Food Aid Allocation Policies: Donor Coordination and Responsiveness to the Needs of Recipient Countries

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Abstract

This study employs a multivariate Tobit model to investigate whether food aid flows of the main donor countries – USA, EU (Community Aid and Member States), Canada, Japan and Australia – respond to recipient countries' needs and the extent to which the donors interact in their food aid allocation. The response of global food aid is also analyzed with a censored least absolute deviation (CLAD) model to highlight the overall performance of aggregate food aid. The empirical results generally indicate that both global and bilateral food aid are effective instruments in improving food security at the national level in recipient countries. In particular, global food aid is found to be significantly targeted to poorer countries, as well as countries facing temporary food crises, sudden natural disasters and conflicts. All major donor countries are found to direct their food aid shipments to poorer countries and appear to significantly coordinate their food aid shipments, so that food aid from other donors are generally treated as complements. While highly significant persistence is found in each donor's and global food aid allocation, variables representing donor interests were generally insignificant at conventional levels.

Keywords: food aid, need-orientation, donor coordination

1. Introduction

While food prices have dramatically risen over the past years, available evidence show that global food aid deliveries have almost continuously declined since 1999 and reached a record low of 5.9 million tons in 2007 (WFP, 2008). The negative correlation between food prices and food aid quantities has been widely criticized, and given the burden of high food prices for net-importing low-income countries there have been many recent pleas for more effective use of food aid resources (Abdulai et al., 2005). Food aid has featured prominently in the currently deadlocked Doha Round talks, where developing countries have been concerned with the need-orientation of food aid flows and have therefore called for binding commitments from donors to ensure that food aid flows actually respond to recipients' demand.

Given the significance of effective targeting of food aid to recipient countries, a number of studies have examined how well food aid is targeted to beneficiaries. However, the findings and conclusions from these studies appear to be ambiguous. For example, empirical studies on US food aid revealed contradictory results regarding its response to poverty and food availability indicators (Gabbert and Weikard, 2000; Barrett, 2001; Neumayer, 2005; Young and Abbott 2008).

This study extends the existing literature by combining the two-stage approach of Barrett and Heisey (2002), which measures responsiveness to food shocks and levels of food availability, with the maximum likelihood search strategy proposed by Young and Abbott (2008), which accounts for the possible distinction of donors between minor or positive food shocks and severe food crises. Furthermore, additional need indicators and measures of donor interest are included.

An important issue that appears to be missing in the empirical literature is the potential interactions between donor countries in their food aid allocations. The present study aims at filling this gap by employing a multivariate Tobit model that investigates whether food aid flows of the main donor countries – USA, EU (Community Aid and Member States), Canada, Japan and Australia – respond to recipient countries' needs and the extent to which the donors coordinate their allocations. Moreover, the coefficients of each donor's regressions are estimated more efficiently when information on all of the equations' error terms is considered. The response of globally aggregated food aid is also analyzed with a censored least absolute deviation (CLAD) model to highlight the overall performance of this policy instrument. This approach is used for the first time in the food aid literature and provides results for censored endogenous variables that are robust to heteroscedasticity and non-normal error distributions (Powell, 1984).

The paper is organized as follows. The section that follows describes determinants of food aid allocation on the macro level and the data included in our model. The third section presents the analytical approach employed in the study. The empirical results are then presented and discussed, while the final section presents some concluding remarks.

2. Food Aid and Its Allocation Determinants

The present study mainly focuses on whether food aid flows effectively respond to various indicators of recipient countries' needs. Data on border crossing food aid shipments for the period 1972-2004 were obtained from the FAO. Given that non-cereal food aid is composed of various goods of different processing grades, which are difficult to aggregate, only cereals food aid is employed in the present study. This serves as a reasonable proxy for overall trends in food aid, since cereals food aid ranged from 84% to 91% of total food aid shipments over the period.

Nationwide aggregate food availability remains a limiting factor in many developing countries. Thus, in line with Barrett and Heisey (2002), donors' efforts to stabilize national food markets and to counteract on global food inequalities are captured with cereal food production data, which have been obtained from the FAO. Other components of food availability are not incorporated because 1) the inclusion of commercial food imports as an explanatory variable of food aid flows probably lead to endogeneity bias and 2) food inventories lack of insufficient data availability and are generally not of much importance for most recipients (Barrett, 2001).

In cases where poor households are not able to afford sufficient food to prevent malnutrition, food availability on local markets alone cannot capture the need for food aid. Therefore, data on real GDP per capita (with constant prices, base year: 2000) is used to measure the scale of poverty within a recipient, and have been obtained from the April 2008 version of the Expanded Trade and GDP Data.[1] This dataset is an extension of the Penn World Table (PWT version 6.2) and deals with systematic missing values by using values derived from the CIA World Factbook GDP data or by filling in estimates based on the first non-missing PWT value adjacent to a series of missing values (for details, see Gleditsch 2002).

Given that dreadful events may trigger considerable amounts of food aid shipments to the affected countries, need indicators of natural catastrophes and man-made conflicts have also been incorporated in our analysis. To account for the different nature of man-made, sudden natural and gradual natural disasters, each of these disaster categories have been separately included in the food aid allocation equation. Donors' responsiveness to conflicts in recipient countries is measured by data taken from the Major Episodes of Political Violence (MEPV) database provided by the Center for Systemic Peace.[2] The conflict intensity variable included is the total summed magnitudes of societal and interstate conflicts, with higher values indicating more severe levels of conflict. Data on natural catastrophes were obtained from the EM-DAT Disaster Database, which is provided by the Centre for Research on the Epidemiology of Disasters. The acuteness of annual disasters is measured using the number of total affected people in the country, i.e. the sum of affected, injured and homeless people. The sudden disaster variable is the aggregate of total affected people of volcanoes, slides, floods, earthquakes, wild fires, wind storms, waves/surges and insect infestations. The gradual disaster variable consists of total affected people of droughts, extreme temperatures and epidemic disasters.

Other than humanitarian objectives may bias the need-orientation of food aid. A possible objective of donor countries may be to maintain a regional sphere of influence by preferably sending food aid to nearby countries (Neumayer, 2005). To account for this, great circle distances between donors' and recipients' capital cities are included in the model, which have been obtained from the distance between capital cities dataset provided by Gleditsch and from the Topografisch Verbond Elbruz.[3] For food aid shipments coming from Europe, the capital to capital distance to Brussels is used.

Donors' allocation may also be biased by preferences for recipients with similar social orders. For example, it is explicitly stated in the US Food-for-Progress program that the Freedom in the World (FIW) rating is used as an allocation criterion (USDA, 2008). Because all analyzed donors are democracies with high FIW freedom ratings, this can be presumed to be a universal indicator for donor interest in similarly high freedom of the recipients. Thus, FIW data provided by Freedom House (2008) is included in the analysis, which incorporate indices of civil liberties and political rights for each country. We use the unweighted sum of both indices and transpose the scale to derive an FIW index that ranges from 2 (least free) to 14 (most free).

To account for different population sizes, all volume figures and natural disaster casualties were converted to a per capita basis using annual population data reported in the FAO Production Yearbook. A total of 151 recipient countries and six major donor countries are included in the analysis. The two independent components of the European Union food aid program are analyzed separately in the present study. These components include food aid managed by the European Commission, and food aid managed individually by the European Union member states, which are aggregated into food aid flows from member states.[4] Figure 1 illustrates the significance of analyzed and other donors in global food aid shipments.

3. Analytical approach

As suggested by Barrett and Heisey (2002), donors' efforts to stabilize national food markets are captured by the response to deviations from the trend of nonconcessional food availability. The first stage therefore involves an estimation of the growth rate in food availability for each recipient country:

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

where DFP_{it} represents the domestic food production per capita in year t for recipient country i, $year_t$ is a trend variable, and μ_{it} is the residual error term. Given that (1) is a logarithmic trend regression, β_{1i} can be interpreted as a growth rate (in %) and the residuals μ_{it} capture the deviation from the recipients' food availability trend at each year t in percentage points.

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. The second-stage of the estimation therefore involves finding a threshold, with which these two cases can be distinguished for each donor. Therefore, we define crisis shocks (*CS*) as the deviations below some fraction (κ) of one standard deviation from recipients' food production trend:

$$CS_{ijt} = Minimum[\mu_{it} + \kappa_j \; StdDev[\mu_{it}],0] \tag{2}$$

where $StdDev[\mu_{it}]$ computes the standard deviation of the food production trend deviations of recipient country i in year t. The term $\kappa_j \; StdDev[\mu_{it}]$ represents the threshold at which donor j begins to respond with food aid. Because food production levels in recipient countries are likely to change over time, CS should indicate actual food crises more appropriately than indicators based on the deviation of the whole sample period's mean as employed by Young and Abbott (2008). To estimate a parameter κ_j that best fits the donors' response to food shocks, for each donor a series of food aid allocation models is estimated, where the fraction of one standard deviation (κ_j) is systematically varied from 0 to 3 using 0.1 steps. As proposed by Young and Abbott (2008), those κ_j parameters are chosen that maximize the allocation models' log-likelihood function for each donor.

The food aid allocation model used in this procedure is specified as a dynamic Tobit model, which accounts for the fact that the endogenous food aid variable cannot have negative values, and is defined as follows:

$$\begin{aligned} FA_{ijt} &= \gamma_{j0} + \gamma_{j1}\, CS_{ijt} + \gamma_{j2}\, DFP_{it} + \gamma_{j3}\, FA_{ijt-1} + \sum_o \tau_{jo}\, Z_{ito} + \sum_r \theta_{jr}\, D_{ir} + \sum_t \lambda_{jt}\, Y_t + \eta_{ijt} \quad \text{if } \overline{FA_{ijt}} > 0 \\ FA_{ijt} &= 0 \quad \text{if } \overline{FA_{ijt}} \le 0 \end{aligned} \tag{3}$$

where FA_{ijt} is food aid shipped from donor j to recipient i in year t (in tons per recipient's population). CS_{ijt} and DPF_{it} are the crisis shock and food production per capita variables, respectively, so for a need-oriented donor both should have a negative influence, indicating food aid generally flows countercyclical and in favor of those recipients with lower food availability. Lagged values of food aid flows (FA_{ijt-1}) are included to avoid omission bias that may occur in the estimation if past levels of food aid flows tend to effect current food aid, as well as the existence of serial correlation in the residuals. Z_{ito} are further food aid determinants described in section 2. Regional (D_{ir}) and year (Y_t) fixed effects are included to measure regional characteristics and year-specific events, respectively.

Log-likelihood ratio tests for joint significance resulted in a significant influence of both variable groups for every donor. The error term is denoted as η_{ijt}.

Global food aid allocation

The third estimation stage involves using the censored least absolute deviation (CLAD) technique proposed by Powell (1984) to estimate global food aid allocation. The major advantages of this semi-parametric approach are the robustness to unknown conditional heteroscedasticity and the provision of consistent and asymptotically normal estimates for a wide range of error distributions. The median CLAD estimator is obtained by solving

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

where n is the sample size, FA_g is global food aid flows and x_g is the correspondent vector of regressors. For the computation of the CLAD estimator β_g, Buchinsky's iterative linear programming algorithm (ILPA) is used (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), who suggests using the bootstrapping procedure, and computed robust standard errors using 10,000 bootstrap samples.

Food aid allocation of the main donor countries

Since food aid donors respond to similar stimuli and are likely to interact with each other, or coordinate their activities, the error terms in specification (3) are likely to be correlated. Thus, after the second estimation stage specification (3) is estimated in a simultaneous system of equations including all main donor countries, so that more efficient coefficient estimates are obtained. In addition, the application of such a multivariate Tobit model allows for testing the significance of error term correlation, so that implications can be drawn on how donors cooperate with each other. For a vector FA_j, representing the amount of food aid sent to the recipients by donor j, and a vector x_j of regressors defined in (3), the multivariate Tobit model is specified as follows:

$$FA_j = x_j \beta_j + \varepsilon_j \quad ; \quad \varepsilon_j \sim MVN(0, \Sigma) \quad for \quad j = 1, \dots, m \tag{4}$$

The high dimensional integrals that enter the likelihood function of (4) are simulated using the GHK-algorithm (Train, 2003). We employ a method documented in Williams (2000) to compute robust cluster variance estimators that avoid heteroscedasticity bias due to possible intra-country correlation.

5. Empirical Results

5.1 Global food aid allocation

The estimates from the CLAD model on global food aid are reported in Table 1. The negative and significant response to crisis shocks shows that food aid is targeted towards countries facing temporary food crises. The negative, but insignificant coefficient of recipients' food availability levels however indicates that global food aid is insensitive to cross-country food inequalities, which may indicate that chronic hunger due to low levels of food availability in recipient markets is not effectively addressed with food aid. Evidence for a need-oriented global use of food aid can again be found in the estimated negative influence of real GDP, which is significant at the 1% level. The coefficients for 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 man-made disasters. Consistent with the findings from other studies, levels of previously shipped food aid significantly affect current global food aid flows, supporting the inertia hypothesis (Gupta et al. 2003; Young and Abbott, 2008). There appears to be no significant effect of the transposed FIW index value on the allocation of global food aid. The coefficients of the regional dummy variables indicate that Asian recipients received significantly fewer amounts of food aid.

5.2 Food aid allocation of the main donor countries

The results of the multivariate Tobit model analysis are presented in Table 2.[5] As reported at the end of Table 2, the log-likelihood ratio test of the null hypothesis that the ρ-parameters are equal to zero is rejected, thus supporting the simultaneous estimation method used here. All the estimated correlation coefficients are positive and significantly different from zero at the 1% level of significance. The positive correlation parameters suggest that each donor generally ships additional food aid to a particular recipient country, when other donors provide food aid to this recipient. Thus, it appears planning authorities of different donor countries cooperate considerably with each other on the issue of food aid allocation.

Parameter estimates are given for the individual donor countries in separate columns of Table 2. Quite interesting is the observation that food crises and low levels of food availability significantly increase Canadian and both European food aid shipments, but on the other hand are both of no significance for US, Japanese and Australian food aid allocation. A striking finding is that the coefficients representing real GDP per capita are all negative and significantly different from zero, indicating that all donor countries have generally shipped food aid to poorer countries.

Food aid programs administered by EU Member States generally respond to both natural disaster categories with increased food aid shipments. However, the US appears to be sending increased food aid to countries that face sudden disasters, but is generally insensitive to gradual disasters. In contrast, Japan seems to respond positively to gradual disasters, but not to sudden ones. The European Community, Canada and Australia do not appear to be significantly responding to natural catastrophes. Only the European Community responds significantly to man-made disasters.

Quite interesting is the finding that none of the donor countries' aid programs appear to be significantly responsive to the variable for political freedom in recipient countries. Another result noteworthy is the positive and statistically significant lagged effects in all donor food aid programs, confirming the striking presence of inertia of food aid.

Geographic proximity, measured by spatial distance between donor and recipient countries also seem to be an important factor influencing food aid shipments to recipients. Specifically, Australia and the EU Member States appear to be shipping more food aid to countries closer to them compared to those at more distant locations. The estimated results for the dummy variables representing geographic regions indicate that the USA, the European Community and Canada send fewer amounts of food aid to Asia, whereas Australia sends more to its nearby region. Japanese and Australian food aid is sent in favor of countries located in North Africa and the Mideast as well as Sub-Saharan Africa. Canada sends significantly less food aid to Sub-Saharan Africa and the Transition Countries. Except for their favoritism of countries in close proximity, the European Member States have no regional preferences.

6. Conclusions

In spite of frequent criticism, the empirical results obtained from the CLAD and multivariate Tobit models suggest that food aid flows have met important humanitarian objectives and that geopolitical interests generally do not play a decisive role in food aid allocation. In all estimations highly significant food aid persistence is found. The positive and highly significant error term correlation parameters for every donor equation indicate that donor countries indeed co-ordinate their food aid shipments. This result might be also an indication for an effective work of multilateral organizations like the WFP or NGOs that are sourced by a multitude of donor countries. The positive correlations of error terms indicate that a recipient is likely to receive food aid from multiple donors at a given time. Accordingly, the estimation results clearly show that food aid shipments of different donors are not treated as substitutes by food aid planning authorities.

Overall, the results do indicate that food aid remains an effective instrument that is employed in response to a multitude of crisis situations. Thus, when well targeted at the micro level to reduce its potential disincentive effects, food aid can help improve food security and nutrition in recipient countries.

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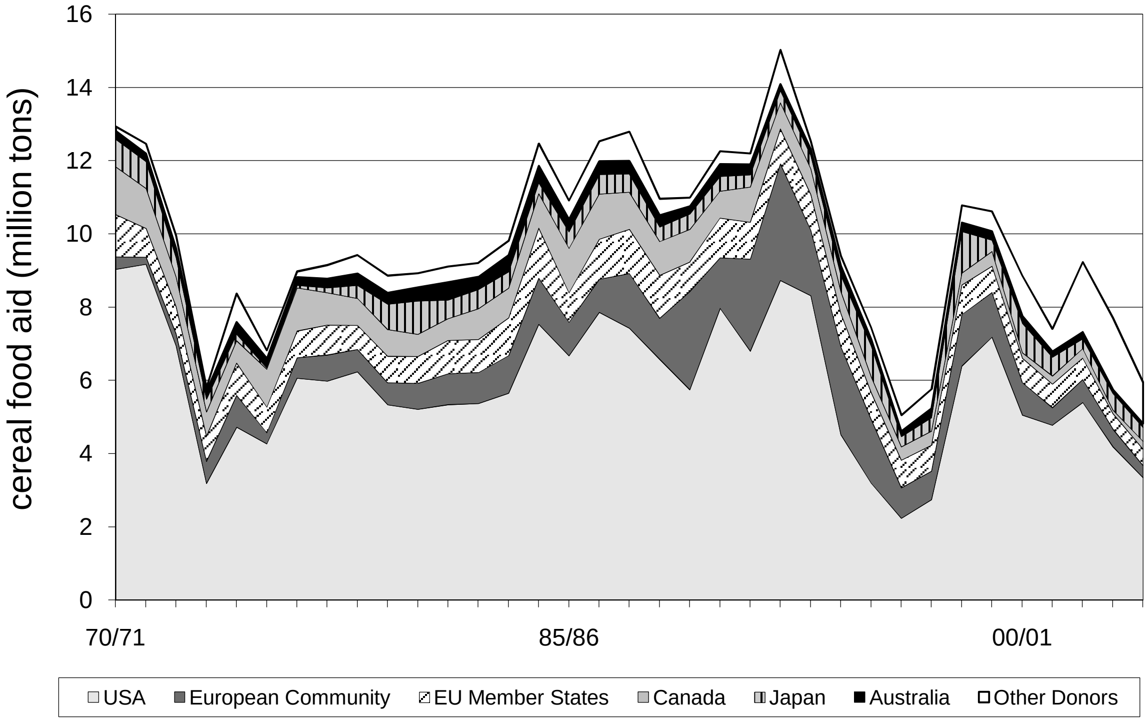
Figure 1. Food aid flows of major donors (1970/71 – 2004/05)



Source: FAO

Table 1. CLAD Median Regression Results

	FA_GLOBAL (0.00 SD)	
Variable	**Coefficient estimate**	**t-statistics**
FOODCRISIS	-0.0015943	(-2.50)**
CEREALPROD	-0.0013447	(-1.45)
RGDP	-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)
DONOR_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	0.0016514	(2.55)**
Initial sample size:		4503
Final sample size:		2877
Pseudo R^2:		0.41

Notes: t-statistics in parentheses. ***, ** 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 the final 2877 observations. Year fixed effects are not reported.

Table 2. Multivariate Tobit Regression Results

Variable	FA_USA (0.0 SD)	FA_ECOMMUNITY (0.3 SD)	FA_EUSTATES (0.0 SD)	FA_CANADA (2.4 SD)	FA_JAPAN (0.0 SD)	FA_AUSTRALIA (1.6 SD)
FOODCRISIS	-0.00248	-0.00380	-0.00257	-0.01449	-0.00060	0.00090
	(-1.46)	(-2.69)***	(-2.68)***	(-3.35)***	(-0.90)	(0.54)
CEREALPROD	-0.00374	-0.00917	-0.00396	-0.00857	-0.00360	0.00053
	(-1.09)	(-2.87)***	(-2.13)**	(-2.14)**	(-1.43)	(0.40)
RGDP	-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)
DONOR_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	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. Year fixed effects are not reported. The log-likelihood ratio test is given by 2 (L1 - L0) where L1 is the unrestricted maximum log-likelihood and L0 is the maximum log-likelihood of the restricted comparison model (Maddala, 1983). Three specifications are used as comparison models: A multivariate constant-only model, a univariate specification including all exogenous variables and a univariate constant-only specification. With the last two specifications, the simultaneous estimation framework is tested and L0 equals the aggregated maximum log-likelihood values of separately estimated Tobit models.

Notes

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[1] Expanded GDP and Trade Data available at: http://privatewww.essex.ac.uk/~ksg/exptradegdp.html

[2] MEVP data available at: http://www.systemicpeace.org/inscr/inscr.htm

[3] Gleditsch, Kristian Skrede. ND. Distance between capital cities data, v. 1.0. Available at: http://privatewww.essex.ac.uk/~ksg/data-5.html. Topografisch Verbond Elbruz data available at: http://www.elbruz.org/General/db/capitaltocapital.php

[4] The EU Member States series consists of the EU-15 states' food aid flows over the whole 1972-2004 period, except Portugal due to lack of data.

[5] The multivariate Tobit model and the CLAD model have been estimated with Stata Version 10 using the program routines *MVTOBIT*, written by Mikkel Barslund, and *CLAD*, written by Dean Jolliffe, Bohdan Krushelnytskyy and Anastassia Semykina.