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Inertia and Herding in Humanitarian Aid Decisions

David Fielding

Department of Economics, University of Otago*

Abstract

Using panel data for the period 1995-2008, we model the aid allocation decisions of the three largest official donors of humanitarian aid: the United States government, the United Kingdom government and the European Commission. We find evidence that donor decisions depend on both the recipient's need and the donor's economic interest, but with marked asymmetries in the relative importance of different factors across the three donors. Moreover, some donors exhibit much more inertia than others in responding to new areas of need, and some are much more influenced by the decisions of other donors. Despite being a relatively small donor, the United Kingdom is particularly influential.

Key words: Humanitarian aid; Dynamic panel model

JEL classification: H59; O19

*Address for correspondence: Department of Economics, University of Otago, P O Box 56, Dunedin 9054, New Zealand, email david.fielding@otago.ac.nz

“Close to one quarter of the aid already devoted to Pakistan [after the 2010 floods] has come from this country. The response from the international community as a whole, however… has just been lamentable. It's been absolutely pitiful.” UK Deputy Prime Minister Nick Clegg, August 16 2010.

1. Introduction

A substantial fraction of the total official overseas development assistance reported by the OECD Development Assistance Committee (DAC) is in the form of humanitarian aid, that is, aid intended to provide relief from the burden of unanticipated disasters, both natural and man-made. In the last decade, humanitarian aid has accounted for 6-7% of total aid. It is typically directed towards the least fortunate groups of people on the planet, at imminent risk of death through disease or hunger. One unique characteristic of humanitarian aid is that it is largely a response to a shock. Donors may budget for a certain total amount of humanitarian aid in any given year, but the allocation of aid to specific countries in response to new disasters is largely unplanned. Donor responses to large disasters, such as the South Asian tsunami of 2004, or the Haitian earthquake and Pakistani floods of 2010, often involve an unbudgeted allocation of funds.

There is some concern in the international community about the speed with which donors respond to new disasters; the quotation above is an example of this. There are a number of reasons why donors may exhibit some inertia in releasing funds for humanitarian aid. Firstly, the decision to continue an existing aid programme is less newsworthy than the decision to instigate a new programme, or to discontinue an existing one. Changes in policy are likely to attract public attention, and politicians must then devote resources to justifying the change. These entry and exit costs can generate hysteresis effects in political decision-making.[1] Secondly, effective aid delivery may be impossible until the donor has established some infrastructure in the recipient country; this fixed economic cost can also generate hysteresis effects. If there is such inertia, the short-run response to a disaster will be less generous than the long-run response, and in the short run, more people will die.

Donor inertia can be measured by the extent to which a particular's donor's aid decisions this year depend on aid its decisions last year, *ceteris paribus*. In addition, aid decisions by a particular donor may depend on the recent decisions of other donors. On the one hand, donors might share the burden of humanitarian relief; if one donor is already active in a country, other donors may choose to focus their efforts elsewhere. In this case, the amount of aid to a particular country from one donor will be a negative function of the past amount of aid from others. On the other hand, donors might exhibit herding behavior, giving more assistance to those countries where other donors are already active, either because of an existing aid infrastructure, or because the presence of other donors makes the aid easier to justify to voters. Herding effects represent inertia at the aggregate level.

In this paper, we use panel data on the aid allocation decisions of the largest humanitarian aid donors to explore these issues. We find evidence that donor decisions depend not only on the recipient's need, but also on the donor's economic interest, suggesting that aid does need to be motivated by political and economic justifications, at least sometimes. However, the role that self-interest plays in aid allocation decisions varies across donors. Moreover, some donors exhibit much more inertia than others, and some are much more influenced by the decisions of other donors. The identification of leaders and followers among donors facilitates an estimate of overall donor influence, which is not necessarily proportional to the amount of aid that the donor gives.

[1] The effect is analogous to hysteresis in private investment decisions (Dixit, 1989).

The next section reviews the existing literature on aid allocation decisions, which provides the context for our own econometric model. This review is followed by a discussion of our data, our modeling strategy, and our results.

2. The Aid Allocation Literature

Formal econometric models of aid allocation date back to McKinlay and Little (1977, 1978a,b), and there are now over 20 published studies, a selection of which are summarized in Table 1. The data used are typically observations of the amount of aid allocated by a particular donor to different recipients. Some studies use cross-sectional data for a particular year or group of years, but most researchers pool data across several years to produce a panel data set. Most studies have some focus on recipient characteristics that are fixed (or at least, change very slowly) over time; they therefore rarely use a fixed-effects estimator.[2] A handful of studies fit a dynamic aid model including the lagged dependent variable (for example, Carey, 2007; Schraeder *et al*., 1998), or allow bilateral aid to a recipient to depend on the aggregate amount of aid given to that recipient by all other donors (for example, Berthélemy and Tichit, 2004; McGillivray and Oczkowski, 1992). However, no study does both simultaneously, and no study models the impact of individual bilateral donor decisions on the choices of other donors. There is therefore no study that estimates the extent to which the evolution of aid patterns over time depends on interactions between the decisions of different donors.

Most studies are designed to identify the relative importance of different recipient characteristics on the amount of aid received from individual donors. In most cases, the variable of interest is total aid, but a few studies focus on a particular aid category, such as humanitarian assistance. Recipient characteristics include measures of need, such as *per*

[2] Among the few authors to use a fixed-effects estimator are Fleck and Kilby (2006, 2010), who focus on the impact of changes in the donor government's political stance on aid allocation decisions.

capita income, infant mortality, or, in the case of humanitarian assistance, the number of people affected by a war or disaster. However, many studies also include measures of donor self-interest, such as the value of donor exports to the recipient or the degree of political support the recipient gives to the donor, measured in various ways. Following Alesina and Dollar (2000), some studies include indices of different dimensions of recipient government institutional quality, including trade openness, democracy and civil liberty. The significance of such factors could reflect donor perceptions of aid effectiveness, or the use of aid as an incentive for political reform. Most studies also allow for the degree of social, cultural or geographical distance between donor and recipient to affect aid volumes; this motivates the inclusion in the aid regression of fixed characteristics such as whether the recipient was ever a colony of the donor, or the kilometer distance between the recipient's capital city and the donor's. A number of studies (for example, Feeny and Clarke, 2007; Rioux and Van Belle, 2005; Strömberg, 2007) investigate the impact of media coverage of the recipient in the donor country.

When each observation is the amount of aid from a particular donor to a particular recipient in a particular year, many observations are equal to zero. Least Squares estimates are therefore unlikely to be consistent, and some authors fit Type-1 Tobit models to the data. However, it is possible that the decision whether to give anything at all (the 'gateway decision') is motivated by a set of criteria different to those motivating the decision about how much to give. For example, a donor might choose to give aid only to countries with close historical or cultural ties, and to determine the allocation of aid between these few recipients on the basis of need. Modeling such a process requires two regression equations, one for the initial binary choice (for example, a Logit or Probit equation), and one for the subsequent allocation decision, using only those observations for which the amount of aid is strictly positive. Consistent estimation at the second stage is dependent on an effective way of dealing with the endogeneity of the sample selection; one might, for example, use a Heckman correction. Such an approach was pioneered by McGillivray and Oczkowski (1991), and followed by authors such as Meernick *et al*. (1998) and Berthélemy (2006).

Our aim is to estimate the dynamics of humanitarian aid allocation: we focus on the extent to which a particular donor's aid allocation decisions depend on that donor's past decisions, and also on other donors' decisions. We do so in a framework that controls for year and country fixed effects, and allows the gateway decision to depend on factors different to the final allocation decision. Table 1 shows how our study relates to the existing literature by noting which of these modeling characteristics is shared by other papers. No existing paper shares all of these characteristics, and in order to fit a dynamic panel data model in the presence of endogenous sample selection, we rely on an estimator recently developed by Semykina and Wooldridge (2010).

3. Data on Humanitarian Aid and its Correlates

3.1 Data sources

Our humanitarian aid data come from the OECD DAC Creditor Reporting System database, extracted from http://stats.oecd.org on 06/01/10. The database records annual commitments from each donor to each recipient country in current US Dollars, along with a deflated series using a donor-specific price index. The donors include both individual industrialized country governments and multilateral organisations. Humanitarian aid is defined as assistance for "disaster prevention and preparedness; the provision of shelter, food, water and sanitation, health services and other items of assistance for the benefit of affected people and to facilitate the return to normal lives and livelihoods; measures to promote and protect the safety, welfare and dignity of civilians and those no longer taking part in hostilities and rehabilitation, reconstruction and transition assistance while the emergency situation persists."

The data are available for the period 1995-2008. Over this period, the United States government has the largest average annual share in total humanitarian aid (33%). Multilateral European Union aid accounts for the second largest share (19%), and the next largest donor is the United Kingdom government (7%). Multilateral EU aid is funded out of the budget of the European Commission, and outside of the UK, individual EU governments all have bilateral humanitarian aid flows accounting for less than 5% of the world total. In modeling humanitarian aid commitments, we will restrict our attention to the three largest donors: the US government, the UK government, and the European Commission. We will estimate the extent to which each of these three donors responds to the aid commitments of the other two, and of all other donors in aggregate.[3]

Our model of humanitarian aid will incorporate year and recipient country fixed effects, and also those determinants of the willingness to give aid that vary over time. In the existing literature, these determinants include measures of both recipient need and donor self-interest. Our recipient need variables are as follows.[4]

(i) The total number of people affected by natural disasters in each recipient in each year, as reported in the database of the Centre for Research on the Epidemiology of Disasters, extracted from www.cred.be on 06/01/10.

(ii) The total number of refugees in each recipient in each year, as reported in the United Nations High Commissioner for Refugees' *Statistical Yearbook* (UNHCR, 1996-2009).

[3] In principle, the European Commission's response to bilateral EU commitments could be different from its response to commitments by non-EU donors other than the US. However, aid from these donors (principally Australia, Canada and Japan) constitutes a very small share of the world total, so making such a distinction in our empirical model is impracticable.

[4] One further need variable that has been considered in previous studies is the incidence of civil war, as recorded in, for example, the Correlates of War database (www.correlatesofwar.org). When we include indices of civil war intensity in our model they are not statistically significant, and there is no significant change in the estimated effect of any other variable.

(iii) The level of *per capita* GNP in each country in each year, as reported in the World Bank's *World Development Indicators* (World Bank, 1996-2009). *Ceteris paribus*, countries with higher levels of *per capita* GNP may be better able to deal with a disaster affecting a given number of people.

(iv) The total population of each country in each year, as reported in the World Bank's *World Development Indicators* (World Bank, 1996-2009). *Ceteris paribus*, countries with a larger population may be better able to deal with a disaster affecting a given number of people.

(v) The political stability of each recipient in each year, as reported in Kaufmann *et al*. (2009). *Ceteris paribus*, countries with more political stability may be better able to deal with a disaster affecting a given number of people. The Kaufmann *et al*. measure is an aggregate index constructed from a number of underlying indicators of political stability; the measure is normalized so that across the whole of their sample, it has a mean of zero and a variance of one. (In our sample, the variance is slightly less than one.)

Many of the donor self-interest variables appearing in previous studies are fixed recipient characteristics that are invariant over time, and are not included in our panel data model. These are such variables as historical, religious or cultural ties, geographical proximity, and whether the recipient is a petroleum exporter. However, one recipient characteristic which does vary over time is its relative importance as a trading partner of the donor. Donors might have a special interest in aiding recipients with whom they have strong overall economic ties, in which case aid will be increasing in the share of the recipient in both the donor's total imports and its total exports. Alternatively, donors might be more motivated to give aid to recipients who represent important export markets, and less motivated to give aid to recipients who already benefit from financial flows from the donor in the form of donor imports. In this case, aid will be increasing in the share of the recipient in the donor's total exports and decreasing in the share of the recipient in the donor's total imports. Our two donor interest variables are therefore as follows.

(i) The share of recipient *i* in the imports of donor *p* in year *t*. For the US, the data are taken from the database of the International Trade Administration, extracted from www.trade.gov on 06/01/10. For the UK and the EU, the data are taken from the Eurostat database, extracted from http://epp.eurostat.ec.europa.eu on 06/01/10. In the case of the EU, the data relate to the imports of the EU-15 member states.

(ii) The share of recipient *i* in the exports of donor *p* in year *t*, as reported in the sources used for donor imports.

One further potential explanatory variable is worthy of comment. Several papers explore the impact of media coverage of disasters on humanitarian aid flows. Such coverage may be endogenous to the level of aid, so it is then necessary to use an Instrumental Variables estimator. The set of potentially valid instruments is limited, but it is possible to use data on the incidence of other newsworthy international events as an instrument: such events might deflect media attention from contemporaneous disasters. For example Strömberg (2007) uses the timing of Olympic Games in this way. Such an instrument will be collinear with the fixed time effects in our model. Therefore, although we are not able to identify the impact of media coverage on humanitarian aid flows, our fixed effects model does control for variations in the exogenous determinants of media coverage used in previous studies.

3.2 Data transformations

The data summarized above are available for the 119 developing countries listed in Appendix 1. (However, as noted in the appendix, the US trade data are missing for one of these countries, the EU trade data for three, and the UK trade data for four.) Table 2 summarizes the distribution of annual humanitarian aid flows to each recipient for the sample that we will be using (1997-2008) for each of the three donors: the US government, the UK government, and the European Commission. In this table, aid is measured in constant 2008 Dollars, values for the years before 2008 being adjusted using each donor's GDP deflator. The table shows that the non-zero observations are highly skewed, and models using the level of aid as the dependent variable produce parameters that are very sensitive to small changes in sample size. A log-linear model fits the data better and produces robust parameters, so our dependent variable is equal to the log of aid from donor p to recipient i in year t measured in constant 2008 Dollars, if this figure is positive, and otherwise equal to zero; this quantity is designated $aid_p(i,t)$. Similarly, the explanatory variables $affected(i,t)$ and $refugees(i,t)$ are equal to the log of the number of people affected by natural disasters, and the log of the number of refugees, in recipient i in year t, if this figure is positive, and otherwise equal to zero.[5] The explanatory variable $income_p(i,t)$ is the log of *per capita* GNP in recipient i in year t, measured in US Dollars and deflated in the same way as the dependent variable, using the price index for donor p. For example, $income_{US}(Mexico,2001)$ is Mexican GNP in 2001, deflated using US prices. The explanatory variable $population(i,t)$ is the log of the total population size. There are three explanatory variables for which a logarithmic transformation is not used. These are the political stability index, $stability(i,t)$, and the shares of recipient i in donor p's imports and exports, $imports_p(i,t)$ and $exports_p(i,t)$.

Table 3 presents some descriptive statistics for the explanatory variables in our model. These variables will be used to fit three different regression equations, one for each donor, and the sample size does vary slightly across the regressions, so three sets of descriptive

[5] Because of the zero observations, the transformation of our aid variable is not invariant to the scale of measurement, which would be problematic if we fitted the data using a Type-1 Tobit model. However, with our sample selection model, the problem does not arise. The transformations of the disaster-affected and refugee variables are also not invariant to the scale of measurement. However, changing the scale from the number of people to the number of tens (or hundreds, or thousands) of people makes little difference to our results.

statistics are shown in the table. The table shows that the variation in the magnitude of disasters, as captured by *affected*(i,t) and *refugees*(i,t), is greater than the variation in the capacity of recipients to deal with them, as captured by $income_p(i,t)$ and *population*(i,t). Also, the variation in import shares is greater than the variation in export shares. This is true of both the overall variation, $Var(x(i,t))$, and the within-country variation, $Var(x(i,t) - x(i))$, where $x(i)$ is the within-country mean, $\Sigma_t\, x(i,t) / 12$. Another feature of the data that will be relevant to our analysis is the low correlation of import and export shares across donors, once one has controlled for country fixed effects. This is shown in the second part of the table, which reports correlation coefficients for $[imports_p(i,t) - imports_p(i)]$ and $[exports_p(i,t) - exports_p(i)]$ across the donors. On average, recipients increasing their share of one donor's imports or exports over time have not increased their shares of other donors' imports or exports.

4. The Model of Humanitarian Aid

We fit two types of regression equation: a gateway equation which predicts whether a particular donor gives any humanitarian aid to a particular recipient in a particular year, and a levels equation which predicts the amount given, if anything is given at all. These models allow for country and time fixed effects, and also incorporate persistence and herding effects.

Our first set of regressions is designed to estimate the factors driving the gateway decisions of the three donors: the US government, denoted *US*; the UK government, denoted *UK*; and the European Commission, denoted *EU*. The dependent variable in these regressions is a binary variable indicating whether a donor gave any aid at all to recipient i in yeat t: $s_p(i,t) = 1$ if $aid_p(i,t) > 0$, otherwise $s_p(i,t) = 0$, where $p \in \{US, UK, EU\}$. We allow for some persistence in these decisions, and for herding effects: $s_p(i,t)$ depends on $s_r(i,t\text{-}1)$ and $s_r(i,t\text{-}2)$, where $r \in \{US, UK, EU, other\}$. Our model is a Probit equation specific to donor p. The following equation is for the US, but the UK and EU equations have the same form:

$$P(s_{US}(i,t) = 1) = \Phi(E[y(i,t)]), \tag{1}$$

$$y(i,t) = \kappa(t) + \nu(i) + \Sigma_r\, \rho_{1r} \cdot s_r\,(i,t\text{-}1) + \Sigma_r\, \rho_{2r} \cdot s_r\,(i,t\text{-}2) + \Sigma_j\, \psi_j \cdot x_j(i,t) + u(i,t)$$

$\Phi(.)$ is the cumulative normal density function. The $\kappa(t)$ and $\nu(i)$ terms represent year and country fixed effects, and $u(i,t)$ is a normally distributed residual. The ρ_{1r} and ρ_{2r} parameters capture both persistence (when $r = US$) and herding effects (when $r \neq US$). Lags up to order 2 are included in the model; higher order lags turn out to be statistically insignificant. The x_j term denotes the exogenous regressors in our model: $x_j \in \{affected,\ refugees,\ income_{US},\ imports_{US},\ exports_{US},\ population\}$. The lagged values of s_r on the right hand side of equation (1) are not strictly exogenous, so care is needed in estimating the parameters. Following Wooldridge (2005), we can generate consistent estimates of the ρ and ψ parameters in this type of equation by fitting a random-effects Probit model:

$$P(s_{US}(i,t) = 1) = \Phi(E[y(i,t)]), \tag{2}$$

$$y(i,t) = \kappa(t) + \varepsilon(i) + \Sigma_r\, \tilde{\rho}_r \cdot s_r\,(i,0) + \Sigma_r\, \rho_{1r} \cdot s_r\,(i,t\text{-}1) + \Sigma_r\, \rho_{2r} \cdot s_r\,(i,t\text{-}2) + \Sigma_j\, \tilde{\psi}_j \cdot x_j(i)$$

$$+ \Sigma_j\, \psi_j \cdot x_j(i,t) + u(i,t)$$

The fixed effect $\nu(i)$ in equation (1) is replaced by a normally distributed random effect, $\varepsilon(i)$, plus a function of (i) the initial values of s_r and (ii) the mean values of $x_j(i,t)$ in each country over the sample period, denoted $x_j\,(i)$. The properties of the random-effects Probit estimator are discussed in Guilkey and Murphy (1993).

Three exogenous donor-specific regressors are included in equation (1); Table 3 shows that two of them ($imports_p$ and $exports_p$) are not very highly correlated across donors. Therefore, if we choose to treat equation (1) as a reduced-form representation of a model in which donors influence each others' decisions contemporaneously, we have a means of identifying the contemporaneous effects, using, for example, $imports_{US}(i,t)$ and $exports_{US}(i,t)$

as instruments for $s_{US}(i,t)$ in the $s_{UK}(i,t)$ equation. Such a strategy will be discussed briefly in the next section.

Our second set of regressions is designed to estimate the factors driving the level of aid given to country i in year t, if any is given at all. The following discussion uses US aid as an example; the models used for the other two donors are just the same. Note that these models do not include any herding effects: *ceteris paribus*, $aid_{US}(i,t)$ does not depend on $aid_{UK}(i,t\text{-}1)$ or $aid_{EU}(i,t\text{-}1)$. Adding these effects to the model described below does not produce any statistically significant coefficients.

The factors driving the level of aid might be different from those driving the gateway decision; in other words, the size and significance of coefficients on the x_j variables might vary between the gateway equation and the levels equation. Moreover, we should allow for some persistence in the level of aid, if this level was positive in the previous year. Incorporating such persistence means that we need to deal with two selection effects: whether $aid_{US}(i,t)$ is positive and whether $aid_{US}(i,t\text{-}1)$ is positive. Our selection model incorporates the following three regimes.

Regime 1: $$aid_{US}(i,t) = \alpha(t) + \beta(i) + \gamma \cdot aid_{US}(i,t\text{-}1) + \Sigma_j\, \delta_j \cdot x_j(i,t) + \upsilon(i,t) \qquad (3)$$

when $s_{US}(i,t) = 1$ and $s_{US}(i,t\text{-}1) = 1$, otherwise…

Regime 2: $$aid_{US}(i,t) = \alpha(t) + \beta(i) + \theta + \Sigma_j\, \delta_j \cdot x_j(i,t) + \upsilon(i,t) \qquad (4)$$

when $s_{US}(i,t) = 1$ and $s_{US}(i,t\text{-}1) = 0$, otherwise…

Regime 3: $$aid_{US}(i,t) = 0 \qquad (5)$$

In principle, we could include more lags and more regimes, but these extra lags are not statistically significant in our data. The $\alpha(t)$ and $\beta(i)$ terms represent year and country fixed effects, and $\upsilon(i,t)$ is a regression residual. When fitting this model, we must allow for the endogeneity of both the regime selection and the value of the lagged dependent variable. This can be achieved by adapting the method of Semykina and Wooldridge (2010).[6] Combining equations (3-4), we have the following equation for positive values of $aid_{US}(i,t)$:

$$aid_{US}(i,t) = \alpha(t) + \beta(i) + \theta \cdot [1 - s_{US}(i,t\text{-}1)] + \gamma \cdot aid_{US}(i,t\text{-}1) + \Sigma_j\, \delta_j \cdot x_j(i,t) + \upsilon\,(i,t) \qquad (6)$$

A consistent estimate of the γ and δ parameters in equation (6) can be produced by fitting a pooled 2SLS regression to those observations for which $s_{US}(i,t) = 1$:

$$aid_{US}(i,t) = \alpha(t) + \theta \cdot [1 - s_{US}(i,t\text{-}1)] + \gamma \cdot \widehat{aid_{US}}\,(i,t\text{-}1) + \Sigma_j\, \delta_j \cdot x_j(i,t) + \Sigma_j\, \phi_j \cdot x_j(i) \qquad (7)$$

$$+\ \eta_1 \cdot \hat{\lambda}\,(i,t) + \eta_2 \cdot \hat{\lambda}\,(i,t\text{-}1) + \eta_3 \cdot \hat{\lambda}\,(i,t) \cdot [1 - s_{US}(i,t\text{-}1)] + \eta_4 \cdot \hat{\lambda}\,(i,t\text{-}1) \cdot [1 - s_{US}(i,t\text{-}1)] + \upsilon\,(i,t)$$

where $\widehat{aid_{US}}\,(i,t\text{-}1) = 0$ if $aid_{US}(i,t) = 0$, otherwise $\widehat{aid_{US}}\,(i,t\text{-}1)$ is the fitted value from a first-stage regression of $aid_{US}(i,t\text{-}1)$ on the other equation (7) regressors plus $x_j(i,t\text{-}1)$, $aid_{US}(i,0)$ and $s_{US}(i,0)$. That is, the effect of lagged aid on its current value is identified by using its value in the first period as an instrument. $\hat{\lambda}\,(i,t)$ is the Inverse Mills Ratio from a year-specific Probit regression for $s_{US}(i,t)$ fitted to the whole sample of countries. This Probit is slightly different to the one in equation (2):

$$P(s_{US}(i,t) = 1) = \Phi(E[y(i,t)]), \qquad (8)$$

$$y(i,t) = \kappa(t) + \Sigma_r\, \tilde{\rho}_r\,(t) \cdot s_r\,(i,0) + \Sigma_j\, \tilde{\psi}_j(t) \cdot x_j(i) + \Sigma_j\, \psi_j(t) \cdot x_j(i,t) + \Sigma_j\, \zeta_j(t) \cdot x_j(i,t\text{-}1)$$

$$+\ \pi(t) \cdot aid_{US}(i,0) + u(i,t)$$

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[6] Semykina and Wooldridge (2010) derive an estimator for any panel data model with endogenous regressors and sample selection; we apply this estimator to the special case in which the endogenous regressor is the lagged dependent variable. Our model is different to the one described in Semykina and Wooldridge (2007), which deals with persistence in a variable that is sometimes unobserved: our zeroes are not missing values, but genuine observations.

The four $\hat{\lambda}$ terms in equation (7) correct the endogeneity of sample selection in both the current period and the previous period. Note the differences between equation (8) and equation (2): consistency of the estimates of the γ and δ parameters in equation (7) requires that only strictly exogenous variables appear on the right hand side of equation (8), so lags of s_r are excluded, but we compensate for the absence of dynamics in the selection equation by including lags of x_j, and by allowing all of the regression coefficients to be specific to each year. Identification of the model requires that equation (8) include some instruments that are excluded from the first-stage regression for $aid_{US}(i,t\text{-}1)$; these instruments are $s_{other}\,(i,0)$, $s_{UK}(i,0)$, and $s_{EU}(i,0)$. In other words, we assume that whether the other donors initially gave any aid to country *i* affects whether the US gives any aid to country *i* this year, but otherwise the initial aid decisions of the other donors have no influence the size of the US aid package.

If it happens that there is no selection bias, then the η coefficients in equation (7) will be nuisance parameters, and their inclusion will reduce the efficiency of our other parameter estimates. Therefore, part of our modeling strategy will be to test the significance of these parameters, and if they are insignificantly different form zero, exclude the $\hat{\lambda}$ terms from our final regression equation.

5. Results

5.1 The gateway model

The results for the gateway model are presented in Tables 4-6. With data for 1995-2008 and two lags in the model, our sample period is 1995-2008. Each table shows the estimated values of the ρ_{1r}, ρ_{2r} and ψ_j coefficients in equation (2) for one of the three donors: the US government, the UK government, and the European Commission. Estimates of the other regression coefficients are not reported, but are available on request. The tables also show the corresponding heteroskedasticity-consistent standard errors and marginal effects.[7] It can be seen that many of the individual ρ_{1r} and ρ_{2r} coefficients are insignificantly different from zero, and each table includes a second set of results in which these coefficients are set to zero for $r \neq p$ (that is, all of the herding effects are suppressed). This restriction never makes any substantial difference to the size or significance level of the other coefficients. In particular, our estimates of persistence do not depend on whether we allow for herding effects. We begin by discussing the magnitude of the effect on aid of different dimensions of recipient need and donor self-interest, and then discuss our estimates of persistence and herding.

For all three donors, the magnitude of disasters has a significant immediate impact on the probability of delivering some humanitarian aid, but the size of the effect is moderate. Table 3 shows that the within-country standard deviation of *affected,* $\sqrt{Var\left(affected(i,t) - affected(i)\right)}$, is 3.76. Combining this figure with the marginal effects reported in Tables 4-6, we see that on average, a one standard deviation increase in the number of people affected by disaster raises the probability of some humanitarian response by 5.6 percentage points in the US and the UK, and by 3.4 percentage points in the EU.[8] Making the same calculations for *refugees* (s.d. = 1.15), we see that a one standard deviation increase in the number of refugees raises the probability of some humanitarian response by 3.7 percentage points in the US and the EU, but in the UK the effect is statistically insignificant. In the US, the probability of giving some humanitarian aid also depends on the recipient's economic capacity, as measured by $income_{US}$. The standard deviation of $income_{US}$

[7] The marginal effect of $x_j(i,t)$ is $\Phi' \cdot \psi_j$, evaluated at the mean value of Φ. The marginal effect of $s_r(i,t\text{-}k)$, a binary variable, is the deviation in Φ from its mean when $s_r(i,t\text{-}k)$ changes from zero to one, calculated using ρ_{kr}.

[8] The figure for the UK is calculated as 3.76 (the standard deviation of *affected* in Table 3) × 1.5 (the marginal effect of *affected* in Table 5, as a percentage); similarly, the figure for the EU is calculated as 3.76 × 0.9 (the marginal effect of *affected* in Table 6, as a percentage).

is 0.15, and the marginal effect on $income_{US}$ reported in Table 4 indicates that, on average, reducing a recipient's *per capita* income by one standard deviation increases the probability of some humanitarian assistance by 6.2 percentage points. However, there is no correspondingly significant effect in the UK or in the EU. Political stability also matters for US aid. The standard deviation of *stability* is 0.3, and a one standard reduction in this variable entails a three percentage point increase in the probability of some US aid. The effect in the UK is the same size, but there is no significant effect in the EU. For no donor is recipient population size a significant explanatory variable.

Trade flows are also a significant determinant of the probability of some humanitarian assistance from the US and the UK, though not from the EU. This may reflect a difference between bilateral and multilateral donors in the political economy of aid allocation. Moreover, the response of US aid allocation to changes in trade flows differs from the response of UK aid allocation. A standard deviation increase in the share of a recipient as a source of US imports raises the probability of some US aid by 3.6 percentage points; the corresponding figure for the export share is 3.8 percentage points. Becoming a more important US trading partner – either as an exporter or as an importer – increases the likelihood of receiving some humanitarian assistance. In the UK, the *exports* coefficient is statistically insignificant, and the *imports* coefficient is significantly *less* than zero. That is, countries already receiving some revenue from exports to the UK are less likely to receive any humanitarian assistance. A standard deviation increase in the share of a recipient as a source of UK imports lowers the probability of some UK aid by 5.2 percentage points. This asymmetry between the US and the UK suggests that different donors perceive the relationship between trade and donor self-interest in different ways.

We now turn to the persistence and herding effects. Aid from all three donors exhibits a substantial amount of persistence. Table 4 shows that if a country received any humanitarian aid from the US government in the previous year, its chances of receiving some aid this year are 26 percentage points higher, *ceteris paribus*. If it received any aid two years ago, its chances of receiving some aid this year are 13 percentage points higher. Table 6 shows that the effects in the EU are of a similar order of magnitude. If a country received any humanitarian aid from the European Commission in the previous year, its chances of receiving some aid this year are 32 percentage points higher, *ceteris paribus*. If it received any aid two years ago, its chances of receiving some aid this year are 17 percentage points higher. The effects in the UK, reported in Table 5, are only half as large, but still significantly greater than zero. Disasters in countries with no history of receiving humanitarian aid from the US government or European Commission are much less likely to attract the attention of these donors. Disasters in countries with no history of receiving humanitarian aid from the UK government are somewhat less likely to attract its attention.

Tables 4 and 6 show that the US government and European Commission also exhibit herding behavior. The probability of a country receiving some humanitarian assistance from the US government is 17 percentage points higher if the UK government was active there in the previous year. The UK government influences the European Commission in a similar way; in this case, the marginal effect is 12 percentage points. Both of these effects are statistically significant. However, the UK government is not influenced by the recent decisions of any other donor. In this sense, the UK is a leader and the larger donors are followers. Although the UK accounts for a relatively small proportion of total humanitarian assistance, its decision to engage with a disaster encourages larger donors to follow suit. The other, even smaller donors appear to have less of an influence on US and EU decisions, although there is some evidence in Table 5 that the US government responds to aid from other donors two years ago.

Since the US and UK government decisions $s_{US}(i,t)$ and $s_{UK}(i,t)$ depend on the volume of these countries' trade with each recipient, we could use the trade volumes as instruments, including $s_{US}(i,t)$ in the models of $s_{UK}(i,t)$ and $s_{EU}(i,t)$, and $s_{UK}(i,t)$ in the models of $s_{US}(i,t)$ and $s_{EU}(i,t)$. However, doing this does not produce any statistically significant coefficients on the endogenous regressors. To the extent that there is herding behavior, it appears to be a response to the past aid decisions of other donors, not to their current aid decisions.

5.2 The model of aid levels

Table 7 summarizes our regression results for the level of humanitarian aid, produced by fitting equations (7-8) to the data.[9] First of all, we note the F-statistics for the joint significance of the $\hat{\lambda}$ terms in equation (7), which are reported at the bottom of the table. For none of the three donors are the four $\hat{\lambda}$ terms jointly significant at the 10% level; for none of the three donors are the two simple terms, $\hat{\lambda}(i,t)$ and $\hat{\lambda}(i,t\text{-}1)$, jointly significant.[10] There is no evidence of any sample selection bias, and it is highly likely that the η coefficients in equation (7) are nuisance parameters, so the rest of Table 7 is devoted to a second set of regressions in which these coefficients have been set to zero. We report only our estimates of the γ and δ coefficients and their heteroskedasticity-consistent standard errors.[11] The γ coefficients indicate the degree of persistence in aid levels, and the δ coefficients indicate

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[9] In these regressions lagged values of the x variables are used as instruments, so we lose one period from the estimation sample, which is now 1998-2008, not 1997-2008.

[10] For all three donors, the instruments for λ are statistically significant in the selection equation (equation (8)), so the insignificance of the λ terms in equation (7) does not reflect a weak instruments problem. In the model of aid_{UK}, two of the instruments, $s_{other}(i,0)$ and $s_{US}(i,0)$, are statistically significant. This is despite the insignificance of $s_{other}(i,t\text{-}1)$, $s_{US}(i,t\text{-}1)$, and $s_{EU}(i,t\text{-}1)$ in Table 5, which reports the equation (2) coefficient estimates. The initial aid decisions of other donors are correlated with current UK decisions, even if subsequent changes in the decisions of these other donors are not.

[11] We do not report estimates the θ coefficient in equation (7). This coefficient is not invariant to the scaling of aid_p, so no particular interpretation can be attached to it.

the impact on aid levels of the recipient need and donor self-interest variables. More detailed results are available on request, including the results for the first set of regressions including the $\hat{\lambda}$ terms, and the equation (8) coefficient estimates.

The table shows that the indicators of recipient need, *affected* and *refugees*, do influence the level of humanitarian aid. However, unlike in the gateway equations, *refugees* is at least as important as *affected*. In countries where the donor is active at all, a 1% increase in the number of refugees increases US government aid by 0.10%, UK government aid by 0.25% and European Commission aid by 0.09%. The number of people affected is statistically significant only in the EU equation, where a 1% increase in this variable increases aid by 0.03%. (As we have seen, the variation in *affected* is greater than the variation in *refugees*, so the two variables are of roughly equal importance in the EU equation.) The other statistically significant exogenous regressors in Table 7 are $exports_{US}$ and $income_{UK}$. A one percentage point increase in the share of a country in US exports raises US aid by 0.35%, and a 1% increase in the country's *per capita* income reduces UK aid by 2%. None of the other recipient capacity variables is statistically significant. As we have seen, political stability is a significant determinant of the probability that the US and UK governments will decide to deliver some aid, but once this decision has been made, political stability is not relevant to the level of assistance given.

Table 7 also shows a considerable degree of persistence in the level of aid. As with the gateway equations, this persistence is more marked in the US and the EU than it is in the UK. The coefficient on the lagged dependent variable in the US equation is 0.58, and in the EU equation it is 0.50. In other words, the immediate response of these donors to an increase in recipient need – if they respond at all – is roughly half as large as the response in the steady state. The equivalent coefficient in the UK equation is 0.19, implying an immediate response to an increase in recipient need that is just over 80% as large as the steady state response. Not only are donors slow in making the decision to deliver humanitarian assistance to a country in need; once they have made this decision, it takes time for the level of assistance to rise to its steady state level.

6. Conclusion

Fitting dynamic panel models to annual humanitarian aid data for the three largest official donors and 119 recipient countries, we find strong evidence for persistence in aid allocation. Donors are slow to respond to new disasters with any aid at all, and when they do respond, it takes some time for aid to reach its steady-state level. This persistence effect is most marked for the two largest donors, the US government and the European Commission; for the third largest donor, the UK government, there is a more moderate persistence effect. Moreover, humanitarian aid from the US and the UK depends on their trade with the recipient country. This suggests that such aid is not always directed towards those parts of the world where the hardship is most severe, at least in the first instance. Understanding the underlying reasons for persistence in humanitarian aid flows is an important topic for future research.

The other striking feature of the data is the herding effect. The aid allocation decisions of the two largest donors, the US government and the European Commission, depend on past decisions by the UK government, even though the UK's total humanitarian aid contribution is less than 40% of the EU's and less than 25% of the US's. Moreover, UK government decisions are independent of those made by the US government and the European Commission. With the lower degree of persistence in UK aid allocation decisions, this gives the UK an influence over worldwide humanitarian assistance that far exceeds its own individual contribution. The UK is faster to respond to new disasters than the US and EU, and when it does respond, the US and EU are more likely to follow suit in subsequent years. Understanding the political economy underlying these dynamics is another important topic for future research.

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Appendix 1: Recipient Countries Included in the Panel

Albania	Croatia	Kyrgyz Republic	Serbia[¶]
Algeria	Djibouti*	Laos	Seychelles
Angola	Dominican Republic	Lebanon	Sierra Leone
Argentina	Ecuador	Lesotho	Slovenia
Armenia	Egypt	Liberia	South Africa
Azerbaijan	El Salvador	Macedonia	Sri Lanka
Bangladesh	Equatorial Guinea	Madagascar	St. Lucia
Belarus	Eritrea	Malawi	St.Vincent[¶]
Belize	Ethiopia	Malaysia	Sudan
Benin	Fiji	Maldives	Suriname
Bhutan	Gabon	Mali	Swaziland
Bolivia	Gambia	Mauritius	Syria
Bosnia	Georgia	Mexico	Tajikistan
Botswana	Ghana	Moldova	Tanzania
Brazil	Grenada	Mongolia	Thailand
Burkina Faso	Guatemala	Morocco	Togo
Burundi	Guinea	Mozambique	Trinidad
Cambodia	Guinea-Bissau[§]	Namibia	Tunisia
Cameroon	Guyana	Nepal	Turkey
Cape Verde	Haiti	Nicaragua	Turkmenistan
Central Afr. Republic	Honduras	Niger	Uganda
Chad	Hong Kong	Nigeria	Ukraine
Chile	India	Pakistan	Uruguay
China	Indonesia	Panama	Uzbekistan
Colombia	Israel	Papua New Guinea	Vanuatu
Comoros	Jamaica	Paraguay	Venezuela
Congo Dem. Republic	Jordan	Peru	Vietnam
Congo Republic	Kazakhstan	Philippines	Yemen[¶]
Costa Rica	Kenya	Rwanda	Zambia
Côte d’Ivoire	Korea Republic	Samoa	

Missing trade data: * *Data missing for the US.*

[§] *Data missing for the UK.*

[¶] *Data missing for the UK and the EU.*

Table 1: Characteristics of Existing Studies of Aid Allocation

	Aid Type	*Bilateral Donors in the Study*	*Does the Model Include…* *Dynamics?*	*Fixed Effects?*	*Responses to Other Donors?*	*Gateway Decisions?*	*Endogenous Selection?*
Alesina & Dollar (2000)	Total bilateral	US plus 11 others	No	No	No	No	No
Bermeo (2008)	Total bilateral	France, Japan, UK, US	No	No	No	No	No
Berthélemy (2006)	Total bilateral	All DAC members	No	No	Yes	Yes	Yes
Berthélemy & Tichit (2004)	Total bilateral	All DAC members	No	No	Yes	Yes	Yes
Canavire *et al*. (2005)	Total bilateral & total IDA	US plus 8 others	No	No	No	No	No
Carey (2007)	Total bilateral & total EU	France, Germany, UK	Yes	No	No	Yes	No
Cooray & Shahid-uzzaman (2004)	Total bilateral	Japan	No	No	No	No	No
Drury *et al*. (2005)	Humanitarian bilateral	US	No	No	No	No	No
Feeny & Clarke (2007)	Humanitarian bilateral	Australia	No	No	No	No	No
Fleck & Kilby (2003, 2010)	Total bilateral	US	No	Yes	No	No	No
Lewis (2003)	Environmental bilateral	US	No	No	No	Yes	No
McGillivray & Oczkowski (1991)	Total bilateral	Australia	No	No	No	Yes	Yes

Table 1 (Continued)

	Aid Type	Bilateral Donors in the Study	*Does the Model Include…* Dynamics?	Fixed Effects?	Responses to Other Donors?	Gateway Decisions?	Endogenous Selection?
McGillivray & Oczkowski (1992)	Total bilateral	UK	No	No	Yes	Yes	Yes
McGillivray (2003)	Total bilateral	US	No	No	No	Yes	Yes
McKinlay & Little (1977, 1978a,b)	Total bilateral	France, UK, US	No	No	No	No	No
Meernick *et al*. (1998)	Total bilateral	US	No	No	No	Yes	Yes
Neumayer (2003)	Total develop-ment banks	None	No	No	No	No	No
Neumayer (2005)	Food bilateral, food EU & WFP	US	No	No	No	No	No
Quinn & Simon (2006)	Total bilateral	France	No	No	No	No	No
Rioux & Van Belle (2005)	Total bilateral	France	No	No	No	No	No
Schraeder *et al*. (1998)	Total bilateral	France, Japan, Sweden, US	Yes	No	No	No	No
Strömberg (2007)	Humanitarian bilateral	All DAC members	No	No	No	Yes	No
Tavares (2008)	Humanitarian bilateral	US plus bilateral aid in aggregate	No	No	No	Yes	No

Table 2: Descriptive Statistics for Untransformed Annual Humanitarian Aid Flows (1997-2008)

donor	*positive / total observations*	the distribution of positive observations (in constant $mn) *mean*	*median*	*maximum*	*std. dev.*
US Government	718 / 1416	20.11	1.89	762.16	72.68
UK Government	406 / 1380	6.89	1.39	119.80	16.21
European Commission	722 / 1392	12.76	3.81	256.18	25.04

Table 3: Descriptive Statistics for the Explanatory Variables in the Probit Equations

(i) Univariate statistics

s.d. (1) denotes $\sqrt{Var\left(x(i,t)\right)}$; s.d. (2) denotes $\sqrt{Var\left(x(i,t)-x(i)\right)}$

	aid_{US} equation (1416 observations)			aid_{UK} equation (1380 observations)			aid_{EU} equation (1392 observations)		
	mean	*s.d.* (1)	*s.d.* (2)	*mean*	*s.d.* (1)	*s.d.* (2)	*mean*	*s.d.* (1)	*s.d.* (2)
affected	6.66	5.51	3.76	6.74	5.52	3.76	6.73	5.51	3.77
refugees	6.98	4.13	1.15	6.96	4.09	1.16	6.98	4.08	1.16
$income_p$	8.06	1.04	0.15	8.22	1.03	0.13	8.20	1.04	0.14
stability	-0.41	0.86	0.30	-0.41	0.86	0.30	-0.41	0.85	0.30
$imports_p$	14.11	3.00	0.71	13.88	2.73	0.75	14.39	2.25	0.46
$exports_p$	14.59	2.42	0.46	14.33	2.03	0.38	14.51	1.96	0.26
population	15.83	1.82	0.07	15.85	1.81	0.07	15.84	1.81	0.07

(ii) Correlations coefficients for [$imports_p(i,t)$ – $imports_p(i)$] and [$exports_p(i,t)$ – $exports_p(i)$]

	$exports_{US}$	$imports_{US}$	$exports_{UK}$	$imports_{UK}$	$exports_{EU}$
$imports_{US}$	0.15				
$exports_{UK}$	0.21	0.20			
$imports_{UK}$	-0.02	0.23	0.16		
$exports_{EU}$	0.27	0.16	0.53	0.09	
$imports_{EU}$	0.03	0.24	0.27	0.40	0.28

Table 4: Dynamic Probit Models of the Presence of US Humanitarian Aid (1997-2008)

The dependent variable is $s_{US}(i,t)$. The sample comprises 118 countries and 1416 observations.

	coeff.	s.e.		m.e.	coeff.	s.e.		m.e.
$s_{US}(i,t\text{-}1)$	0.621	0.123	***	0.244	0.662	0.125	***	0.259
$s_{US}(i,t\text{-}2)$	0.300	0.130	**	0.119	0.333	0.130	***	0.132
$s_{other}(i,t\text{-}1)$					0.059	0.138		0.024
$s_{other}(i,t\text{-}2)$					0.353	0.134	***	0.140
$s_{UK}(i,t\text{-}1)$					0.426	0.122	***	0.168
$s_{UK}(i,t\text{-}2)$					-0.016	0.120		-0.006
$s_{EU}(i,t\text{-}1)$					0.071	0.124		0.028
$s_{EU}(i,t\text{-}2)$					0.174	0.129		0.069
affected(i,t)	0.039	0.011	***	0.016	0.041	0.011	***	0.016
refugees(i,t)	0.075	0.042	*	0.030	0.080	0.040	**	0.032
$income_{US}(i,t)$	-1.436	0.535	***	-0.573	-1.034	0.525	**	-0.412
stability(i,t)	-0.273	0.164	*	-0.109	-0.270	0.162	*	-0.108
$imports_{US}(i,t)$	0.122	0.067	*	0.049	0.129	0.066	*	0.051
$exports_{US}(i,t)$	0.219	0.109	**	0.087	0.200	0.106	*	0.080
population(i,t)	-0.058	1.443		-0.023	0.581	1.425		0.232
residual s.d.	0.449	0.095			0.207	0.140		
ratio of panel-level to total resid. variance	0.168	0.059			0.041	0.053		

*** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level

Table 5: Dynamic Probit Models of the Presence of UK Humanitarian Aid (1997-2008)

The dependent variable is $s_{UK}(i,t)$. The sample comprises 115 countries and 1380 observations.

	coeff.	s.e.		m.e.	coeff.	s.e.		m.e.
$s_{UK}(i,t\text{-}1)$	0.549	0.111	***	0.167	0.541	0.113	***	0.164
$s_{UK}(i,t\text{-}2)$	0.262	0.113	**	0.077	0.255	0.114	**	0.074
$s_{other}(i,t\text{-}1)$					0.069	0.164		0.019
$s_{other}(i,t\text{-}2)$					-0.049	0.160		-0.014
$s_{US}(i,t\text{-}1)$					0.049	0.128		0.014
$s_{US}(i,t\text{-}2)$					0.148	0.129		0.042
$s_{EU}(i,t\text{-}1)$					0.063	0.129		0.018
$s_{EU}(i,t\text{-}2)$					0.041	0.131		0.011
affected(i,t)	0.053	0.012	***	0.015	0.053	0.012	***	0.015
refugees(i,t)	0.022	0.040		0.006	0.020	0.040		0.006
$income_{UK}(i,t)$	0.294	0.525		0.083	0.357	0.536		0.100
stability(i,t)	-0.376	0.141	***	0.106	-0.355	0.141	**	-0.100
$imports_{UK}(i,t)$	-0.239	0.063	***	-0.067	-0.245	0.063	***	-0.069
$exports_{UK}(i,t)$	0.119	0.129		0.034	0.119	0.129		0.033
population(i,t)	1.272	1.374		0.359	1.258	1.388		0.354
residual s.d.	0.335	0.092			0.283	0.100		
ratio of panel-level to total resid. variance	0.101	0.050			0.074	0.049		

*** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level

Table 6: Dynamic Probit Models of the Presence of EU Humanitarian Aid (1997-2008)

The dependent variable is $s_{EU}(i,t)$. The sample comprises 116 countries and 1392 observations.

	coeff.	s.e.		m.e.	coeff.	s.e.		m.e.
$s_{EU}(i,t\text{-}1)$	0.918	0.117	***	0.353	0.830	0.119	***	0.321
$s_{EU}(i,t\text{-}2)$	0.456	0.123	***	0.180	0.419	0.124	***	0.165
$s_{other}(i,t\text{-}1)$					0.134	0.135		0.053
$s_{other}(i,t\text{-}2)$					0.172	0.132		0.069
$s_{US}(i,t\text{-}1)$					0.017	0.122		0.007
$s_{US}(i,t\text{-}2)$					0.078	0.125		0.031
$s_{UK}(i,t\text{-}1)$					0.326	0.119	***	0.128
$s_{UK}(i,t\text{-}2)$					0.100	0.116		0.040
$affected(i,t)$	0.020	0.011	*	0.008	0.022	0.011	*	0.009
$refugees(i,t)$	0.074	0.037	**	0.030	0.087	0.038	**	0.034
$income_{EU}(i,t)$	0.021	0.498		0.008	0.106	0.503		0.042
$stability(i,t)$	-0.112	0.148		-0.044	-0.086	0.149		-0.034
$imports_{EU}(i,t)$	-0.015	0.110		-0.006	-0.021	0.111		-0.008
$exports_{EU}(i,t)$	-0.207	0.200		-0.082	-0.241	0.204		-0.096
$population(i,t)$	-0.089	1.301		-0.036	-0.040	1.327		-0.016
residual s.d.	0.293	0.101			0.227	0.115		
ratio of panel-level to total resid. variance	0.079	0.050			0.049	0.047		

*** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level

Table 7: Dynamic Models of the Level of Humanitarian Aid (1998-2008)

aid$_{US}$ equation	coeff.	s.e.		***aid$_{UK}$ equation***	coeff.	s.e.		***aid$_{EU}$ equation***	coeff.	s.e.	
$aid_{US}(i,t\text{-}1)$	0.583	0.060	***	$aid_{UK}(i,t\text{-}1)$	0.193	0.093	**	$aid_{EU}(i,t\text{-}1)$	0.500	0.067	***
$affected(i,t)$	0.007	0.019		$affected(i,t)$	0.023	0.026		$affected(i,t)$	0.033	0.015	**
$refugees(i,t)$	0.102	0.061	*	$refugees(i,t)$	0.249	0.092	***	$refugees(i,t)$	0.088	0.042	**
$income_{US}(i,t)$	-0.505	0.808		$income_{UK}(i,t)$	-2.008	1.075	*	$income_{EU}(i,t)$	0.373	0.827	
$stability(i,t)$	-0.181	0.184		$stability(i,t)$	-0.053	0.240		$stability(i,t)$	-0.248	0.179	
$imports_{US}(i,t)$	-0.055	0.101		$imports_{UK}(i,t)$	0.042	0.118		$imports_{EU}(i,t)$	-0.170	0.136	
$exports_{US}(i,t)$	0.349	0.183	*	$exports_{UK}(i,t)$	0.185	0.264		$exports_{EU}(i,t)$	0.090	0.271	
$population(i,t)$	2.739	2.295		$population(i,t)$	4.811	3.324		$population(i,t)$	0.448	1.928	
R^2	0.583			R^2	0.348			R^2	0.435		
residual s.d.	1.682			residual s.d.	1.737			residual s.d.	1.409		
observations	711			observations	356			observations	654		

Joint significance of:	***aid$_{US}$ equation***	***aid$_{UK}$ equation***	***aid$_{EU}$ equation***
$\hat{\lambda}(i,t)$, $\hat{\lambda}(i,t\text{-}1)$, $\hat{\lambda}(i,t)\cdot[1\text{-}\ s^{p}(i,t\text{-}1)]$, $\hat{\lambda}(i,t\text{-}1)\cdot[1\text{-}\ s^{p}(i,t\text{-}1)]$	F(4,680) = 1.12	F(4,325) = 0.24	F(4,623) = 1.88
$\hat{\lambda}(i,t)$, $\hat{\lambda}(i,t\text{-}1)$	F(2,680) = 1.51	F(2,325) = 0.64	F(2,623) = 1.89

*** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level