Food Aid Donor Cooperation and Responsiveness to Recipient Country Need

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February 2009

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Abstract

We employ censored least absolute deviations and multivariate Tobit estimators to investigate whether food aid flows from the main donor countries respond to recipient country needs as reflected in low food availability, low income, or both. We also explore the hypothesis that donor countries specifically coordinate their food aid shipments to recipient countries. Food aid in aggregate and from each donor is significantly targeted at poorer countries and is highly persistent over time. Food aid responses to food availability shortfalls, natural disasters and violent conflict are common but more modest and uneven across donors. Finally, we find strong evidence of donor coordination in food aid allocation.

Keywords: food aid, donor cooperation, censored LAD regression, multivariate Tobit, developing countries

JEL Classification Numbers: F35, I38, O19, Q18

1. Introduction

Food aid has long been a controversial instrument for closing the gap between food consumption needs and supply available from domestic production, inventories and commercial imports. Debates over the efficacy of food aid have grown as global deliveries have fallen precipitously over the past two decades, from 14 million metric tons (MMT) in 1988 to a record low of 5.9 MMT in 2007 (WFP, 2008). A key issue in both the literature and in policy debates – such as in the deadlocked WTO Doha Round negotiations – concerns food aid allocation patterns, in particular the question of whether they respond to recipients' needs (Gabbert and Weikard 2000; Barrett 2001; Jayne et al. 2001; Barrett and Heisey 2002; Gupta et al. 2004; Barrett and Maxwell 2005; Neumayer 2005; WTO 2006; Young and Abbott 2008). Most of the literature finds little responsiveness of food aid flows to recipient country need indicators. But existing studies suffer a range of methodological flaws that leave the matter in doubt.

One especially important issue missing in the existing literature concerns potential interactions among donor country food aid allocations. Are flows significantly correlated among donors, either positively, reflecting joint response, or negatively, reflecting geographic specialization by donors? This paper fills that important gap in the empirical literature while attending to a number of other methodological concerns that bedevil previous studies. Specifically, it employs a multivariate Tobit model with controls for several typically-omitted relevant variables to investigate whether food aid flows from the main donor countries – the United States (US), European Union (EU) – both European Community (EC) aid and that of individual member states – Canada, Japan and Australia – respond to recipient countries' needs and the extent to which the donors interact in their food aid allocation. We also estimate globally aggregated food aid allocation patterns using a censored least absolute deviation (CLAD) estimator, a semi-parametric approach not previously used in the food aid literature.

The rest of the paper is organized as follows. Section 2 briefly reviews the key issues, highlighting the literature's findings on food aid responsiveness to recipient country needs. Section 3 then presents and explains the estimation approach employed, followed by a description of the data used. The empirical results are then presented and discussed in Section 4. Section 5 concludes.

2. Food Aid and Food Needs

Although the Food Aid Convention, the international treaty that governs food aid allocations, directs donor countries to prioritize recipient country needs, the perception remains that food aid flows are driven more by agricultural surplus disposal, donor trade promotion and geopolitical interests than by humanitarian objectives (McGillivray 2003; Barrett and Maxwell 2005). This may affect the distribution of available food aid resources as well as the overall volume of food aid donor countries provide. Moreover, donors may differ in the degree to which they emphasize the needs of recipient countries in allocating food aid. For example, US food aid remains governed by legislation aimed at promoting domestic agricultural and shipping interests (Barrett and Maxwell 2005), while the EU clearly defined recipient need as the major priority in food aid allocation more than a decade ago (Cathie, 1997).

Food aid targeting matters because it is an increasingly scarce resource. Over the 1972-2004 period we study, global cereal food aid averaged only 3.8% of total cereal food availability in recipient countries. That share has fallen subsequently. Global cereal food aid is evidently a marginal resource that can hardly fill shortfalls in local cereal production. Table 1 shows the cereals food aid, domestic production and commercial imports figures for the five largest food aid recipients over this period.[1] Even among these largest food aid recipient economies, commercial imports are always greater – usually by an order of magnitude or more –than food aid volumes and domestic food production is far larger still. When well targeted, however, food aid can help save lives, particularly where local food markets fail and local and regional food availability is insufficient (Barrett and Maxwell, 2005).

[Place Table 1 here]

This paper thus builds on a literature that explores whether food aid flows effectively respond to recipient countries' needs. Following Barrett (2001) and Barrett and Heisey (2002), we employ nonconcessional food availability – defined as domestic production plus commercial imports – as an indicator of recipients' needs. Ideally, one would use individual or household level food access variables as the key explanatory variable; but there are no cross-country data that enable micro-level analysis of differential targeting among donor and recipient countries.[2] However, since more than three dozen countries lack sufficient nonconcessional food supplies to meet nationwide aggregate macronutrient requirements (Barrett and Maxwell 2005), macro-level analysis at the level of recipient countries still provides a reasonable first cut at examining donors' food aid targeting effectiveness.

The findings in the literature to date are quite mixed. Gabbert and Weikard (2000) analyzed food aid allocation by four donor countries and the WFP by employing a method that weights the total amount of food donated by the amount of undernourishment in the recipient country. They found that the US performed worst in the case of project food aid, but was among the best in allocating emergency food aid according to recipient need. Barrett (2001) identified a range of flaws in the Gabbert and Weikard approach and introduced a simple econometric framework that differentiates between food aid's supply stabilization and progressive transfer roles. His approach has become the workhorse method for subsequent studies. We too follow that general approach, but with the refinements explained below. Barrett (2001) found that US food aid flows only modestly towards recipients with lower food availability levels and fails to stabilize food availability in recipient countries. Barrett and Heisey (2002) found that World Food Programme food aid responded more robustly to recipient country need indicators than did US food aid.

Neumayer (2005) noted that food availability alone cannot capture the need for food in situations where hunger results from extreme poverty (i.e., poor food access) such that poor households cannot afford sufficient food to prevent malnutrition, even when local markets avail adequate food supplies. Like Neumayer, we therefore include a control for the extent and depth of poverty, measured by recipient country gross domestic product per capita (GDPpc) in purchasing power parity terms. Neumayer (2005) found that average calorie supply and GDPpc affected a country's likelihood of receiving food aid, but not the amount of food aid delivered conditional on being a recipient.

Neumayer (2005) also argues that one needs to factor in geopolitical considerations that commonly condition donor food aid allocation choices. One such variable is the spatial distance between a donor and a recipient, which is commonly inversely related to the donor's geopolitical influence over the recipient as well as to the cost of food aid shipments. Another factor may be the political freedom of a recipient country, since the major donors are all market-oriented democracies that profess a preference for promoting similar social orders. We therefore include controls for these donor geopolitical interest variables in our regression specifications.

More recently, Young and Abbott (2008) pointed out that donors naturally respond to disasters, thus failure to account for especially dreadful events that trigger considerable food aid shipments may lead to mistaken inference. They found that although food aid flows do not seem to be well targeted to poorer countries, they do respond to severe production shortfalls in recipient countries and to violent conflict. We follow Young and Abbott's good example and include controls for severe shortfalls and disasters of various sorts. In particular, we differentiate between violent conflicts and sudden ("rapid onset") and gradual ("slow onset") natural disasters, as these may induce markedly different responses from donors. For example, conflict commonly increases global awareness of a problem, which can stimulate greater humanitarian assistance levels, but also involves international political tensions and insecurity for aid workers that often impede food aid flows. Similarly, food is often harder to mobilize and less needed in response to sudden onset natural disasters such as tsunamis or earthquakes, than it is for slow onset ones such as droughts, but the former typically draw far greater international news coverage, generating additional public pressure on donors to send food aid. It is unclear how these effects net out, but one might reasonably expect them to differ by type of disaster.

We build on this existing literature, for the first time incorporating the full range of factors that have been variously introduced. We also make some important methodological refinements, as the next section explains.

3. Analytical approach

We employ the basic estimation strategy introduced by Barrett (2001) and enhanced by Barrett and Heisey (2002) and then by Young and Abbott (2008). The basic strategy is to regress food aid flows per capita on controls for the factors enumerated above. There are three steps to this estimation.

In the first step, we estimate the growth rate in food availability for each recipient country:

$$\ln(DFP_{it}) = \beta_{0i} + \beta_{1i}\ year_t + \mu_{it} \tag{1}$$

where DFP_{it} represents the domestic food production per capita in year t for recipient country i, a proxy employed for nonconcessional food availability to avoid endogeneity bias associated with including commercial import volumes; $year_t$ is a trend (integer count) variable, and μ_{it} is the residual error term. Given that (1) is a logarithmic trend regression, β_{1i} can be interpreted as the average percentage growth rate and the mean zero, independent and identically normally distributed (*iid N*) residuals μ_{it} capture the deviation from the recipient's food availability trend at each year t in percentage points.

The second stage of the estimation involves finding donor-specific thresholds at which specific donors begin responding to food production shortfalls. As argued by Young and Abbott (2008), donors may be more sensitive to severe food shocks than to deviations near or above food production trend levels, introducing a crucial non-linearity in food aid response. To address this, we define production shortfall (*PS*) as the negative deviation from the food production trend per equation (1):

$$PS_{it} = Minimum[\mu_{it}, 0] \tag{2}$$

Because food production levels in recipient countries exhibit time trends, PS_{it} reflects food availability shocks more appropriately than do indicators based on the deviation from the sample period mean, as employed by Young and Abbott (2008). Food crises (F*C*) are defined as deviations below some fraction (κ) of one standard deviation from recipients' food production trend:

$$FC_{ijt} = Minimum[\mu_{it} + \kappa_j \; \sigma[\mu_{it}],0] \tag{3}$$

where $\sigma[\mu_{it}]$ represents the standard deviation of the recipient country food production trend deviations. The term $\kappa_j \, \sigma[\mu_{it}]$represents the threshold at which donor *j* begins to respond with food aid. To estimate the parameter κ_j that best fits each donor's response to recipient country food shocks, we employ the maximum likelihood search method proposed by Young and Abbott (2008). For each donor, we separately estimate food aid allocation models that include different measures of FC_{ijt} based on systematically varying the fraction of one standard deviation, κ_j, from $\kappa_j = 0$ (implying $FC_{ijt} = PS_{it}$) to $\kappa_j = 3$, by 0.1 steps, resulting in 31 estimated equations per donor. We then compare the maximum log-likelihood values of these 31 estimations for each donor and choose the parameter κ_j that maximizes the log-likelihood function globally.

The main food aid allocation model we estimate is a dynamic Tobit model, which allows for a censored dependent variable. A censored estimator is necessary because food aid flows cannot be negative and are commonly equal zero. Table 2 indicates a median of zero for most recipients in most years under most donors' food aid programs.

[Place Table 2 here]

The model is specified as follows:

$$\begin{aligned} &\overline{FA_{ijt}} = \gamma_{j0} + \gamma_{j1}\, FC_{ijt} + \gamma_{j2}\, DFP_{it} + \gamma_{j3}\, FA_{ijt-1} + \sum_o \tau_{jo}\, Z_{ito} + \sum_r \theta_{jr}\, D_{ir} + \sum_t \lambda_{jt}\, Y_t + \eta_{ijt} \\ &FA_{ijt} = \overline{FA_{ijt}} \text{ if } \overline{FA_{ijt}} > 0 \\ &FA_{ijt} = 0 \text{ if } \overline{FA_{ijt}} \leq 0 \end{aligned} \tag{4}$$

Where $\overline{FA_{ijt}}$ is the latent continuous dependent variable, FA_{ijt} is the actual, censored food aid volume shipped from donor j to recipient i in year t (in MMT per capita in recipient population terms) and FC_{ijt} and DFP_{it} are the crisis shock and domestic food production per capita variables, respectively. The parameter γ_{j1} then reflects food aid's stabilizing effect in response to a crisis shortfall, whereas the distributional or progressivity effect is reflected in the γ_{j2} parameter. If these parameter estimates are (statistically and economically) significantly negative, food aid flows countercyclically and disproportionately towards recipients with lower food availability, i.e., it is needs-oriented. We include lagged values of food aid flows (FA_{ijt-1}) to control for the likely serial correlation associated with well-established inertia in food aid flows (Diven 2001, Barrett and Heisey 2002, Gupta et al. 2003). Z_{ito} are exogenous variables not based on food measures that either indicate the neediness of recipient i's population, or represent characteristics potentially of interest to donor j. Variables in the Z_{ito} vector include purchasing power parity adjusted GDPpc, civil conflict intensity, persons affected by sudden or gradual disasters, the political freedom index of a recipient, as well as the distance between recipient and donor capitols. These variables are defined and the source data identified in section 4. D_{ir} represent regional fixed effects that account for region-specific, time-invariant unobserved characteristics – such as colonial history, dominant language, infrastructure, or average climate – that may influence food aid flows to individual countries. Y_t are year fixed effects that account for year-specific events common to all recipients – such as global food prices – that may affect donors' food aid shipments. Likelihood ratio tests for joint significance of the regional (H_0: $\theta_{jr} = 0 \; \forall \; r$) and year-specific ($H_0$: $\lambda_{jt} = 0 \; \forall \; t$) fixed effects confirmed the need to control for these unobservables for every donor. The mean zero, *iid* N error term is denoted η_{ijt}.

A. Global food aid allocation

We use two different third estimation stages in order to address somewhat different questions. First we estimate global – i.e., not donor-specific, $FA_{it} \equiv FA_{ijt}$ – food aid allocation patterns using Powell's (1984) censored least absolute deviation (CLAD) estimator. The major advantages of this semi-parametric approach are its robustness to unknown conditional heteroscedasticity and the provision of consistent and asymptotically normal parameter estimates in the presence of non-normal error distributions.[3] Wooldridge (2002) points out that heteroscedasticity is often present in panel data analysis with lagged dependent variables as regressors as a result of possible intra-country correlation; which, of course, leads to biased standard errors. The objective in the CLAD estimation is to explore recipients' food aid receipt patterns with respect to all donors, while avoiding these econometric complications that bedevil all the existing empirical results in this literature.

The CLAD estimator focuses on the sample median rather than mean, thereby obviating the heteroscedasticity and non-normality problems common to Tobit regressions and other parametric specifications. Powell's (1984) CLAD estimator solves the optimization problem:[4]

$$\min_{\beta_g} S_n(\beta_g) = \frac{1}{n}\sum_{i=1}^{n}\left| FA_i - \max\{0, x_i'\beta_g\}\right| \tag{5}$$

where n is the sample size and x_i is a vector of explanatory variables outlined earlier. For the computation of the CLAD estimator β_g, we use Buchinsky's (1994) iterative linear programming algorithm (ILPA). This algorithm involves successions of uncensored quantile regressions. The logic behind ILPA is that while the regression function $x_i'\beta_g$ is in the uncensored region, the median of the dependent variable is not affected by censoring. But if $x_i'\beta_g$ takes values below zero, then more than half of the distribution will pile up at that censoring point, thus the dependent variable is not determined by the regression function because its median equals the censoring point (Chay and Powell 2001). Thus, ILPA iterations consist of two steps. In the first step, a standard quantile regression is estimated. In the second step, those observations for which the predicted values of the dependent variables are less than zero are replaced by the censoring value, zero. The next iteration then starts with data of the shortened sample. When the sample size of two consecutive iterations is the same, a local minimum is obtained (Buchinsky 1994). Given that analytically deriving standard errors that are robust to heteroscedasticity as well as non-independent residuals is a non-trivial issue for quantile estimators, we follow Rogers (1993) and compute robust standard errors using 10,000 bootstrap samples.

B. Food aid allocation of the main donor countries

The other approach we take in the third stage sacrifices the added econometric flexibility of the CLAD estimator for the ability to estimate the system of equations describing each donor's food aid allocations to recipient countries over time. Once the optimal κ_j parameters have been estimated, under this approach we then estimate equation (4) in a system of *m* simultaneous equations, one equation for each of the six donors: Australia (AU), Canada (CA), European Community (EC), EU Member States (ES), Japan (JP) and the US. This extension merely generalizes equation (4) into a multivariate Tobit model wherein the errors are distributed multivariate normal, $\eta_{ijt} \sim MVN(0,\Sigma)$, where Σ is the covariance matrix, wherein we allow for 15 possible non-zero correlation coefficients among the *m* donors with respect to a given recipient country in a specific year.

This approach differs from that of the previous subsection in that we trade off the CLAD estimator's ability to relax the normality assumption on which Tobit estimation rests in favor of simultaneously estimating the system of donor-specific equations, which is infeasible under CLAD. Whereas the CLAD approach enables us to get especially robust estimates of the determinants of aggregate food aid flows into recipient countries, the multivariate Tobit approach permits us to research inter-donor coordination of food aid flows, a topic unexplored in the literature to date.

Not only does the multivariate estimator improve the efficiency of the parameter estimates relative to a univariate Tobit, it also allows us to estimate directly the correlation among donors' food aid allocations. This is of interest because donors have often been criticized for not coordinating food aid shipments sufficiently. If indeed there is no coordination, then the error terms should be uncorrelated across donors, once one controls for the explanatory variables (i.e., $E[\eta_{ijt}\eta_{ikt}] = 0$, where E is the expectation operator and $j \neq k$). If the time-varying, donor-specific unobservables captured by η_{ijt} are negatively correlated across donors, this suggests coordinated specialization, with one donor reducing its food aid relative to what one would otherwise predict while another donor increases its shipments. This could reflect distinct geographic spheres of influence not fully captured by the distance and country fixed effects variables, or just complementary programming approaches (e.g., one specializes in disaster response, another in addressing chronic hunger). Conversely, a positive correlation between donor-specific residuals suggests joint action, with each donor more likely to ship to a recipient country if other donors do likewise. The United Nations' Consolidated Appeals Process (CAP) was established in 1992 precisely to foster closer cooperation and co-financing of disaster response among donors. If the CAP works, the residuals in the estimated equations (4) should be positively correlated.

Given that observations often take zero values for more than two equations (donors), analytical maximization of the likelihood of the multivariate version of equation (4) is not feasible. This is because the resulting high dimensional integrals in the likelihood function effectively prohibit analytical evaluation (Barslund, 2007). Instead they can be approximated using a simulated maximum likelihood estimator.

We use the Geweke–Hajivassiliou–Keane algorithm to simulate the m-dimensional integrals in the likelihood function (Train, 2003). During the simulation process a number (D) of draws is taken from standard normal densities and a multivariate probability is computed using Cholesky factorization. To obtain stable coefficient estimates we used $D = 100$ draws, which is considerably more than the minimum value recommended by Cappellari and Jenkins (2003), who suggested setting D equal to the square root of the sample size. For better accuracy at a given number of draws, randomized Halton draws have been used instead of random draws.[5] We dropped the first elements of each Halton sequence in order to avoid introducing significant correlation between the sequences of different dimensions. The number of discarded elements per Halton sequence (20) was chosen in line with Train (2003), who suggested dropping at least as many elements as the value of the highest prime used for generating the Halton sequences (here: 13). We employ the method documented in Williams (2000) to compute robust cluster variance estimators that avoid bias associated with heteroscedasticity in the multivariate Tobit estimates.

4. Data description

Food aid flows, annual food production, and commercial import data covering the period 1972-2004, were obtained from the FAOStat database (http://faostat.fao.org/). Given that non-cereals food aid is composed of various goods of different processing grades, which are difficult to aggregate, we employ only cereals food aid data. This serves as a reasonable proxy for overall food aid trends since cereals food aid ranged from 84% to 91% of total food aid shipments over the period (Table 3). All volume figures were converted to a per capita basis using annual population data also reported in FAOStat.

[Place Table 3 here]

Data on purchasing power adjusted gross domestic product per capita (with constant prices, base year: 2000) were obtained from the April 2008 version of the Expanded Trade and GDP Data (http://privatewww.essex.ac.uk/~ksg/exptradegdp.html). These data extend the Penn World Table (version 6.2), primarily by plugging gaps in coverage, which occur especially during times of conflict, which is of course of particular interest in the study of humanitarian response (Gleditsch 2002). Conflict is captured by data taken from the Major Episodes of Political Violence (MEPV) database from the Center for Systemic Peace (http://www.systemicpeace.org/inscr/inscr.htm). MEPV provides annual, cross-national, time-series data on interstate, societal, and communal warfare magnitude scores. The overall conflict intensity variable we construct is the aggregate of the MEPV category scores for ethnic violence, ethnic warfare, civil violence, civil warfare, interstate violence and interstate warfare. Since each single MEVP category ranges from 0 (no episode) to 10 (extreme violence), a higher value of total conflict intensity generally indicates a more severe level of violence/warfare in that recipient country.

Data on natural catastrophes were obtained from the Emergency Events Database provided by the Centre for Research on the Epidemiology of Disasters (http://www.emdat.be/). The acuteness of annual disasters is measured using the number of total affected people in the country, i.e., the sum of people affected, injured or left homeless. We constructed two different disaster indicators by aggregating total affected people by disaster events annually: 1) sudden (rapid onset) disasters, which consist of volcanoes, slides, floods, earthquakes, wild fires, wind storms, waves/surges and insect infestations; and 2) gradual (slow onset) disasters, which involve droughts, extreme temperatures and disease epidemics. To account for different population sizes, these indicators were divided by the overall population of the recipient country so that the variables we use represent the proportion of the recipient country population affected by the disaster.

Political freedom within the recipient countries is measured by the civil liberties and political rights indices reported in the Freedom in the World (FiW) publications by Freedom House (2008). The United States Department of Agriculture (USDA) explicitly states that FiW ratings are used as an allocation criterion in its Food for Progress program (USDA, 2008). These indices are based on surveys among analysts who assess the extent to which a country fulfills predetermined criteria of civil liberties and political rights. The civil liberties category incorporates issues of personal autonomy and individual rights, rule of law, freedom of expression and belief as well as associational and organizational rights. The political rights category involves issues of political pluralism and participation, functioning of government as well as electoral process. As proposed by Casper and Tufis (2003), we use the unweighted sum of both indices and transpose the scale to derive an index that ranges from 2 (least free) to 14 (most free).

Geographic proximity between donor and recipient are measured using the great circle distances between their capital cities, as reported by Gleditsch (ND, http://privatewww.essex.ac.uk/~ksg/data-5.html). Eight smaller countries are missing in these data; these gaps were filled with data from the Topografisch Verbond Elbruz (http://www.elbruz.org/General/db/capitaltocapital.php). For European Community food aid shipments, we used the distance to Brussels.

The analysis covers a total of 151 recipient countries and 6 major donor countries (or groups of countries, in the case of Europe). We distinguish here between the two independent components of European Union food aid: shipments managed by the European Commission, termed Community Action, and food aid programmed by individual European Union member states, which we aggregated into total food aid flows from member states.[6] Table 4 presents descriptive statistics for all the variables.

[Place Table 4 here]

The shares of the major donor countries varied over the period under consideration, as shown in Figure 1. The United States, however, was the largest donor in every year, typically by a considerable margin.

[Place Figure 1 here]

5. Empirical Results

We begin by briefly reporting on the estimated donor-specific thresholds that define food crisis response, κ_j. Unlike Young and Abbott (2008), who estimated an optimal κ_j for the US of 1.3 standard deviations below period mean domestic food production, using our slightly different method, we find that globally aggregated food aid as well as three donors – the Japan, the US and individual EU member states collectively – do not appear to vary response nonlinearly. Our estimated threshold for global food aid and those three donors was equal to zero. For EC Community Action food aid, we found a small threshold effect of 0.3. But for Australia and Canada, the estimated crisis shortfall was substantial, at 1.6 and 2.4 standard deviations below the trend-adjusted year-specific domestic food production level. The results that follow all employ these donor-specific optimal threshold estimates.

A. Global food aid allocation

The estimates from the CLAD model on global food aid are reported in Table 5. The first two rows show the coefficient estimates for the stabilization (γ_{j1}) and progressivity (γ_{j2}) parameters, respectively. Both estimates are negative, as expected, although only the stabilization parameter estimate is statistically significantly different from zero, and it is quite small in magnitude. This is consistent with prior results by Barrett (2001), Barrett and Heisey (2002) and Young and Abbott (2008), all of whom use different data and estimators than we do.[7] This suggests that aggregate food aid flows into countries is targeted more towards countries facing temporary food crises than towards those with low food availability levels associated with chronic hunger, although even the stabilization effect is quite modest.

We do find a negative and statistically significant effect of real GDP on food aid receipts, as did Neumayer (2005). Given that these regressions control for food availability, the strong suggestion of this result is that food aid responds more to chronic food access problems (low income for a given level of food availability per capita) than to chronic food availability problems (low food availability for a given level of per capita income). Our results differ from Young and Abbott's (2008), who found no significant effect of poverty on food aid shipments. However, they employed a country's United Nations' classification as a least developed country (LDC) or non-LDC as a proxy measure. But this non-time-varying measure cannot capture changes in income levels that do not lead to changes in the country's classification; our finer-grained income measure is preferable to this proxy classification approach.

The estimated coefficients on the variables representing sudden disasters and conflicts are both positive and significantly different from zero, indicating that global food aid responds positively to casualties caused by sudden natural and violent conflict. The positive, but insignificant coefficient for gradual natural catastrophes shows that global food aid shipments are far less responsive to slow onset disasters even though the pace of these natural catastrophes typically gives donors early warning and adequate time to deliver commodities when they are needed. Young and Abbot (2008) get similar results with respect to food aid response to disasters.

As in previous studies, the preceding year's level of food aid receipts is quite strongly correlated with the current year's food aid flows, with an estimated autoregressive parameter of 0.78, strongly supporting the inertia hypothesis (Barrett and Heisey 2002; Gupta et al. 2004; Young and Abbott 2008). Recipient country political freedoms have no discernible effect on food aid receipts. The regional dummy variable coefficient estimates indicate that Asian countries receive less food aid, ceteris paribus, than do other regions.[8]

[Place Table 5 here]

B. Donor-specific food aid allocation patterns

Table 6 reports the results of the multivariate Tobit model analysis. As reported at the bottom of Table 6, the multivariate Tobit specification was tested against other specifications. The likelihood ratio test of joint ρ significance overwhelmingly rejects the null hypothesis that the correlations among donor country food aid shipments are all equal to zero, implying that one cannot defensibly estimate six separate Tobit models, thus supporting the simultaneous estimation method used here. Indeed, all the estimated bivariate correlation coefficients are positive, ranging from 0.13-0.29, and significantly different from zero at the one percent level. This is consistent with the hypothesis that the Consolidated Appeals Process effectively induces joint action by donors; they typically respond robustly together (relative to what one might predict based on recipient food availability, income, location, past food aid receipt history, etc.), or come up somewhat short uniformly.

The statistically significant correlation coefficient estimates also signal added efficiency in estimation using the multivariate approach. Likelihood tests against multivariate and univariate constant-only models unambiguously show that the exogenous variables of model (4) jointly contribute to explaining variation in food aid flows. Donor-specific parameter estimates appear in separate columns in Table 6. The pattern of stabilization and progressivity effects appear similar across countries. All statistically significant point estimates have the same sign and are substantially larger in magnitude than the corresponding global food aid estimates reported in Table 5. Interestingly, the donor-disaggregated results suggest significant progressivity and stabilization effects for the food aid programs of Canada and Europe (both EC community action and EU member states' individual programs), but no significant effect of either sort for US, Japanese or Australian food aid.

By contrast, real GDP per capita negatively and statistically significantly affects food aid shipments from each donor, most strongly for the US and least for Australia. There is clear, universal emphasis on shipping to countries with more acute food access, rather than food availability problems. This striking finding matches that of Neumayer (2005).

Donors appear to respond differently to natural and man-made disasters. In particular, food aid programs administered by EU Member States generally respond to both rapid and slow onset natural disasters with increased food aid shipments, but not in conflict situations, while the EC's joint food aid program exhibits exactly the opposite pattern. The US food aid program has a statistically significant response only to sudden natural disasters while Japan's only responds positively and significantly to gradual disasters, but not to sudden ones. Neither Canada nor Australia exhibit any statistically significant food aid response to any sort of disaster, whether natural or man-made.

Interestingly, none of the donor countries' food aid programs appear significantly responsive to political freedom in recipient countries, and the geographic distance effects, although uniformly negative, are only statistically significant in the case of Australia and the EU member states. Geopolitical considerations appear less of a factor in the past thirty years than they were in food aid's early days in the 1950s and 1960s (Barrett and Maxwell 2005). These results with respect to inter-country distance contrast with those of Neumayer (2005), who found negative and significant effects but did not include regional fixed effects as we do.

All donors' food aid programs exhibit inertia, as reflected in the positive and statistically significant estimated coefficients on the lagged food aid volumes. Along with GDPpc, this is the only variable that is highly significant in all donor equations and, moreover, has the same sign for all donors. But the differences among donors are striking. Food aid flows from Australia and EU member states are more than four times as persistent as those from Canada, which shows the least persistence in food aid programming by recipient country.

[Place Table 6 here]

6. Conclusions

This paper offers a new glimpse at how food aid flows respond to the needs of recipient countries. We attend to a range of econometric concerns about the existing literature and for the first time explore the hypothesis that donor countries significantly coordinate food aid shipments to recipients. Our results yield three important findings.

First, consistent with most of the previous literature, we find that food aid flows have been targeted towards poorer countries and countries facing temporary food production shortfalls, although the food availability stabilization effects are quite modest. Food access concerns associated with low incomes trump food availability issues in guiding food aid programming.

Second, the media effects associated with violent conflict and sudden natural disasters induce significant added food aid response to such crises, while less widely broadcast, slow onset natural disasters such as drought generally draw no significant increase in food aid flows. This is a curious finding since food aid is arguably best suited to gradual response to slow onset disasters for which donors typically have effective early warning. The relatively greater logistical complications of response in conflict zones and to rapid onset disasters such as hurricanes, tsunamis and earthquakes appear dominated by the media attention these types of disasters bring.

Third, we generate the first known estimates of inter-donor food aid coordination. We find relatively large, positive and statistically significant correlation coefficients among all six food aid donors' programs. It appears that international coordination effectively induces joint food aid responses (and non-response). Possible explanations for this include the efficiency gains attainable from jointly using existent aid resources such as aid workers' expertise, transport vehicles, storage facilities and the United Nations' Consolidated Appeals Process, and shared international perspectives on the likely cooperativeness of local authorities in facilitating timely commodity deliveries.

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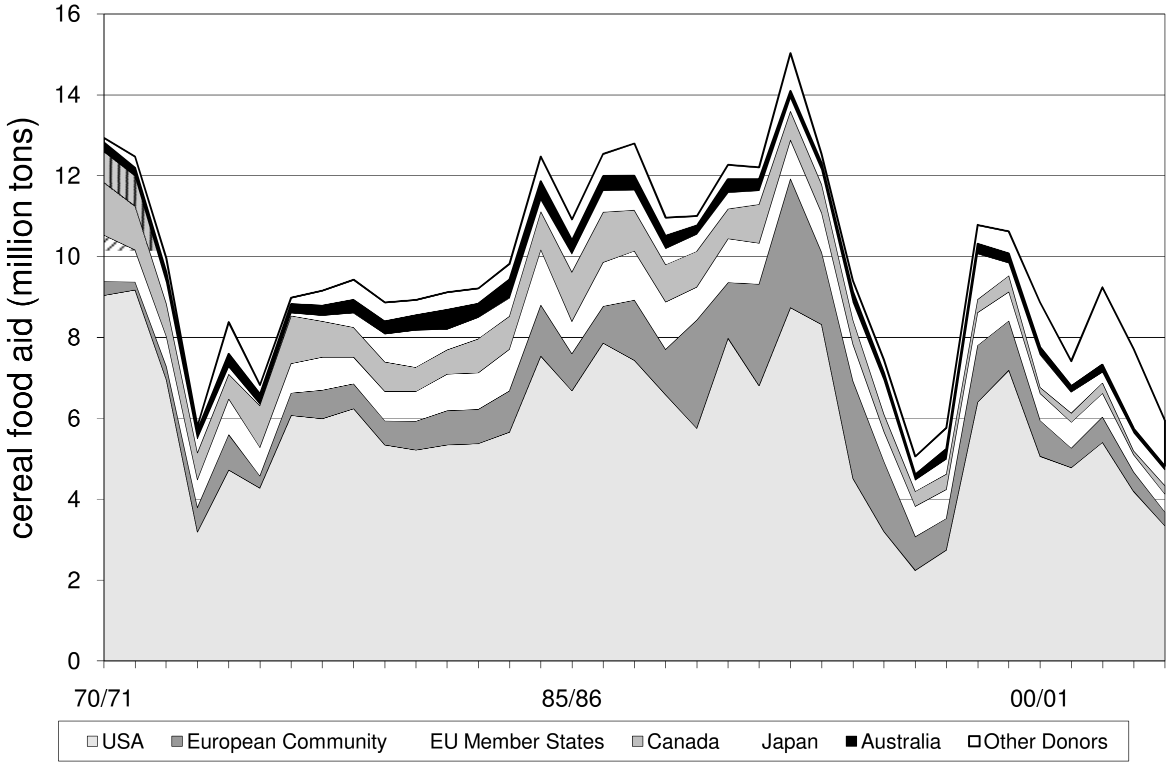
Figure 1. Food aid flows of major donors (1970/71 – 2004/05)



Source: FAO

Table 1. Food aid shipments of five major recipient countries

(annual average 1970-2004, metric tons)

	Bangladesh	**Egypt**	**Ethiopia**	**India**	**Indonesia**
Cereal food aid	956,510	929,000	481,483	473,973	369,471
Cereal food aid per capita	0.01015	0.01988	0.00903	0.00071	0.00247
Cereal (proportion)	0.99	0.96	0.95	0.81	0.94
Cereal food production	25,880,583	12,214,079	6,207,980	174,901,522	44,392,515
Cereal food production per capita	0.24736	0.22437	0.12882	0.21499	0.25116
Cereal food imports	2,057,657	6,985,427	530,952	1,496,577	3,608,226
Cereal food imports per capita	0.02005	0.12967	0.00986	0.00223	0.01983

Source: FAO

Table 2. Annual share in recipients' cereal food availability[1] (1970/71 – 2004/05)

	Mean	Std. dev.	Median	75%-Quantile	Minimum	Maximum
Cereal food production	0.5746	0.3539	0.6841	0.8923	0	1
Commercial cereal imports	0.3869	0.3435	0.2663	0.6724	0	1
Global cereal food aid	0.0383	0.0747	0.0058	0.0411	0	0.6379
Cereal food aid of specific donors to aid eligible recipient countries						
Canada	0.0031	0.0208	0	0.0004	0	0.5752
EC	0.0057	0.0197	0	0.0024	0	0.3405
EU Member States	0.0068	0.0232	0	0.0036	0	0.4074
Japan	0.0038	0.0165	0	0.0011	0	0.3680
USA	0.0217	0.0448	0.0019	0.0220	0	0.4686

[1] Domestic food production plus commercial imports

Source: FAO

Table 3. Composition of food aid shipments, by commodity type
(annual average, metric tons)

	1970-79	1980-89	1990-99	2000-04
Wheat and wheat flour	6,516,199	7,722,128	6,169,506	4,519,341
Coarse grains	1,012,876	1,524,299	2,510,038	1,447,323
Other cereals	1,777,200	1,513,880	1,437,403	1,924,566
Cereals	9,306,274	10,760,306	10,116,947	7,891,230
Non-cereals	162,965	898,537	1,338,534	1,397,882
Total food aid	9,469,239	11,658,843	11,455,482	9,289,112

Source: FAO

Table 4. Descriptive statistics

Variable	Definition of variables (unit)	Mean	S.d.
Dependent variables			
FA (Global)	Global cereal food aid (tons/capita)	0.0080	0.0190
FA (Australia)	Australian cereal food aid (tons/capita)	0.0003	0.0018
FA (EC)	European Community's cereal food aid (tons/capita)	0.0004	0.0037
FA (EU states)	EU Member States' cereal food aid (tons/capita)	0.0009	0.0050
FA (Canada)	Canadian cereal food aid (tons/capita)	0.0011	0.0055
FA (Japan)	Japanese cereal food aid (tons/capita)	0.0004	0.0022
FA (US)	US cereal food aid (tons/capita)	0.0044	0.0126
Common independent variables			
FC	Food crisis = Production shortfall (% negative trend deviation)	-0.086	0.205
DFP	Domestic cereal food production of the recipient (tons/capita)	0.171	0.200
GDPpc	Real GDP, constant 2000 prices (1000 international $ / capita)	4.339	4.162
SUDDENDIS	Sudden disaster casualties (total affected people / capita)	0.009	0.057
GRADUALDIS	Gradual disaster casualties (total affected people / capita)	0.008	0.063
CONFLICT	Total conflict index (0 (no conflict) - 60 (theoretical max))	0.923	2.105
FIWTRANS	Transposed FIW-index (2 (least free) - 14 (most free))	7.356	3.729
Capital-capital distances			
DISTANCE (Australia)	Distance from recipients' capital to Canberra (1000 km)	12.781	3.671
DISTANCE (Canada)	Distance from recipients' capital to Ottawa (1000 km)	8.784	3.481
DISTANCE (Europe)	Distance from recipients' capital to Brussels (1000 km)	6.767	3.472
DISTANCE (Japan)	Distance from recipients' capital to Tokyo (1000 km)	10.757	3.644
DISTANCE (USA)	Distance from recipients' capital to Washington DC (1000 km)	8.892	3.798
Regional fixed effects			
AMERICA	Reference region: Latin America and Caribbean	0.243	0.429
ASIA	1 if recipient is located in Asia	0.193	0.395
MIDEAST_NA	1 if recipient is located in North Africa or the Middle East	0.107	0.309
SUBSAHARA	1 if recipient is located in Sub-Saharan Africa	0.338	0.473
TRANSITION	1 if recipient is a transition country or is located in Europe	0.119	0.324

Table 5. Censored Least Absolute Deviation regression results
Dependent variable: aggregate food aid receipts

	Coefficient estimate	**t-statistic**
FC	-0.0015943	(-2.50)**
DFP	-0.0013447	(-1.45)
GDPpc	-0.0003244	(-3.52)***
SUDDENDIS	0.0051166	(2.24)**
GRADUALDIS	0.0007114	(0.35)
CONFLICT	0.0000526	(1.70)*
FIWTRANS	7.87E-07	(0.03)
FA_{t-1}	0.7764186	(41.01)***
ASIA	-0.0012171	(-3.53)***
MIDEAST_NA	-0.0001814	(-0.52)
SUBSAHARA	-0.0005176	(-1.51)
TRANSITION	-0.000881	(-0.62)
CONSTANT (γ_0)	0.0016514	(2.55)**
Optimal κ	0.0	
Pseudo R^2	0.41	
Observations	4503	

Notes: ***, ** and * denote statistical significance at the 1, 5 and 10 % levels, respectively. The Pseudo R^2 reported is that of the last ILPA iteration with a final sample size of 2877 observations. Optimal κ represents the donor-specific threshold.

Table 6. Multivariate Tobit Regression Results

	US	EC	EU States	Canada	Japan	Australia
Optimal κ	0.0	0.3	0.0	2.4	0.0	1.6
FC	-0.00248	-0.00380	-0.00257	-0.01449	-0.00060	0.00090
	(-1.46)	(-2.69)***	(-2.68)***	(-3.35)***	(-0.90)	(0.54)
DFP	-0.00374	-0.00917	-0.00396	-0.00857	-0.00360	0.00053
	(-1.09)	(-2.87)***	(-2.13)**	(-2.14)**	(-1.43)	(0.40)
GDPpc	-0.00148	-0.00119	-0.00061	-0.00113	-0.00070	-0.00032
	(-5.90)***	(-3.78)***	(-3.73)***	(-3.10)***	(-4.62)***	(-3.45)***
SUDDENDIS	0.01112	0.00377	0.00498	0.00686	0.00229	-0.00299
	(2.47)**	(1.31)	(2.75)***	(1.00)	(1.11)	(-0.78)
GRADUALDIS	0.00266	0.01123	0.00416	0.00427	0.00245	0.00011
	(0.57)	(1.20)	(1.72)*	(0.93)	(2.14)**	(0.08)
CONFLICT	0.00023	0.00032	0.00011	0.00023	-0.00005	0.00006
	(1.28)	(2.18)**	(1.41)	(1.43)	(-0.82)	(1.29)
FIWTRANS	0.00017	-0.00009	-0.00005	0.00017	-0.00006	0.00001
	(1.23)	(-1.03)	(-0.86)	(1.26)	(-0.61)	(0.21)
FA_{t-1}	0.77580	0.42680	0.82277	0.20545	0.73130	0.93422
	(17.60)***	(5.06)***	(14.65)***	(5.02)***	(8.93)***	(18.64)***
DISTANCE	-0.00005	-0.00024	-0.00028	-0.00013	-0.00017	-0.00019
	(-0.29)	(-1.24)	(-2.12)**	(-0.61)	(-1.35)	(-2.51)**
ASIA	-0.00691	-0.00380	-0.00075	-0.00453	0.00146	0.00229
	(-2.90)***	(-2.37)**	(-0.80)	(-1.70)*	(0.75)	(2.95)***
MIDEAST_NA	-0.00203	0.00036	0.00088	0.00121	0.00242	0.00264
	(-1.03)	(0.26)	(1.01)	(0.87)	(1.82)*	(3.50)***
SUBSAHARA	-0.00138	-0.00069	0.00088	-0.00351	0.00343	0.00272
	(-0.83)	(-0.61)	(1.17)	(-1.87)*	(2.96)***	(3.68)***
TRANSITION	-0.00081	0.00193	-0.00171	-0.00605	0.00035	-0.00429
	(-0.41)	(0.92)	(-1.50)	(-2.33)**	(0.26)	(-1.11)
CONSTANT (γ_0)	0.00146	-0.00034	0.00102	-0.00482	-0.00004	-0.00284
	(0.74)	(-0.16)	(0.72)	(-2.04)**	(-0.02)	(-2.54)**

Cross-equation correlations

ρ_{AU_CA}	0.270	(7.52)***	ρ_{CA_EC}	0.222	(5.58)***	ρ_{EC_JP}	0.179	(4.84)***
ρ_{AU_EC}	0.292	(4.62)***	ρ_{CA_ES}	0.167	(4.43)***	ρ_{EC_US}	0.181	(4.29)***
ρ_{AU_ES}	0.217	(4.41)***	ρ_{CA_JP}	0.160	(4.03)***	ρ_{ES_JP}	0.185	(7.37)***
ρ_{AU_JP}	0.206	(5.02)***	ρ_{CA_US}	0.133	(3.81)***	ρ_{ES_US}	0.191	(5.95)***
ρ_{AU_US}	0.196	(5.25)***	ρ_{EC_ES}	0.248	(6.97)***	ρ_{JP_US}	0.158	(3.54)***

Log-likelihood ratio test: joint ρ significance

χ^2-statistic	587.2
p-value	0.00

Log-likelihood ratio test against constant-only model:	**univariate**	**multivariate**
χ^2-statistic	11830.78	8944.01
p-value	0.00	0.00

Observations 4318

Notes: t-statistics in parentheses. ***, ** and * denote statistical significance at the 1, 5 and 10 % levels, respectively.

Notes

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[1] Some significant changes have occurred over the period under consideration. These aggregates mask changes over the period. Food aid to India and Indonesia declined from 1.014 MMT and 0.752 MMT per year in the 1970s to only 0.113 MMT and 0.188 MMT annually in 2000-2004, respectively. Meanwhile, Bangladesh and Ethiopia became the largest recipient of food aid in the 1990s and remain consistently among the top food aid recipients worldwide.

[2] Jayne et al. (2001) conducted this sort of micro-level analysis for Ethiopia.

[3] Note that a semi-parametric estimator assumes a functional form for the regression but assumes no functional form for the error process. This is an advantage of semi-parametric techniques, since no assumption on the error terms is needed. As such it is robust to non-normality and heteroscedasticity (Powell, 1984).

[4] For expositional purposes the index t has been dropped.

[5] The favorable properties of Halton draws over random draws include generally better density coverage at a given number of draws and a tendency to generate probabilities that are self-correcting over observations due to a negative correlation of draws between consecutive observations (Train, 2003).

[6] The EU Member States series consists of the EU-15 states' food aid flows over the whole 1972-2004 period (actual membership status was not considered), except Portugal due to lack of data.

[7] Our findings contrast with those of Gupta et al. (2004), who found significant progressivity in global food aid flows over the period 1970-2000, but no stabilizing effect. However, they used a straight Tobit model, which is vulnerable to violations of homoscedasticity, and included few explanatory variables, likely leading to some omitted relevant variables bias.

[8] Year fixed effects are not reported but are available by request from the lead author. The multivariate Tobit model and the CLAD model were estimated with Stata Version 10.