A Signal of Altruistic Motivation for Foreign Aid: A Theoretical Model and Empirical Test*

Andrea Civelli — *University of Arkansas*

Andrew W. Horowitz — *University of Arkansas*

Arilton Teixeira — *FUCAPE Business School*

Abstract

We develop a theoretical model showing that countercyclical transfers from a wealthy donor to a poorer recipient generate a signal of altruistic donor motivation. Using 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 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. These results contribute to understanding, and control for, endogeneity in the distribution of ODA.

JEL Codes: F35, F34, O47, O11, O19

Keywords: Foreign Aid, Donor Motivation, Bilateral Aid, Altruism

*We thank Christopher Kilby, Eric Bond, Stephen Smith, James Foster, Jon Rothbaum, Benedikt Rydzek, and other seminar participants at Vanderbilt University, George Washington University, Villanova University, the *34th* Annual Econometric Society Meetings in Brazil, the 9th Annual Conference on Economic Growth and Development at Indian Statistical Institute, LuBra-Macro Conference in Recife, and the XIV AEEFI Conference on International Economics for insightful comments and suggestions. We also thank Aaron Johnson and Hongwei Song for research assistance. Arilton Teixeira thanks CNPq (Brazilian National Research Council) for financial support. The usual disclaimers apply.

Andrea Civelli: Economics Department, University of Arkansas, Fayetteville (AR), andrea.civelli@gmail.com. Andrew Horowitz: Economics Department, University of Arkansas, horowitz@uark.edu. Arilton Teixeira: FUCAPE Business School, Victoria (Brazil), arilton@fucape.br

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 et al., 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 test for the presence, and/or to estimate the weight, of two broad categories of donor motive: self-interest and altruism (Section 2 reviews the literature). Though much progress has been made in motive measurement, no general consensus exists on the weighting of these broad categories, their sub-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 endeavors to contribute to the understanding and measurement of donor motive with an alternative approach to motive identification. We develop a simple donor optimization model that allows any mixture of weight on self-interest and altruism motives. The solution to the optimization problem itself generates a signal of altruistic motive above an identified threshold. The signal is associated with a countercyclical transfer pattern and we find it present empirically in seventeen percent of donor-recipient pairs. External validation exercises are consistent with meaningful external validity.

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 the question, we will 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 will 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 find that countercyclical altruism is more likely to be observed the poorer and smaller the recipient, the better the recipient's institutions, and in the presence of a colonial link between the donor and recipient. The likelihood of the signal is independent of trade or military relations between donor and recipient – all characteristics consistent with the 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.[1] In the second out-of-model exercise we embed the partition of donors generated by our signal in adaptations of two of the most highly cited ODA-growth regressions analyses (Rajan and Subramanian 2008 and Clemems et al. 2012). 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 long-run effect on recipient growth than aid from donors without the signal. Furthermore, the estimates of the contemporaneous effects of the altruistic donors' ODA display strong evidence of reverse causation bias, which is not found for the non-signal-bearing group.

The remainder of the paper is organized as follows: Section 2 provides a review of the literature and additional background material. Section 3 develops our theoretical model of bilateral ODA that yields a testable empirical condition for altruistic motivation. Section 4 provides our empirical results. Section 5 contains our external validity exercises. Section 6 presents robustness exercises. Section 7 summarizes and suggests future extensions. Appendices address details of 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 first provide an overview of the motives literature and how this paper endeavors to contribute. We then provide very brief reviews of three related topics: ODA and growth, ODA and business cycles, and the Commitment to Development Index. For those desiring a broader introduction to the topic of foreign aid, Temple (2010) provides a broad survey and assessment while Addison and Tarp (2014) provide an overview of ten recent papers on a variety of themes.

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

[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.

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), 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. McKinlay 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's (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's (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 of recipient merit is representative of a growing trend in the literature during this period (Burnside and Dollar 2000 were seminal in this regard). 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 that 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; Schrader, Hook, and Taylor 1998; de Mesquite 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, and a theoretical understanding of the properties of measures seems a natural next step for the motive literature. This is a principal objective of this paper.

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 et al. (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 relative to both donor and recipient. Arellano et al. (2009) examine the effects of aid volatility on poor African countries, finding aid volatility has significant negative welfare effects on

[2] Werker et al. (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.

recipients. Bulir and Hamaan (2008) develop new measures of aid volatility and argue effective procyclical volatility has complicated macro policy for recipients. Pallage, Robe, and Bérubé (2006) 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 et al. (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.

3 The Model

In this section we develop a theoretical model that generates a distinguishing empirical signal for altruistic relationships among specific donor-recipient pairs.

3.1 Theoretical Framework and Optimal ODA Decision

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.[4] We first solve the problem of disbursement to a single

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

[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

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

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

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

$$\sum_{r=1}^{N_R} A_s \leqslant C_{d,0} \tag{2}$$

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

$$\mathbb{W}(A) = \mathbb{U}(C_d)\,\mathbb{G}(A) \tag{3}$$

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

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

this paper and strategic disbursement.

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.[5] It is reasonable to assume that there is no gain from either component if no ODA donation is made to a recipient. Therefore $\mathbb{G}_r(0) = \mathbb{R}_r(0) = \mathbb{D}_r(0) = 1$. Note that this specification allows a donor to be motivated by pure self-interest, pure altruism, or any combination of the two. This type of utility decomposition is similar in spirit to that introduced by Andreoni (1989 and 1990) in the charitable donations literature and it has also been used in charitable auction theory (see, for instance, Engers and McManus 2001) and in previous work in the ODA literature (as in Chong and Gradstein 2008).[6]

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:

$$C_r = C_{r,0} + A_r \tag{4}$$

Equation (4) makes explicit the relationship between $\mathbb{D}_r(A_r; X_{\delta r})$ and recipient consumption, C_r, for given

[5] Let $\mathbb{U}_r(C_r)$ indicate the recipient's own-consumption utility with C_r a function of A_r (see 4). 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 $\mathbb{D}''_r \propto \mathbb{U}''_r$.

[6] 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.

$C_{r,0}$ 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 (2) 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 (2), 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. Finally, we modify the utility function with two simplification 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.[7] We can now re-write the utility function (3) after substituting for constraint (1) as

$$w(a) = u\left(c_{d,0} - \sum_r a_r\right) + \sum_r \rho_r(a_r; X_{\rho r}) + \sum_r \delta_r(a_r; X_{\delta r}) \tag{5}$$

where, in order to simplify notation, let $z = Z \,/\, \bar{Y}$ be variable Z normalized by 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

$$-u_c(c_{d,r_0} - a_r) + \rho_{r,a}(a_r; X_{\rho r}) + \delta_{r,a}(a_r; X_{\delta r}) = 0 \tag{6}$$

where $c_{d,r_0} = c_{d,0} - \sum_{j \neq r} a_j$. That is, c_{d,r_0} is donor consumption *before* donation to recipient r. Since we are interested in the solution for small positive a_r, we take a first order approximation of (6) around $a_r = 0$

$$-\bar{u}_c + \bar{u}_{cc} a_r + \bar{\rho}_{r,a} + \bar{\rho}_{r,aa} a_r + \bar{\delta}_{r,a} + \bar{\delta}_{r,aa} a_r = 0 \tag{7}$$

in which, in order to simplify notation, we denote the derivatives of the three components in (6) evaluated

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

at $a_r = 0$ with over-bars.[8] The corresponding optimal ODA is

$$a_r^* = \frac{\bar{u}_c - \bar{\rho}_{r,a} - \bar{\delta}_{r,a}}{\bar{u}_{cc} + \bar{\rho}_{r,aa} + \bar{\delta}_{r,aa}} \tag{8}$$

The solution a_r^* has a very clear interpretation. Since the second order derivatives evaluated at zero ODA are all negative, the denominator of (8) is negative. In order to have $a_r^* > 0$ as solution, the numerator of (8) needs to be negative too. The necessary condition for positive ODA is then

$$\bar{u}_c < \bar{\rho}_{r,a} + \bar{\delta}_{r,a} \tag{9}$$

that is, the marginal gain of setting a positive ODA must overcome the marginal loss due to the fall in the donor's own consumption. If condition (9) is not satisfied, then $a_r = 0$ and we have a "corner" solution.

3.2 Counter-cyclical ODA and Altruism Condition

In this section we show that in our framework sufficiently strong counter-cyclical ODA can serve as a signal of altruism above a threshold level, which we will call ***countercyclical-altruism***.[9] To this end we first postulate the following reduced-form relationship between donor's and recipient's incomes

$$y_r = \beta_0 + \beta_r y_d + \varphi X + \varepsilon \tag{10}$$

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 (10), β_0 is a constant and X can be thought of at this stage as embodying other relevant determinants of the recipient's income. Finally, ε is an i.i.d. residual with mean zero. It is not necessary to impose any restrictions on β_r so that the income of donor and recipient may be correlated positively, negatively, or not at all. 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 their trade mix.

We now compute the derivative $da_r^* \,/\, dy_d$ starting from (8). Using the fact that $\rho_r(\cdot)$ does not depend

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

[9] 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.

on donor's income, the definition of y_r in (10), and again the optimal solution for a_r^*, we obtain[10]

$$\frac{da_r^*}{dy} = \frac{\bar{u}_{cc} - \beta_r \bar{\delta}_{r,ac} - \left(\bar{u}_{ccc} + \beta_r \bar{\delta}_{r,aac}\right) a_r^*}{\bar{u}_{cc} + \bar{\rho}_{r,aa} + \bar{\delta}_{r,aa}} \tag{11}$$

The concept of counter-cyclical ODA in our model is associated with a negative derivative in (11). Being the denominator of this ratio 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 (11); for the determination of the sign of the derivative we can therefore focus only on

$$\bar{u}_{cc} - \beta_r \bar{\delta}_{r,ac} > 0 \tag{12}$$

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

$$\frac{\beta_r \bar{\delta}_{r,ac}}{\bar{u}_{cc}} > 1 \tag{13}$$

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 (13) can be satisfied only when β_r is positive too. For a given $\beta_r > 0$ and $\bar{u}_{cc} < 0$, condition (13) 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 (13) 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.[11] 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 3.3 below, the threshold altruism level of (13) will be embodied in a positive altruism parameter. This parameter threshold (13) 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 counter-cyclical ODA. In summary, *countercyclical-altruism* occurs when voluntary transfers from a richer to a poorer agent move inversely with changes in both agents' income.

[10] 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 (11).

[11] 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.

3.3 Empirical Strategy

Empirical evaluation of condition (12), requires specification of functional forms for $\mathbb{U}$, $\mathbb{R}_r$, and $\mathbb{D}_r$. As a baseline case we choose a very general power function for each of these components. We check the robustness of our results for different type of functional form specifications 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 $\mathbb{U}(c_d) = (c_{d,r_0} - a_r)^{\sigma}$.

On the other hand, aside from the natural concavity property in return functions, there is little precedent for selecting specific functional forms for $\mathbb{R}_r(\cdot)$ and $\mathbb{D}_r(\cdot)$. In the interest of simplicity, we adopt a power function for these two new components as well. Specifically, $\mathbb{R}_r(a_r; X_{\rho r}) = (1 + a_r)^{\rho_{r,0}}$ 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, $\mathbb{D}_r(a_r; X_{\delta r}) = \left(\frac{c_{r,0}+a_r}{c_{r,0}}\right)^{\delta_{r,0}}$ where $\delta_{r,0}$ expresses the degree of altruism of the donor toward recipient r.[12,13]

Adopting these functional forms, the first order condition (7) 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

$$\sigma c_{d,r_0}^{-1}\left(1 + c_{d,r_0}^{-1} a_r^*\right) = \rho_{r,0}\left(1 - a_r^*\right) + \delta_{r,0} c_{r,0}^{-1}\left(1 - c_{r,0}^{-1} a_r^*\right) \tag{14}$$

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 Section 4.2 and in the online Appendix S2, 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

[12] 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.

[13] The equivalent log-additive versions of the utility components are:

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

The expressions for $\rho_r(\cdot)$ and $\delta(\cdot)_r$, as well as those for $\mathbb{R}_r(\cdot)$ and $\mathbb{D}_r(\cdot)$ above, omit the set of "shifter" variables for notational simplicity. 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.[14]

Under the assumed functional forms, condition (13) becomes

$$\frac{\beta_r \delta_{r,0} c_{r,0}^{-2}}{\sigma c_{d,r_0}^{-2}} > 1 \tag{15}$$

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 (15) can be reduced to the following condition on $\delta_{r,0}$:

$$\delta_{r,0} > \frac{\sigma c_{r,0}^2}{\beta_r c_{d,r_0}^2} \tag{16}$$

That is, the altruism parameter must exceed a threshold level to satisfy the countercyclical-altruism condition. Inequality (16) is the function specific analog to the theoretical condition (13). 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 (15), 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 (9), the donor sets a positive ODA only if $\sigma c_{d,r_0}^{-1} - \rho_{r,0} - \delta_{r,0} c_{r,0}^{-1} < 0$.

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

$$\sigma c_{d,r_0}^{-1} = \rho_{r,0^*} + \delta_{r,0^*} c_{r,0}^{-1} \tag{17}$$

[14] Additional estimation issues concern the specific functional forms chosen. The left hand side of condition (13) 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.

Taking the differential of (17) with respect to y_d gives

$$\sigma c_{d,r_0}^{-2} = \beta_r \delta_{r,0^*} c_{r,0}^{-2} \tag{18}$$

Finally, combining (15) and (18), we obtain the countercyclical-altruism condition for a negative $da_r^* \,/\, dy_d$

$$\beta_r \left(\delta_{r,0} - \delta_{r,0^*}\right) > 0 \tag{19}$$

We can obtain an estimate of $\delta_{r,0^*}$ (along with $\rho_{r,0^*}$) from (17) and compare it to the estimate of $\delta_{r,0}$ from (14) in order to evaluate the condition in (19). The threat of potential bias in the estimates of $\delta_{r,0}$ and $\delta_{r,0^*}$ is reduced in evaluating (19), 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 this appealing version of the countercyclical-altruism condition.

Condition (19) is satisfied when the difference between the two parameters is larger than zero and $\beta_r > 0$

$$\beta_r \left(\delta_{r,0} - \delta_{r,0^*}\right) > 0 \text{ and } \beta_r > 0, \left(\delta_{r,0} - \delta_{r,0^*}\right) > 0 \tag{20}$$

as well as in a second case when

$$\beta_r \left(\delta_{r,0} - \delta_{r,0^*}\right) > 0 \text{ and } \beta_r < 0, \left(\delta_{r,0} - \delta_{r,0^*}\right) < 0 \tag{21}$$

The actual *countercyclical-altruism* donor-recipients pairs are identified only by the conditions in (20) because it corresponds to the case in which the altruism parameter $\delta_{r,0}$ is bigger than the minimum degree of altruism found in (17) 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 (17) 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 (17) 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 $\left(\rho_{r,0^*} \;\; \delta_{r,0^*}\right)$ from (17) 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 $\left(\delta_{r,0} - \delta_{r,0^*}\right) < 0$ 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.

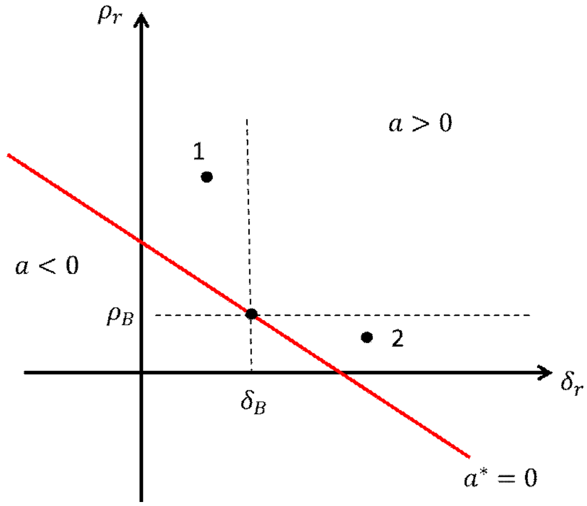

Figure 1: ODA decision and the *countercyclical-altruism* condition. Graphical interpretation of the ODA decision and of the *countercyclical-altruism* condition. The estimates of $(\rho_{r,0^*} \quad \delta_{r,0^*})$ from (17) are $(\rho_B,\ \delta_B)$. The *countercyclical-altruism* condition could be satisfied at point 2 but not point 1 when $\beta_r > 0$.

4 Empirical Estimation

4.1 ODA Accounting and Data

Letting A be total ODA donations, the donor's resource constraint (1) 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.[15] Appendix A lists the 156 countries in our sample. All analysis utilizes 2005 International Dollars per person – the reporting basis

[15] 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.

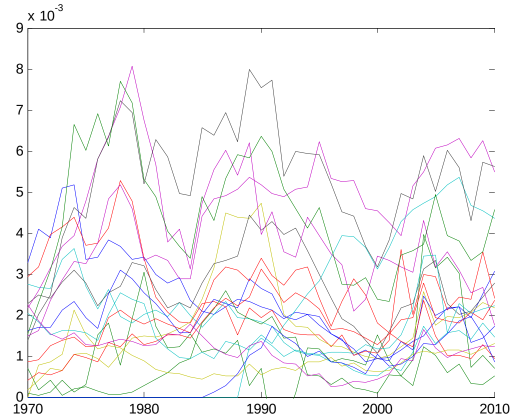

Figure 2: Total ODA Disbursements as a ratio of GDP for the 19 DAC Donors - Sample 1970 – 2010. Each color represents a unique donor.

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 2 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, as explained in the next subsection, 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).[16]

Figure 3 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 3 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

[16]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.

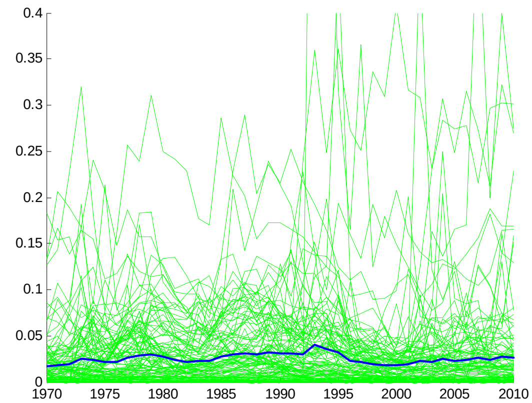

Figure 3: Total ODA Disbursements as a ratio of GDP for all recipients - Sample $1970 - 2010$. Each green line represents one of the recipients. The dark line is the mean ODA across recipients

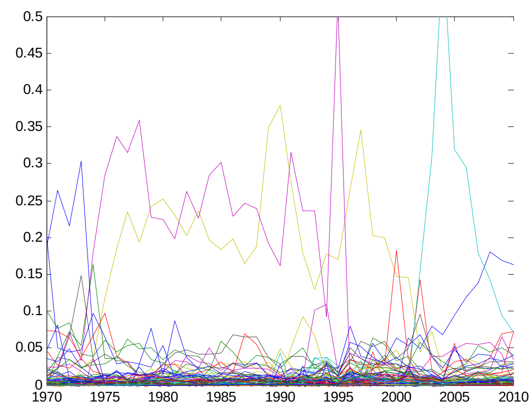

Figure 4: Shares of US ODA disbursements by recipient from 1970 to 2010. Each line represents a unique recipient.

ODA, while the 10 largest US recipients together receive on average 53% of total US ODA disbursements. US ODA disbursements are presented in Figure 4.

4.2 Estimation

We now test whether the *countercyclical-altruism* signal from the theoretical model, inequality (19), 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 (equation 10); the first order condition of the donor's optimization problem (equation 14); and the condition for zero ODA (equation 17). 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

$$y_{r,t} = \beta_0 + \varphi_r y_{r,t-1} + \beta_r y_{d,t} + \varepsilon_{1,t} \tag{22}$$

$$\underbrace{c_{d,r_0}^{-1}\left(1 + c_{d,r_0}^{-1} a_r^*\right)}_{y_{1,t}} = \rho_{r,0}\underbrace{(1 - a_r^*)}_{x_{1,t}} + \delta_{r,0}\underbrace{c_{r,0}^{-1}\left(1 - c_{r,0}^{-1} a_r^*\right)}_{x_{2,t}} + \gamma_0' Z_t + \varepsilon_{2,t} \tag{23}$$

$$\underbrace{c_{d,r_0}^{-1}}_{y_{2,t}} = \rho_{r,0^*} + \delta_{r,0^*}\underbrace{c_{r,0}^{-1}}_{x_{3,t}} + \gamma_{0^*}' Z_t + \varepsilon_{3,t} \tag{24}$$

where $\varepsilon_{i,t}$ for $i = 1, 2, 3$ are standard residual terms. Equation (22) modifies (10) by introducing an auto-regressive term. This is a simple way to capture idiosyncratic structural characteristics and business cycle determinants. An alternative specification might include variables such as population change, trade dynamics, government characteristics, and other factors implicit in the auto-regressive term. Equations (14) and (17) are normalized by σ in equations (23) and (24). This normalization makes the estimation independent of the curvature of $\mathbb{U}(\cdot)$ without affecting the significance of the altruism signal. Moreover, the four parameters $\left[\rho_{r.0}\ \delta_{r,0}\ \rho_{r,0^*}\ \delta_{r,0^*}\right]$ in (23) and (24) 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 S2 shows that, for fairly general representations of the effects of time-invariant shifters, the altruism signal in (19) remains valid. Finally, we introduce an identical vector of (time-varying) control variables, Z_t, in both (23) and (24). 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.[17]

Equations (22)-(24) 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.[18] The full vector of estimated parameters is $\theta = \left[\beta_0\ \varphi_r\ \beta_r\ \rho_{r,0}\ \delta_{r,0}\ \rho_{r,0^*}\ \delta_{r,0^*}\ \gamma_0'\ \gamma_{0^*}'\right]'$. We rely on the asymptotic properties of the GMM estimator to conduct the *countercyclical-altruism* test on inequality 19. 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

[17] 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.

[18] 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.

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.[19]

One estimation issue is that, for some pairs, it may be difficult to distinguish equation (23) and (24) 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 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 paper. Finally, the sample used for estimation includes 35 observations from 1976 to 2010 for our 2603 pairs.

4.3 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

[19]More formally, the asymptotic distribution of $\hat{\theta}$ is $\sqrt{T}\left(\hat{\theta}-\theta\right)\rightarrow N(0,V)$, 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, the asymptotic distribution of $\hat{\beta}_r\left(\hat{\delta}_{r,0}-\hat{\delta}_{r,0^*}\right)$ is approximated by

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

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 $\hat{\theta}$

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

in which 0_z is a row vector with length equal to twice the number of controls included in the regression equations (23) and (24).

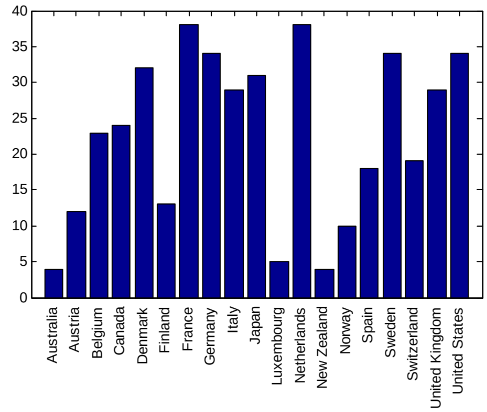

Figure 5: Number of significant pairs that satisfy the *countercyclica-altruism* condition by donor.

idiosyncratic altruistic motivation among specific donor-recipient pairs, but to theoretically 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 approximately 17% of the pairs satisfy the *countercyclical-altruism* condition at the five percent confidence level with positive β_r. There are an additional 7% of the pairs that pass condition (21) with a negative β_r. The total share displaying the negative $da_r^* \,/\, dy_d$ signal is then 24%. Hence, although the altruism signal is not present in the large majority of ODA transfers, neither is it insignificant. Figure 5 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 22.5 per donor. The complete list of specific pairs in Figure 5 is reported in Table S1 of Appendix S1 in the online Supplementary Material.

An interesting interpretation of Figure 5 is as the extensive margin of donor altruism. In this Figure, we are counting the number of recipients that cross the threshold for each 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, Netherlands, and Denmark are ranked as top-five donors (among 27) in both the Overall and Aid dimensions of CDI. Similarly, these countries rank in the top six 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

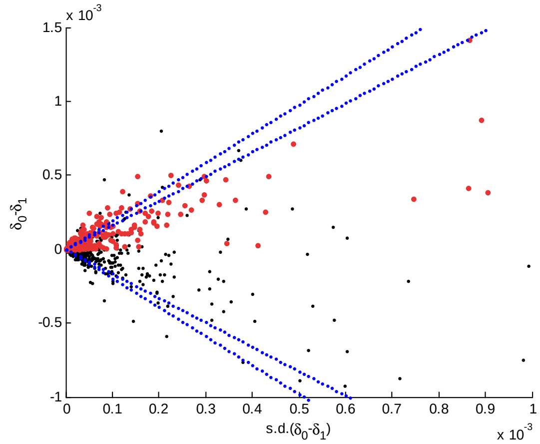

Figure 6: Point estimates of the difference $\delta_{r,0} - \delta_{r,0^*}$. Red dots identify pairs that satisfy the *countercyclical-altruism* condition (20). In black is the complement set of country pairs. Parameters significance is indicated by blue dotted lines. External lines are the 5% significance thresholds Internal lines are the 10% level.

most CDI dimensions, display a relatively small numbers of countercyclical-altruistic relationships in our model.[20] Larger economies, such as Germany, France, and the US, tend to have rank higher in countercyclical 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 6 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 (20) 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 $\rho_{r,0}$.

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 (20) 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 7 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 $\left(\rho_{r,0} - \rho_{r,0^*}\right)$ for all donor-recipient pairs. This is analogous to drawing Figure 1 after re-centering the axis on $(\rho_B \;\; \delta_B)$. The theoretical intuition represented in Figure 1 is that the majority of the *countercyclical-altruism* pairs should

[20]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.

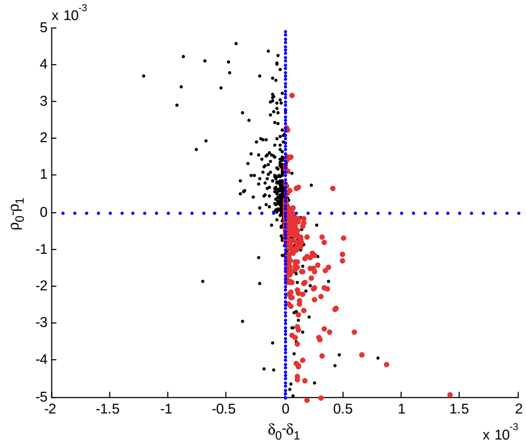

Figure 7: Bridging empirical results and the model - empirical counterpart of Figure 1. Plot of $(\delta_{r,0} - \delta_{r,0^*})$ versus $\left(\rho_{r,0} - \rho_{r,0^*}\right)$. Red dots identify pairs that satisfy the *countercyclical-altruism* condition (20). All others in black.

be found in the south-east quadrant of Figure 7 and this is indeed the case below. Figure 7 also illustrates that counter-cyclical ODA can occur when $\left(\rho_{r,0} - \rho_{r,0^*}\right)$ is positive. We see some such pairs in Figure 7 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. Equation (18) shows 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 $\mathbb{U}(\cdot)$ 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 insights on this mechanism can be seen in Figure 8. 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 exer-

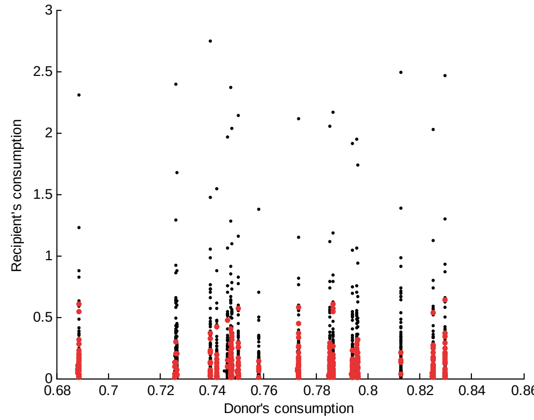

Figure 8: Donor-recipient relative consumption levels and the countercyclica-altruism decision. Recipient's consumption $c_{r,0}$ versus donor's consumption c_{d,r_0}. Red points correspond to the pairs significantly satisfying the countercyclical-altruism condition.

cise, 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 two seminal ODA-growth regressions 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), and care more about the long run effectiveness of their aid relative to non-countercyclical altruists. All else equal, colonial linkage is important, but 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 for example, Berthélemy 2008 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 can be used as the dependent variable in a cross section logit regression. Many of the explanatory variables are traditionally associated with either humanitarian or commercial incentives to provide aid. These categories should map fairly closely to the altruistic and self-interest motivations of our theoretical model. As such, we expect the humanitarian variables to be significant in the logit if countercyclical-altruism is capturing the more generic notion of altruism. On the other hand, to the extent the commercial variables correspond to our "self-interest," we expect them to be insignificant or negatively associated with signal-significance in our logit.

The explanatory variables are transformed to capture the average attributes of a donor-recipient pair over the sample of the signal estimation, since the preferences of the donor are assumed to be fixed. The results reported in Table 1 are based on independent variables expressed in relative donor-recipient terms. Variables in relative terms are preferred because they provide more variability over the unit of analysis of the cross-section logit regression. We obtain very similar estimates using variables in absolute terms for the recipients as shown in Appendix C. Hence, Table 1 results are quite robust. The humanitarian/altruistic determinants should include per-capita consumption, the mortality rate or life expectancy, institutional quality, and the inflation rate. Also arguably associated with humanitarian/altruistic motivation is population size. Military expenditure could be fit in either (or neither) category, depending on the context of the expenditures and bilateral relations. The clear commercial/self-interest variables are bilateral trade and bilateral military trade (e.g., Berthélemy 2008 proxies selfish ODA motivations by trade). We also include 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. Finally, a dummy variable indicates a former colony. 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. Theoretically, both of these map to altruism since they express donor care for recipient utility. A positive association between colonial linkage and signal significance should therefore be interpreted as evidence of a correspondence between the signal and more generic altruism. For sake of brevity in the exposition, a detailed description of the data sources, samples, and manipulations is left for Appendix C.[21]

Columns (a) and (e) of Table 1 capture the effect on signal-significance of some variables traditionally related to humanitarian/altruistic motivations. Most estimates are very stable across different specifications. In particular, relative consumption per-capita is very stable and powerfully significant across virtually all specifications (p-values are reported in parentheses). To interpret these results note that, since these are odds ratios, an estimate greater than 1 indicates that signal-significance is more likely when the explana-

[21] For each variable, we try to match as closely as possible the estimation sample of the signaling model. When not possible, we usually adopt the largest available sample.

The determinants in relative terms are constructed either as ratios of the country-level variables (for population, consumption per capita, life expectancy, mortality rate, and military expenditures) or as the difference between the country-level variables (for institutions quality and inflation). Former colonial status, ODA from other donors, and military trade are defined only at the donor-recipient pair level. Multilateral ODA is clearly defined only at the recipient level. Finally, bilateral trade is defined as the sum of imports and exports between a donor and a recipient divided by the sum of total imports and exports of the donor. This variable is defined only at the donor-recipient level, and for two different sources.

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	$(h)^1$	(i)	(j)	(k)	(l)	$(m)^2$	$(n)^3$
consumption	**.16** (.00)	**.14** (.00)	**.11** (.00)	**.14** (.00)	**.17** (.00)	**.14** (.00)	**.14** (.00)	**.1** (.00)	**.14** (.00)	**.11** (.00)	**.15** (.00)	**.17** (.00)	**.13** (.06)	**.19** (.03)
population	**.98** (.01)	**.98** (.02)	**.98** (.01)	**.97** (.00)	**.97** (.01)	**.98** (.02)	**.98** (.02)	**.98** (.01)	**.98** (.02)	**.98** (.02)	**.97** (.00)	**.98** (.00)	**.95** (.00)	**.98** (.03)
institutions	**1.34** (.00)	**1.27** (.01)	**1.52** (.00)	**1.30** (.00)	**1.49** (.00)	**1.24** (.02)	**1.24** (.02)	**1.35** (.00)	**1.22** (.03)	**.49** (.00)	**1.25** (.02)	**1.45** (.02)	**1.67** (.00)	**1.84** (.00)
mortality	**1.05** (.00)													
life expect.		**.30** (.04)	.49 (.25)	**.22** (.01)	.66 (.55)	**.32** (.05)	**.33** (.06)	.58 (.36)	**.33** (.07)	.53 (.31)	**.27** (.05)	.76 (.70)	1.54 (.71)	.27 (.18)
inflation			.63 (.40)		.68 (.49)					.60 (.37)		.67 (.47)	.86 (.97)	.69 (.93)
military exp.			.93 (.75)		.74 (.25)					.74 (.25)		.82 (.50)	.55 (.25)	.71 (.34)
colony						2.60 (.00)	**2.60** (.00)	**2.20** (.00)	**2.61** (.00)	**2.24** (.00)	**2.50** (.00)	**2.22** (.00)	**1.86** (.04)	**1.91** (.02)
trade							.96 (.71)	1 (.67)	.96 (.72)	.91 (.52)	.95 (.65)	.96 (.79)	1.11 (.47)	.91 (.60)
military trade									1 (.85)	1 (.58)	1 (.50)	1 (.52)	1 (.37)	1 (.40)
multilateral ODA				**1.21** (.00)	**1.20** (.01)						**1.23** (.00)	**1.20** (.01)	**1.39** (.00)	**1.15** (.05)
other ODA				**.001** (.01)	2.82 (.74)						**.004** (.03)	7.53 (.51)	.44 (.91)	**.00** (.05)
Obs	2527	2584	2071	2584	2071	2584	2563	2242	2507	2062	2507	2062	1020	1247
Pseudo R^2	.04	.04	.04	.05	.04	.05	.05	.05	.05	.05	.05	.05	.05	.04

Table 1: Logit model for the altruism signal - Odds Ratios. The dependent variable is our countercyclical-altruism binary signal from the baseline estimation model. The independent variables are expressed in relative terms either as recipient to donor ratios of the country-level variables for population, consumption per capita (consumption), mortality, life expectancy (life expect.), and military expenditures (military exp.) or as the difference between recipient and donor country-level variables for institutions quality (institutions) and inflation. Colony, trade, military trade, multilateral ODA, and other ODA respectively correspond to the former colonial status dummy, bilateral trade, military trade, multilateral ODA, and ODA from other donors. These are defined at the donor-recipient level with exception of multilateral ODA, which is defined only at the recipient level. Bilateral trade is defined from two different sources. More details about the definition and the sources of the variables are provided in Appendix C. P-values are reported in parentheses. 1) in column (h) the second definition of the trade variable is used (see Appendix C); 2-3) in columns (m) and (n) estimates for the Burnside and Dollar (2000) and Rajan and Subramanian (2008) subsamples.

tory variable increases. An odds ratio less than 1 indicates less likely signal-significance as the variable increases. For example, the .16 estimate for consumption in column (a) indicates that if the recipient to donor per-capita consumption ratio increases by one unit, the pair is about $6-7$ times less likely to be countercyclically-altruistic. This result supports a significant intersection of countercyclical-altruism and popular, more generic, notions of altruism. The other "humanitarian" variables likewise indicate congruence between countercyclical and popular altruism. An increase of one unit in the recipient to donor life expectancy ratio reduces signal-significance by between 3 to 4 times in most specifications. A one unit improvement of the difference in the average institution quality indexes, instead, increases the likelihood of the countercyclical-altruism signal by 1.3 times.[22]

Turning to the commercial/self-interest variables, columns (f) to (l) introduce two variables typically associated with self-interest: bilateral trade and military trade. Bilateral trade has a small negative and

[22] Mortality rates at birth plays a role similar to life expectancy (as it can be seen comparing column a to column b); we prefer to keep life expectancy since available for a larger sample. Inflation and military expenditure are not particularly significant instead.

statistically insignificant effect on the likelihood of the countercyclical-altruism signal. This again indicates that our signal is distinct from commercial interests. Similarly, military trade has no effect on the likelihood of the countercyclical-altruism signal.

Also the variables with a less direct linkage to altruistic motivations provide interesting results and further, conditional support for the signal. In the case of population, consistently with the literature on ODA allocation which finds a negative effect of a recipient's population on donors' ODA decisions, donors are slightly less likely to be countercyclically-altruistic to recipients countries with larger populations. The effect is statistically significant but quite small. The interpretation of the significance of population in such regressions is typically related to altruistic motivations since aid is potentially more effective in small countries than larger countries with less efficient political and bureaucratic structures. Our estimate is consistent with this type of interpretation. Moving to colonial linkage, the coefficient of the colonial dummy in columns (f) to (l) indicates a powerful and robust effect. Being a former colony makes a recipient about 2.5 times more likely to receive countercyclical altruistic transfers from a donor than other recipients. Importantly, introducing the colonial dummy does not affect the significance of the humanitarian factors found in the first specifications of the logit model. At the same time, the colonial effect is independent from the commercial variables, which do not affect the incidence of the signal. These two clear characteristics 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) link so powerfully to business cycles. Furthermore, the colonial indicator usually is found in less than ten percent of the countercyclical-altruistic pairs, and therefore is not driving the signal. Hence, as mentioned above, the colonial effect is more likely related to cultural and institutional affinities between donors and recipients in our context.

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 results 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. This effect is highly significant too. Contrarily, other ODA is erratic in both sign and significance as a determinant of the signal. It is only significant when negatively related to the signal suggesting aid from other donors is viewed as a substitute by cyclical-altruistic donors.

Surveying the full sequence of specifications in Table 1 some significant regularities emerge. First, countercyclical-altruism is powerfully related to low recipient consumption and the institutional capacity to utilize the aid. Second, the commercial factors typically associated with self-interest have a negative, but insignificant effect on the likelihood of countercyclical altruism. Multilateral aid is complementary to the likelihood of the signal. Finally, 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 closely our initial father and son story. As a closing takeaway from this section we note that the specifications in columns (m) and (n) are linked to the next section's analysis of the relation of the signal to growth. The recipient-donor pairs in these two columns only include the recipient countries in the samples from Burnside and Dollar (2000) and Rajan and Subramanian (2008) respectively. The estimates are in line with those of the full sample in column (l), with the exception of life expectations and bilateral trade in column (m) for the Burnside and Dollar's sample, which have opposite, but not significant, effects.

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. This debate, regarding the causal relationship between ODA and recipient growth, remains contentious and unresolved. We acknowledge the diverse methodologies and results in this literature by choosing as reference frameworks two of the most highly cited competing ODA-growth models: Rajan and Subramanian (2008) (hereafter RS) and Clemens et al. (2012) (hereafter CL). In adapting these models for our validation exercise first note that if donors' place differential weight on the altruistic and self-interest effects of aid, as seems likely, those with more weight on recipients' utility should choose ODA with more positive effects on recipient income growth, at the margin. For a given amount of ODA there are many dimensions of donor choice that could result in different growth effects. These include sector and structure (including time) of disbursement and/or repayment. For example, CL disaggregates 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 RS growth equation to reflect our partitioned donor set. This can be done compactly with the regression model:

$$g_{i,t} = c + f\left(A^{a}, A^{na}\right) + \mathbf{Z}_{i,t}\boldsymbol{\beta} + \boldsymbol{\varepsilon}_{i,t} \tag{25}$$

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 (25) are defined as in RS and the time subscript indicates a five-year average, also as in RS.[23] Now incorporating elements of CL we focus on three specification for $f\left(A^{a}, A^{na}\right)$, in which both contemporaneous and one-period lagged ODA are included:

$$f\left(A^{a}, A^{na}\right) = \begin{cases} \beta_{a} A^{a}_{i,t} + \beta_{na} A^{na}_{i,t} \\ \theta_{a} A^{a}_{i,t-1} + \theta_{na} A^{na}_{i,t-1} \\ \beta_{a} A^{a}_{i,t} + \beta_{na} A^{na}_{i,t} + \theta_{a} A^{a}_{i,t-1} + \theta_{na} A^{na}_{i,t-1} \end{cases}$$

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. All models are estimated using recipient and period fixed-effects and standard errors clustered by recipient country.[24] Estimation results of these models are reported in Table 2 for the un-partitioned model, the baseline specification of our altruism signaling model (with and without controls), and with CARA utility in the signaling model as a robustness check.[25] With respect to the first validation step, a cursory comparison of the pooled and baseline partitioned models (columns $a - c$ and $d - f$ respectively) in the various forms, reveals striking differences. The pooled donor

[23] 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 RS 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).

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

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

results in columns $(a) - (c)$ are qualitatively similar to those in many traditional growth regressions (including most RS cases) - small, negative, and largely insignificant effects of ODA on growth. The partitioned donor group regressions in columns $(d) - (f)$, on the other hand, deliver opposite signed contemporanous effects, with three of four partitioned groups now statistically significant (versus none significant in the unpartitioned column $a - c$ estimates). Moreover, we strongly reject the null hypothesis of equivalence of contemporaneous growth effects across the donor partition ($H_0 : \beta_a = \beta_{na}$). The equality hypotheses are also clearly rejected for specifications (d) and (f) in all cases (see p-values reported in the last rows of Table 2). The null hypothesis cannot be rejected for model (e) due to the limited significance of the two coefficients. 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 (columns $a - c$) none of the estimated coefficients are significant. Once the donor set is split, however, the contemporaneous coefficient becomes significant and negative for the countercyclical altruists (compare columns a and d) while there is no countercyclical evidence for non-signal bearers. We next use lagged ODA, as suggested by CL, to illuminate reverse causation (negative endogeneity bias) in the contemporaneous coefficients.[26] Comparing columns c and f we see that in the *pooled model* (c) lagging does not indicate any different long and short run effects of ODA on growth.[27] As we move from pooled to partitioned models with lags (column c to f), however, the coefficient changes are consistent with the expected reverse causation bias for the countercyclical-altruists. Specifically, contemporaneous reverse causation between ODA and income growth for signal-bearers implies a more negative estimate of β_a than of β_{na} (now compare columns d and f), as is observed in Table 2. These changes in coefficients between column (d) and (f) are consistent with the presence of an omitted positive long run effect of ODA since the negative simultaneity bias would be attenuated by a positive omitted variable bias in (d), with a net effect that depends on the relative size of the two biases. Controlling with lagged ODA in column (f) illuminates this contemporaneous reverse causation that is obscured in the pooled donor sample. Comparing column (d) to (e), the switch of sign from β_a to θ_a is also consistent with endogeneity bias among altruistic donors, although the estimates have lost standard statistical significance.

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 (i.e., larger - more positive - estimates of θ_a relative to θ_{na}). Donor's with more weight on the self-

[26] These results compare with the first two columns of Table 9 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, and also consider what they term "early impact" aid. These differences seem to matter mostly for the estimate of the effect of the lagged ODA (column b).

[27] These results are comparable, though contradictory, with the first two columns of Table 9 of CL. However, 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, and also consider what they term "early impact" aid.

g_t :	RS Growth Rate											
	All Donors			Partitioned								
				Baseline			Baseline (no contr.)			CARA		
	(a)	(b)	(c)	(d)	(e)	(f)	(d)	(e)	(f)	(d)	(e)	(f)
A_t	-.039		-.025									
	(.062)		(.074)									
A_t^a				**-.380**		**-.613**	-.323		**-.594**	**-.413**		**-.702**
				(.183)**		(.246)**	(.204)		(.239)**	(.183)**		(.199)***
A_t^{na}				.125		**.310**	.102		**.328**	.158		**.402**
				(.104)		(.146)**	(.113)		(.163)**	(.118)		(.163)**
A_{t-1}		-.052	-.042									
		(.087)	(.1)									
A_{t-1}^a					.217	.409		**.439**	**.576**		.286	**.502**
					(.234)	(.261)		(.215)**	(.206)***		(.203)	(.221)**
A_{t-1}^{na}					-.141	**-.308**		**-.207**	**-.367**		-.163	**-.366**
					(.097)	(.144)**		(.111)*	(.147)**		(.105)	(.155)**
Obs	348	348	348	348	348	348	348	348	348	348	348	348
R^2	.60	.60	.61	.61	.61	.61	.61	.61	.61	.61	.61	.62
H_0 : $\beta_a = \beta_{na}$				.04		.01	.13		.02	.00		.00
$\theta_a = \theta_{na}$					.18	.04		.02	.00		.07	.01
$\theta_a \leq 0$					.18	.06		.02	.00		.08	.01
$\theta_{na} \geq 0$					.08	.02		.04	.01		.06	.01

Table 2: Estimation of the growth regressions for the Rajan and Subramanian (RS) model. RS Growth Rate panel uses the extended sample 1971:2005. Extended samples provided by Clemens et al. The dependent variable is GDP per capita growth rate as defined in RS paper. ODA disbursements are in ratio to the donors' GDP. Columns $(a)-(c)$ are results without donor partition by countercyclical-altruism signal; columns $(d)-(f)$ indicate the model with ODA donor partition between A^a and A^{na}. The controls used in RS (not reported) are provided by Clemens et al (2011); fixed effects are included. Donor partition is based on our baseline model. Standard errors clustered at recipient level are reported in parentheses. 1, 5, and 10% significance levels are indicated by ***, **, and * respectively. For the coefficients tests, the p-values of the Wald tests are reported for the null hypotheses listed in the last eight rows of the table.

interest return (e.g., supportive UN votes), 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 be observed by comparing column (d) with columns (e) and (f) but also by juxtaposition with the corresponding pooled models in columns $(a)-(c)$.

Comparing columns (d) and (f) we see that disentangling long and short run growth effects of ODA from signal bearing and non-bearing donors further illuminates the obfuscating effect of pooling donors. The more negative coefficient of A_t^a in (f) relative to (d), is consistent with the disentanglement of contemporaneous reverse causation and the long-run positive impact of ODA on growth among signal bearers. Movements in the opposite direction are observed for the A_t^{na} coefficients, yielding positive estimates of β_{na} in specification (f).[28] Comparing models (d) and (e) provides additional evidence of reverse causation bias in pooled contemporaneous growth regressions as the change in sign for both altruists and non-altruists is consistent across all specifications, and is particularly striking in the baseline without controls. 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 et al. (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.

with an alternative signaling model utility function (CARA) presented in the last three columns of Table 2

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.

6 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 (23) and (24). 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.

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 24% to 16.5%. Changing the set of control variables might also affect the parameter estimates and the composition of the countercyclically-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 (23) and (24) become statistically indistinguishable and the small variability of ODA is absorbed by the controls.[29] 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 saw in growth and logit regressions.

We now turn to the choice of the functional forms. As an alternative to our baseline model of equation (5) 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.[30] In order to avoid non-linear

[29] In fact, 85% 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 15% of new pairs are identified as a consequence of the introduction of the controls. Using four available controls, the *countercyclical-altruism* pairs drop to 9.6% but 90% of them were already included in the altruistic pairs of the model with two controls.

[30] 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. More details about this case are provided in the Appendix.

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 (5) 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.[31] 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 21.5% donor-recipient altruistic pairs (it is 16.5% the baseline); about 81% 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. Specifically, the altruistic share with CARA goes from 23% with no controls to 21.5% with two and to 16.8% with four 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 countercyclically-altruistic pairs for Luxembourg, Norway, and Finland. 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 CARA, the output of the growth regressions for the basic CARA case reported in Table 2 and of the logit regressions reported in Table A1 of Appendix C.2 does not differ from our baseline model. Rather, it even improves the statistical significance of the estimates for the growth models. 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.

[31] 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 et al. (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.

7 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 in donor motive measurement, 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. A wide range of variables have been utilized as explanatory variables in regressions of aid allocation to identify motive, yielding many conflicting conclusions.

In this paper we employ an alternative strategy for motive identification. We develop an integrated theoretical-empirical framework for the identification of significant altruistic motivation in ODA donations at the donor-recipient pair 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 over the period 1970 to 2010 and find that around 17% 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 about 3% for Australia and New Zealand.

In the next phase of our analysis we undertake two out-of-model exercises to better understand the characteristics of the donors-recipient pairs exhibiting the countercyclical-altruism signal and whether donations from countercyclical-altruists have distinguishable effects from those without the signal. Our first out-of-model 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 better institutions, and has a colonial link with the donor. The likelihood of the signal is independent of trade or military relations between donor and recipient. 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.

In the second out-of-model exercise, we adapt two highly cited ODA-growth regression models (Rajan and Subramanian, 2008, and Clemens et al., 2012). We find strong evidence of the negative contemporary relationship between ODA on growth due to reverse causation. That is, consistent with our model, 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 donor displaying the countercyclical altruism signal has a distinguishable, more positive long-run effect on recipient growth than aid from donors without the signal. Though we believe identifying donor motivation is a potentially important step in the direction of understanding ODA causality, much additional work is required in ODA-growth modelling before we confidently establish causation between ODA and long-run growth.

Taken together, we believe the out-of-model exercises provide strong indication that the counter-cyclical altruism signal is capturing a donor-recipient pair characteristic that intersects significantly with more 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 (2011) 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 from virtually any perspective. Though presenting extraordinarily difficult measure challenges, we believe the empirical identification of altruistic motivation to be an important area research in general, and in understanding the effect of foreign aid in particular.

REFERENCES

Addison, Tony, and Finn Tarp. 2014."Aid Policy and the Macroeconomic Management of Aid." *World Development*, Forthcoming.

Alesina, Alberto, and David Dollar. 2000."Who gives foreign aid to whom and why?", *Journal of Economic Growth,* 5: 33-63.

Andreoni, James . 1989. "Giving with Impure Altruism: Applications to Charity and Ricardian Equivalence". *Journal of Political Economy,* 97, 1447–58.

Andreoni, James. 1990. "Impure Altruism and Donations to Public Goods: a Theory of Warm-Glow Giving". *The Economic Journal*, 100: 464-477.

Arellano, C., Bulíř, A., Lane, T., & Lipschitz, L. 2009. The dynamic implications of foreign aid and its variability. Journal of Development Economics, 88(1), 87-102.

Bauer, Péter Tamás. 1976. Dissent on development. Harvard University Press, 1976.

Bearce, David H., and Daniel C. Tirone. 2010. "Foreign Aid Effectiveness and the Strategic Goals of Donor Governments", *The Journal of Politics*, 72(3): 837-851.

Berthélemy, Jean-Claude. 2006. "Bilateral Donors' Interest vs. Recipients' Development Motives in Aid Allocation: Do All Donors Behave the Same?" *Review of Development Economics,* 10(2): 179–194.

Berthélemy, Jean-Claude, and Ariane Tichit. 2004. "Bilateral donors' aid allocation decisions - a three-dimensional panel analysis". *International Review of Economics and Finance,* 13(3): 253-274.

Blackburn, Douglas W., and Andrey Ukhov. 2008. "Individual vs. Aggregate Preferences: The Case of a Small Fish in a Big Pond", Working paper.

Boone, Peter. 1996. "Politics and the effectiveness of foreign aid", *European Economic Review*, 40(2): 289–329.

Bourguignon, Francois, and Mark Sundberg. 2007. "Aid effectiveness: opening the black box", *The American economic review*, 97(2): 316-321.

Bulir, Ales, and Javier A. Hamann. 2008. "Volatility of Development Aid: From the Frying Pan into the Fire?", *World Development*, 36(10): 2048–2066.

Burnside, Craig, and David Dollar. 2000. "Aid, policies, and growth", *American Economic Review*, 90(4): 847–868.

Chong, Alberto, and Mark Gradstein. 2008. "What determines foreign aid? The donors' perspective", *Journal of Development Economics*, 87(1): 1-13.

Clemens, Michael A., Steven Radelet, Rikhil R. Bhavnani and Samuel Bazzi. 2012. "Counting Chickens When They Hatch: Timing and the Effects of Aid on Growth", *The Economic Journal*, 122(June):

590–617.

Cliff, Michael T. 2003. "GMM and MINZ Program Libreries for Matlab". Unpublished Manual.

Dabla-Norris, Era, Camelia Minoiu, and Luis-Felipe Zanna. 2010. "Business Cycle Fluctuations, Large Shocks, and Development Aid: New Evidence", IMF Working Papers, 10/240.

de Mesquita, Bruce Bueno, and Alastair Smith. 2007. "Foreign Aid and Policy Concessions", *Journal of Conflict Resolution,* 51(2): 251-284.

Deaton, Angus. 2010. "Instruments, randomization, and learning about development", Working Paper, Research Program in Development Studies, Center for Health and Wellbeing, Princeton University.

Dreher, Axel, Peter Nunnenkamp, and Rainer Thiele. 2008. "Does US aid buy UN general assembly votes? A disaggregated analysis", *Public Choice,* 136(1-2): 139-164.

Dreher, Axel, Vera Eichenauer, and Kai Gehring. 2014. "Geopolitics, Aid and Growth", CEPR Discussion Paper No. 9904.

Dudley, Leonard, and Claude Montmarquette. 1976. "A Model of the Supply of Bilateral Foreign Aid", *The American Economic Review*, 66(1): 132-142.

Fuchs, A., Dreher, A., & Nunnenkamp, P. 2014. "Determinants of donor generosity: A survey of the aid budget literature", *World Development*, 56, 172-199.

Gleditsch, Kristian S. 2002. "Expanded Trade and GDP Data", *Journal of Conflict Resolution,* 46: 712-24

Gravier-Rymaszewska, Joanna. 2012. "How Aid Supply Responds to Economic Crises: A Panel VAR Approach", Working Paper Series UNU-WIDER, Research Paper 25, World Institute for Development Economic Research.

Hoeffler, Anke, and Verity Outram. 2012. "Need, Merit, or Self-Interest—What Determines the Allocation of Aid?", *Review of Development Economics,* 15(2): 237-250.

Kaufmann, Daniel, Aart Kraay, and Massimo Mastruzzi. 2010. "The Worldwide Governance Indicators: A Summary of Methodology, Data and Analytical Issues", World Bank Policy Research Working Paper 5430.

Kilby, Christopher, and Axel Dreher. 2010. "The impact of aid on growth revisited: Do donor motives matter?" *Economics Letters,* 107(3): 338-340.

Maizels, Alfred, and Machiko K. Nissanke. 1984. "Motivations for Aid to Developing Countries", *World Development,* 12(9): 879-900.

McKinlay, Robert D., and Richard Little. 1979. "The U.S. Aid Relationship: A Test of the Recipient Need and the Donor Interest Models", *Political Studies,* 27(2): 236-250.

Ottoni-Wilhelm, Mark, Lise Vesterlund, and Huan Xie. 2014. "Why Do People Give? Testing Pure and Impure Altruism." NBER Working Paper N. 20497.

Packenham, Robert A. 1966. "Foreign Aid and the National Interest", *Midwest Journal of Political Science*, 10(2): 214-221.

Pallage, Stephane, and Michel A. Robe. 2001. "Foreign aid and the business cycle", *Review of International Economics*, 9(4): 641–672.

Rajan, Raghuram, and Arvind Subramanian. 2008. "Aid and Growth: What does the Cross-Country Evidence Really Show?", *Review of Economics and Statistics,* 90(4): 643-665.

Schraeder, Peter J., Steven W. Hook, Bruce Taylor. 1998. "Clarifying the foreign aid puzzle: A comparison of American, Japanese, French, and Swedish aid flows", *World Politics*, 50(2): 294-323.

Svensson, Jakob. 1999. "Aid, Growth and Democracy", *Economics and Politics*, 11(3): 275–297.

Temple, J. R. 2010. "Aid and conditionality", *Handbook of development economics*, 5: 4415-4523.

Trumbull, Willaim N., and Howard J. Wall. 1994. "Estimating Aid-Allocation Criteria with Panel Data", *Economic Journal,* 104(425): 876-882.

Werker, Eric, Faisal Z. Ahmed, and Charles Cohen. 2009. "How is foreign aid spent? Evidence from a natural experiment." *American Economic Journal: Macroeconomics,* 1(2): 225-244.

Wik, Mette, Tewodros Aragie Kebede, Olvar Bergland, and Stein T. Holden. 2004. "On the measurement of risk aversion from experimental data", *Applied Economics,* 36(21): 2443-2451.

Yesuf, Mahmud, and Randall A. Bluffstone. 2009. "Poverty, Risk Aversion, and Path Dependence in Low-Income Countries: Experimental Evidence from Ethiopia", *American Journal of Agricultural Economics,* 91(4): 1022-1037.

Younas, Javed. 2008. "Motivation for bilateral aid allocation: Altruism or trade benefits", *European Journal of Political Economy.* 24(3): 661-674.

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 Alternative Utility Functional Forms

This section describes more in detail the CARA version of the model used for the robustness exercise in Section 6 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 (5) instead of the log-additive function in (3). In particular, the countercyclical-altruism condition (13) is not affected by the choice of the functional form. Equation (5) is reported here again for convenience

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

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 characterize by the curvature parameter only. We adopt the same type of negative exponential function for $\rho_r(\cdot)$ as we used for $u_r(\cdot)$

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

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

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

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)

$$\sigma_d e^{-\sigma_d c_{d,r0}}\left(1 + \sigma_d a_r^*\right) = \rho_{r,0}\sigma_\rho\left(1 - \sigma_\rho a_r^*\right) + \delta_{r,0}\sigma_r e^{-\sigma_{\bar{r}} c_{r,0}}\left(1 - \sigma_r a_r^*\right)$$

and

$$\sigma_d e^{-\sigma_d c_{d,r0}} = \rho_{r,0^*}\sigma_\rho + \delta_{r,0^*}\sigma_r e^{-\sigma_r c_{r,0}}$$

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

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

and following similar steps. As mentioned above, 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 Data and Robustness

C.1 Dataset for the Logit Regressions

In this Appendix, we provide a description of the sources of the variables used in the logit regression in section 5.1 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 regression in Table 1 uses variables expressed in relative terms for the recipient-donor pair; this seems more correct since it follows the unit of analysis of the altruism signal model too. We report the results of the logit regression also for the variables simply taken in absolute recipient levels for each recipient, along with two other robustness checks using alternative specifications to identify the countercyclically altruistic pairs, in Tables A1.

Population: Population series are from Penn World Tables dataset (PWT 7.1) for both donors and recipients (identifier POP). The same series are used as controls in the estimation stage of the signaling model. The relative recipient to donor population ratio is computed in each period and then the average over the sample $1970-2010$ is taken to obtain the final transformation. The variable in absolute recipient terms is computed as the average over time of the recipient's population series.

Consumption: The consumption variable is expressed in consumption per capita terms. The consumption series are from PWT 7.1 for both donors and recipients (identifier kg). The relative recipient to donor consumption per capita ratio is computed in each period and then the average over the sample $1970-2010$ is taken to obtain the final transformation. The variable in recipient terms is computed as the average over time of the recipient's consumption per capita series.

Institutions Quality: We start from the six indicators of governance quality published by The Worldwide

Governance Indicators (WGI - 2012 Update) that can be found at www.govindicators.org. Details about the sources and the aggregation methodology of these indicators are provided by Kaufmann et al. (2010). The indicators refer to six dimensions: Voice and Accountability, Political Stability and Absence of Violence, Government Effectiveness, Regulatory Quality, Rule of Law, Control of Corruption; they are continuous indexes with values between ± 2.5; and they cover the period $1996 - 2011$. We obtain a single governance index by averaging the six indicators together for each donor and recipient; finally, we take the average over time of the aggregate index. The institutions quality variable is constructed as the difference between the average quality index of the recipient and that of the donor; this can be interpreted as the perceived distance of the quality of the recipient's institutions from the donor's from the donor's perspective. The variable at recipient level is simply the average aggregate index of the recipient. The availability of governance indexes for the entire sample of our model estimation, which starts in the seventies, and for so many recipient countries is quite limited; in this respect, WGI is one of the best available options.

Mortality and Life Expectancy: Both life expectancy and mortality rate at birth are originally obtained from the World Development Indicators (WDI) provided by the World Bank (identifiers SP.DYN.LE00.IN for life expectancy and SP.DYN.IMRT.IN for mortality rate). Life expectancy was include in the controls set in the estimation stage of the signaling model. The relative recipient to donor ratios are computed in each period and then the average over the sample $1970 - 2010$ is taken to obtain the final transformations. The variable in recipient terms is computed as the average over time of the recipient's series. These two variables are proxies for general health conditions and return similar effects in the logit regressions; we prefer to use life expectancy because it coverages a larger sample of recipients.

Inflation: Inflation is constructed as the annual change of the GDP deflator obtained from the PWT 7.1 for both donors and recipients (identifier p). The same series are used as controls in the estimation stage of the signaling model. The variable in recipient absolute terms is computed as the average over time of the recipient's inflation series for the period $1970 - 2010$. The variable in relative terms is constructed as the difference between recipient's and donor's average inflation rate. Inflation can be seen as another variable expressing institutions and economic policy quality.

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. However, we include the last observations after 2010 too. The relative variable is computed as the recipient to donor ratio of military expenditures for each period, then averaged over the sample. The variable in absolute recipient terms is computed as the average over time of the recipient's expenditure series.

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 diverse online sources about history and international political affairs. This variable is clearly defined at the donor-recipient level.

Bilateral Trade: This is the main variable representing self-interest motivations in the logit regression. A source fully covering our main sample is not available; however, we can rely upon two separate sources that cover the earlier and the later part of the sample. The first source is the United Nation Conference on Trade and Development statistics (UNCTADstat) which provides trade flows data for the period $1995-2012$ in current dollars. We use the merchandise trade matrix by partner- product groups, total all products definition. We construct the bilateral trade variable as the sum of imports and exports between a donor 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. The second source is the unilateral trade data provided by Kristian S. Gleditsch and described in Gleditsch (2002). The dataset can be found at http://privatewww.essex.ac.uk/~ksg/exptradegdp.html, it reports trade flows since 1948, and we use it over the period $1970-2000$. The same transformations implemented for the first trade variable apply here too. These are a bilateral variable 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, as well as a combination of the two; therefore we keep the first definition in the baseline specifications of the logit.

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 last observation in 2012. 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 $1970-2010$. The data is obtained from the OECD International Development Statistics online dataset. This variable is defined only at the recipient level.

ODA From Other Donors: This series is constructed subtracting a donor's ODA disbursement to a specific recipient from the total ODA received by that recipient. It is then aggregate by taking the average over the sample $1970-2010$. The ODA data comes from the OECD DAC Aid Statistics dataset and it is transformed into equivalent PPP per capita terms, exactly as in the main application of the paper. This

	Baseline - No Controls						CARA						Recipient Terms			
	(i)	(j)	(k)	(l)	$(m)^1$	$(n)^2$	(i)	(j)	(k)	(l)	$(m)^1$	$(n)^2$	(k)	(l)	$(m)^1$	$(n)^2$
consumption	**.17** (.00)	**.09** (.00)	**.17** (.00)	**.12** (.00)	**.05** (.00)	**.11** (.00)	**.07** (.00)	**.07** (.00)	**.07** (.00)	**.11** (.00)	**.1** (.02)	**.12** (.00)	**.04** (.00)	**.5** (.00)	.1 (.08)	**.06** (.00)
population	1 (.57)	1 (.43)	1 (.12)	1 (.3)	1 (.29)	1 (.31)	1 (.59)	1 (.45)	1 (.25)	1 (.34)	1 (.25)	1 (.40)	**.99** (.00)	**.99** (.00)	**.99** (.00)	**.99** (.00)
institutions	**1.17** (.05)	**1.46** (.00)	**1.24** (.01)	**1.49** (.00)	**1.45** (.00)	**1.78** (.00)	1.12 (.16)	**1.27** (.01)	**1.18** (.05)	**1.26** (.01)	**1.43** (.01)	**1.62** (.00)	1.17 (.12)	1.20 (.10)	1.19 (28)	**1.53** (.00)
life expect.	**.14** (.00)	**.28** (.02)	**.06** (.01)	**.18** (.00)	1.08 (.94)	**.09** (.01)	.46 (.15)	.68 (.50)	**.26** (.05)	.81 (.74)	1.15 (.89)	.34 (.22)	.99 (.13)	1 (.82)	1 (.68)	.99 (.29)
inflation		.60 (.27)		.59 (.27)	1.75 (.86)	1.34 (.93)		.72 (.47)		.78 (.59)	7.59 (.55)	2.33 (.80)		.82 (.67)	17 (.43)	1.20 (.96)
military exp.		1.06 (.74)		.73 (.16)	.82 (.56)	.75 (.23)		1.04 (.83)		.75 (.24)	.72 (.40)	.75 (.30)		1 (.15)	1 (.31)	1 (.18)
colony	1.42 (.09)	1.31 (.23)	1.32 (.18)	1.22 (.37)	1.03 (.11)	.99 (.98)	1.31 (.21)	.95 (.83)	1.24 (.32)	.93 (.76)	.81 (.51)	.87 (.64)	1.30 (.23)	1.01 (.95)	.90 (.75)	1 (.98)
trade	.92 (.38)	.85 (.24)	.89 (.27)	.93 (.59)	1.23 (.20)	.88 (.40)	.81 (.10)	.78 (.14)	.79 (.08)	.87 (.37)	1.05 (.72)	.76 (.20)	.97 (.79)	.95 (.73)	1.07 (.64)	.82 (.35)
military trade	1 (.51)	1 (.93)	1 (.91)	1 (.96)	1 (.37)	1 (.71)	1 (.76)	1 (.50)	1 (.40)	1 (.44)	1 (.21)	1 (.27)	1 (.45)	1 (.32)	1 (.20)	1 (.23)
multilateral ODA			**1.22** (.00)	**1.19** (.00)	**1.22** (.02)	1.13 (.06)			**1.16** (.00)	1.18 (.00)	**1.26** (.01)	1.13 (.07)	**1.44** (.00)	**1.40** (.00)	**1.73** (.00)	**1.36** (.00)
other ODA			**.00** (.00)	.00 (.06)	1.77 (.93)	**.00** (.00)			**.00** (.00)	2.27 (.77)	.09 (.72)	**.00** (.05)	**.00** (.00)	3.59 (.66)	.02 (.54)	**.00** (.00)
Obs	2507	2062	2507	2062	1020	1247	2507	2062	2507	2062	1020	1247	2507	2062	1020	1247
Pseudo R^2	.04	.04	.06	.05	.03	.04	.05	.04	.05	.04	.03	.03	.06	.05	.03	.03

Table A1: 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; the CARA $\sigma_d = \sigma_r = \sigma_\rho = 2$ functional specifications; and the baseline model but with regressors expressed in absolute recipient terms. Columns headers and variables definitions reflect those in Table 1. P-values reported in parenthesis. 1-2) in columns (m) and (n) estimates for the Burnside and Dollar (2000) and Rajan and Subramanian (2008) subsamples.

variable is defined only at the donor-recipient pair level too.

C.2 Robustness of the Logit Regressions Under Other Specifications

In Table A1 we present some robustness checks for the logit regression discussed in Section 5.1. We consider three alternative specifications: the baseline estimation specification with no controls; the main CARA functional specification (with parameterization $\sigma_d = \sigma_r = \sigma_\rho = 2$); and the baseline specification with regressors expressed in absolute recipient terms. The estimates are largely confirmed by these alternative specifications, with the exception of two major differences. The first is that the effect of the population size, which was small but significant, vanishes for the CARA specification and for the baseline with no controls. The second is that the formal colonial status dummy is basically never significant in Table A1 and it also shows some negative effect for the CARA specification.

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 6 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 5.

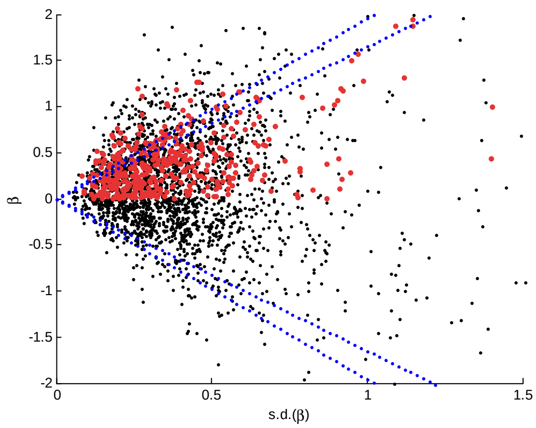

Figure S1: Point estimates of β_r. Red dots identify pairs that satisfy the countercyclical-altruism condition. In black all the others. The significance of the parameters is shown by the blue, dotted lines. The external lines show the 5% significance thresholds. The internal lines the 10% level.

S2 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 (23) and (24), but not for time-varying control factors, under a fairly general class of functional forms for the components of the utility function (3). 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 (5). Let us

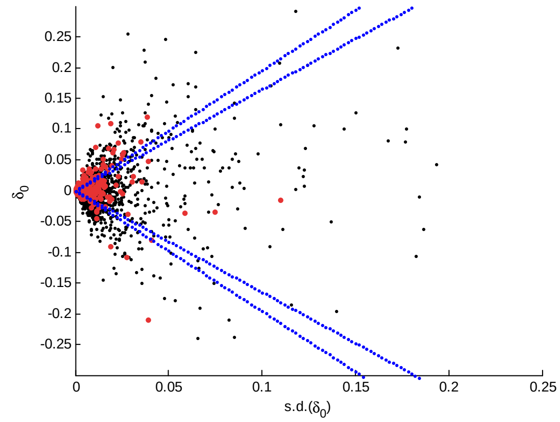

Figure S2: Point estimates of $\delta_{r,0}$. Red dots identify pairs that satisfy the countercyclical-altruism condition (20). In black all the others. The significance of the parameters is shown by the blue, dotted lines. The external lines show the 5% significance thresholds. The internal lines the 10% level.

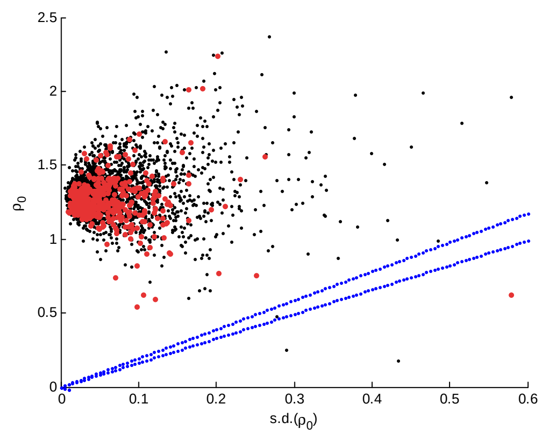

Figure S3: Point estimates of $\rho_{r,0}$. Red dots identify pairs that satisfy the countercyclical-altruism condition. In black all the others. The significance of the parameters is shown by the blue, dotted lines. The top (bottom) blue line show the 5% (10%) significance threshold.

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

Table S1: Recipient countries that satisfy the *countercyclical-altruism* condition. This table lists the countries that satisfy the condition for countercyclical-altruism equation (20) in the main text and summarized in Figure 5.

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 (23) and (24) 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

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

or equivalently

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

As explained in the main text of the paper, the curvature coefficient of the altruism function we estimate, $\delta_{r,0}$ in (23), is actually multiplied by the reference value of the shifting function $f(X_0)$, which is constant. In our econometric model, the vector of controls Z is used as empirical counterpart of $c_{r,0}^{-1}(X_{\delta r} - X_0)$ and the attached vector of coefficients γ_0 is equivalent to $\delta_{r,0}\nabla f(X_0)$. It is clear that neglecting the control variables would introduce a bias in the estimation of the altruism parameter due to the mispecification of the model despite the controls being constant or not. However, the constant factor $f(X_0)$ 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 mispecification 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 $\rho_r\left(\cdot\right)$ 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 (23) and (24) of the model does not influence the altruism results; σ would just work as any other constant re-scaling factor in $f\left(X_0\right)$.