exports from a donor country to the recipient set from the SIPRI Arms Transfers Database (2013 update). Data is reported in millions of SIPRI trend indicator values (TIV) and cover deliveries of major conventional weapons, as defined by SIPRI, from 1970 to 2012. For this variable, it is possible to cover the entire sample of the main model and, consistently with military expenditure, we keep the data up to the 2010 observation. By definition, this is a bilateral variable and it is defined only at the donor-recipient pair level. It is aggregate over time taking the sum of total volume of exports in the sample.

Multilateral ODA: This series is constructed as the share of total ODA disbursed by multilateral agencies to a recipient country. The series is then averaged over the sample $1975-2010$. The data is obtained from the OECD International Development Statistics online dataset and is expressed in percentage terms.

S3 Some Bias Computation for the Altruism Function

The *countercyclical-altruism* test in the paper is robust to estimation bias in the empirical model due to time-invariant omitted control variables in equations (18) and (19), but not for time-varying control factors, under a fairly general class of functional forms for the components of the utility function (A3). Consistently with the form chosen for the total utility, we show this point for a multiplicative case in which a function of the control variables is allowed to directly affect the slope of the altruism component $\delta_r(\cdot)$ in (A5). Let us modify $\delta_r(\cdot)$ for recipient r as follows

$$\delta_r(a_r; X_{\delta r}) = \delta_r(a_r) f(X_{\delta r}) \tag{S1}$$

where $X_{\delta r}$ is a vector of relevant factors for the altruism component. In the first order condition for the optimal decision of a_r^*, this term becomes

$$\delta_{r,a}(a_r; X_{\delta r}) = \delta_{r,a}(a_r) f(X_{\delta r})$$

When the first order condition is linearized, a further term in $X_{\delta r}$ appears in the first order expansion of of $\delta_{r,a}$ now

$$\delta_{r,a}(0) f(X_0) + \delta_{r,aa}(0) f(X_0) a_r + \delta_{r,a}(0) \nabla f(X_0)(X_{\delta r} - X_0)$$

in which $\nabla f(X_0)$ is the gradient of f evaluated at the reference point X_0. This equation justifies the empirical specification of equations (18) and (19) adopted for the estimation stage of the model.

For instance, using our baseline functional form we would have

$$\begin{aligned}
\mathbb{D}_r(a_r; X_{\delta r}) &= \left(\frac{c_{r,0} + a_r}{c_{r,0}}\right)^{f(X_{\delta r})\delta_{r,0}} \\
\delta_r(a_r; X_{\delta r}) &= f(X_{\delta r})\,\delta_{r,0}\left[\log(c_{r,0} + a_r) - \log c_{r,0}\right]
\end{aligned}$$

and a linearized term given by

$$f\left(X_0\right)\delta_{r,0}c_{r,0}^{-1}-f\left(X_0\right)\delta_0 c_{r,0}^{-2}a_r+\delta_{r,0}\nabla f\left(X_0\right)c_{r,0}^{-1}\left(X_{\delta r}-X_0\right)$$

or equivalently

$$f\left(X_0\right)\delta_{r,0}c_{r,0}^{-1}\left(1-c_{r,0}^{-1}a_r\right)+\delta_{r,0}\nabla f\left(X_0\right)c_{r,0}^{-1}\left(X_{\delta r}-X_0\right)$$

As explained in the main text of the paper, the curvature coefficient of the altruism function we estimate, $\delta_{r,0}$ in (18), is actually multiplied by the reference value of the shifting function $f\left(X_0\right)$, which is constant. In our econometric model, the vector of controls Z is used as empirical counterpart of $c_{r,0}^{-1}\left(X_{\delta r}-X_0\right)$ and the attached vector of coefficients γ_0 is equivalent to $\delta_{r,0}\nabla f\left(X_0\right)$. It is clear that neglecting the control variables would introduce a bias in the estimation of the altruism parameter due to the misspecification of the model despite the controls being constant or not. However, the constant factor $f\left(X_0\right)$ does not affect the outcome of the *countercyclical-altruism* test because it is conveniently absorbed by the difference between $\delta_{r,0}$ an $\delta_{r,0^*}$. In order to see this point, let us compare the correct regression equations for $\delta_{r,0}$ and $\delta_{r,0^*}$ when the functional form (S1) is assumed in addition to those used in the baseline theory of the paper to estimate the model. The correct equation for $\delta_{r,0}$ is

$$\begin{aligned} c_{-r,0}^{-1}\left(1+c_{-r,0}^{-1}a_r^*\right) &= \rho_{r,0}\left(1-a_r^*\right)+f\left(X_0\right)\delta_{r,0}c_{r,0}^{-1}\left(1-c_{r,0}^{-1}a_r\right) \\ &\quad +\delta_{r,0}\nabla f\left(X_0\right)c_{r,0}^{-1}\left(X_{\delta r}-X_0\right) \end{aligned}$$

while for $\delta_{r,0^*}$ we have

$$c_{-r,0}^{-1}=\rho_{r,0^*}+\delta_{r,0^*}f\left(X_0\right)c_{r,0}^{-1}+\delta_{r,0^*}\nabla f\left(X_0\right)c_{r,0}^{-1}\left(X_{\delta r}-X_0\right)$$

The only difference between these last two equations and the two equations we estimate is given by the term $f\left(X_0\right)$ that multiplies $\delta_{r,0}$ and $\delta_{r,0^*}$; the estimates we obtain, although biased, are affected in the same way by the misspecification of the regression equations. In practice, the test condition used in the paper would be equivalent to

$$\beta_r f\left(X_0\right)\left(\delta_{r,0}-\delta_{r,1}\right)>0$$

which would give the same results as long as $f\left(X_0\right)$ is positive. Given the definition of $\delta_r\left(a_r;X_{\delta r}\right)$ in (S1), it is very plausible to assume $f\left(X_0\right)>0$. If all the controls are constant, the term $\left(X-X_0\right)$ would drop off the regression equations and the shifting factors would completely be irrelevant. On the other hand, when the controls are not constant, the estimation bias would affect the two parameters in different ways and the test condition would be affected. It is possible to impose some very restrictive assumptions that would rule this possibility out, but these conditions seem very unreasonable. Considering the difference between $\delta_{r,0}$ and $\delta_{r,0^*}$ should attenuate this bias but it would not completely eliminate it. However, it must be noticed that the majority of the controls usually used in panel studies of the allocation of ODA in the empirical literature are actually constant or they change very slowly over time. This is the case, for instance, of religion correspondence between donor and recipient, colonial relationship, corruption indices, or relative population size of the recipient. Therefore, we believe our methodology is well equipped to tackle all these sources of possible bias in the estimation.

Similar conclusions about $\rho_{r,0}$ (and $\rho_{r,0^*}$) can be obtained when the factors affecting $\rho_r(\cdot)$ are explicitly considered as well. However, the bias in $\rho_{r,0}$ is not relevant for the test. Also, if any of the shifting factors in $X_{\rho r}$ affected the estimates of $\delta_{r,0}$ (and $\delta_{r,0^*}$), it would have to be included in $X_{\delta r}$ too. Finally, this discussion also explains why the standardization by σ in equations (18) and (19) of the model does not influence the altruism results; σ would just work as any other constant re-scaling factor in $f(X_0)$.