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# Unofficial Development Assistance: a model of development charities' donation income

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**Abstract**

The empirical literature on the determinants of charities' donation income, distinguishing the charitable cause, is small. We extend it by paying particular attention to development charities, capturing both charity and donor characteristics in a single framework. Using a newly constructed panel covering a quarter of a century, we observe a strong fundraising effect and a unitary household income elasticity. We find evidence that the conventionally identified 'price' effect may be the result of omitted variable bias rather than a genuine response of donors to perceived excesses in fundraising expenditure. Our results further suggest that public spending on development may affect private donations for development. We also find a positive spillover effect of fundraising, suggesting that the efforts of one development charity may increase contributions made to other development charities.

**JEL classification:** L3, D1, D6, F3

**Keywords:** charitable giving, overseas development

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# 1 Introduction

Discussion of development finance is often focused on Official Development Assistance (ODA), given by governments in the form of bilateral or multilateral aid. However, contributions from private individuals are also prominent. These include both remittances from migrants (e.g. Solimano, 2005) and the donations made to charities working abroad for overseas development aid and humanitarian assistance. The latter have received much less attention from researchers. The large theoretical and empirical literatures on charitable giving tend not to distinguish giving by cause (Andreoni, 2006). In this paper, we model donations received by overseas development charities in the UK, the total of which, in 2004–5, equalled about a quarter of the UK's ODA. We use a newly constructed panel on individual charity finances that spans over 25 years. Our focus on giving for overseas development rather than total giving allows us to pay more attention to the particular characteristics of giving to this cause. We draw in part on the theoretical model in Atkinson (2009), which explicitly considers the giving to overseas development charities by private individuals. We extend the existing empirical literature on charities' donation incomes that has focused on charity level factors, such as fundraising and government grants received by charities, by introducing aggregate donor characteristics, ODA, and humanitarian crises within a single framework, allowing also for possible dynamics. Section 2 outlines this approach. Secion 3 describes our newly constructed data. Model specification and estimation issues are addressed in Section 4 along with the results. We discuss the interpretation of the estimated effects as well as fundraising spillover effects in detail in Section 5. Section 6 concludes.

# 2 Modelling charitable giving for development

Charities receive income from sources such as the sale of goods and services, grants, and voluntary contributions in the form of money donations. These donations have generally been modelled as a function of either donor characteristics or charity characteristics. On the donor side, theory describes behaviour based on public goods and 'warm-glow' motives (see Andreoni, 2006) and the empirical literature focuses on modelling donations as a function of personal characteristics such as income using household or individual level data (see Peloza and Steel, 2005). On the charities' side, a smaller body of theory describes their activities (e.g. Steinberg, 1986; Steinberg and Weisbrod, 2005), much of it focused on their objective function. The related empirical work (e.g. Weisbrod and Dominguez, 1986; Khanna, Posnett and Sandler, 1995; Khanna and Sandler, 2000; Tinkelman, 2004) has sought to model donation receipts as a function of charity characteristics such as fundraising expenditure, often testing hypotheses about charity objectives.

In both approaches, the cause (e.g. health, education, development) supported by donations or served by the charity is typically ignored. But in general people give deliberately to a specific cause and charities are established to serve a particular purpose. Atkinson (2009) argues that the public goods and 'warm-glow' models each fail to capture key aspects of giving for international development and proposes a new 'identification' model that incorporates elements of both.[1] Empirical studies may estimate a model for different charitable causes, though there is generally no cause-specific specification. Moreover, models of donor behaviour that ignore the activities of charities, or vice versa, may be mis-specified as the donation expenditure of households and receipts of charities are two sides of the same coin and are a function of both donor and charity characteristics simultaneously. Andreoni (2006) emphasises that 'the interaction between supply and demand for philanthropy has been largely neglected in both theoretical and empirical analysis'. Our empirical model contains elements suggested from work on both sides of the market, integrating both aggregate donor and individual charity characteristics into a single framework, as well as considering development-specific macro determinants of donations to development charities, namely ODA and large humanitarian crises affecting the developing world.

From the donor side, we focus on household income, emphasised in the 'warm-glow'

[1] Atkinson's model is similar in spirit to the 'impact giving' model of Duncan (2004), although Duncan had no specific charitable cause in mind.

approach and the identification model. The quarter-century covered by our panel of charities saw a 2.5 fold increase in real after-tax household incomes in the UK. Income growth was far from steady across the period which covers the recessions of the early 1980s and early 1990s. Besides total income we also consider the impact of changes in its distribution. Over the period as a whole, inequality of incomes rose substantially. Glazer and Konrad (1996) present a signalling model of charitable giving that predicts an increase in giving arising from an increase in inequality. But in the case of international development charities, increases in domestic inequality may cause donors to shift their giving towards domestic services and away from international ones.

Charitable giving receives preferential treatment under UK tax law through an arrangment known as 'Gift Aid' which allows the recipient charity to reclaim the basic rate (22% in 2000) income tax paid on the gift effectively increasing the value of the donation. Prior to 2000, the incentive was limited to cash donations in excess of £600. In 2000, this lower limit was removed and we allow for this change.

From the charity side, we follow the existing practice by considering the impact of fundraising, a constructed 'price', government grants, and other autonomous, or non-voluntary, income. Within Atkinson's identification model, fundraising campaigns help increase the awareness of recipients' need, increasing donations made to the charity undertaking the expenditure. However, that expenditure may also affect donations made to other charities via a spillover effect, not previously considered in the charity literature. The fundraising of one charity may raise awareness of development issues and so increase donations made to all charities in the sector. Or it may increase the relative appeal to donors of that particular charity, diverting contributions away from other development charities. Evidence of a positive spillover effect has been found for private, for-profit firms. For example, Sahni (2013) finds evidence that one restaurant's advertising increases sales made by its competitors serving similar food. We test for the presence of an analogous spillover effect from fundraising.

Following Rose-Ackerman (1982) and Weisbrod and Dominguez (1986), fundraising has also been assumed to affect negatively the 'price' of donations – a measure of the cost to a donor of increasing charitable output of a charity by £1. The identification of the price effect has been central to this literature and appears in nearly every empirical model of donations using charity-level data.

Tinkelman (2004) defines the price as $p_t = 1/(1-f_{t-1})$ where $f = F/D$ is the proportion of total donations, $D$, spent by the charity on fundraising, $F$, in the previous period.[2] Donor utility can be modelled as a function of the welfare of the recipients of the charities' 'output' or charitable expenditure. The price of increasing 'output' by one unit accounts for the proportion of the donation that goes to any expense other than the end-recipients (ignoring any indirect benefit to them). We use Tinkelman's definition and follow him and others (e.g. Okten and Weisbrod, 2000) in excluding administrative expenditure from the construction of our price variable, and our model, as we agree that "there is no clear way of reliably computing the relevant portion of the organization's total administrative costs" (Tinkelman, 2004: 2183). The price is constructed using lags because donors cannot observe price in the period in which they donate as the information necessary for its construction is not available until a charity's annual report is submitted at year-end (Okten and Weisbrod, 2000; Tinkelman, 2004). Use of the lag also addresses possible endogeneity but raises concerns about neglected dynamics. A negative price effect, found by several authors may simply result from omitting an autoregressive process when modelling donations, a possibility we consider explicitly in our model.

We include a control of non-voluntary income, as is often done in the literature (e.g. Khanna et al., 1995; Khanna and Sandler, 2000). Charities with higher levels of non-voluntary income coming from, say, high street shops, may find it easier to raise donations given this added exposure. Conversely, donors may see such charities as less in need of donations.

The issue of how the grant income of a charity affects its donations has received much attention (e.g. Kingma, 1989; Khanna and Sandler, 2000; Andreoni and Payne, 2011). Government grants may crowd out donation income – donors seeing the charity as less

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[2] Very similar definitions are used in Weisbrod and Dominguez (1986), Steinberg (1986), Khanna et al. (1995) and Khanna and Sandler (2000).

needy.[3] Or they may ‘crowd in’ giving, being viewed by donors as a signal that a charity is worth supporting. There are also arguments for no impact: Horne et al (2005) find that US donors have little knowledge of the government grants received by the charities to which they give. In the case of the UK overseas development charities, these grants represented about £250m in 2004–5, compared to donations of about £1bn (Atkinson et al, 2012). Over the period we consider, they grew enormously, by a factor of 10 between the late 1970s and the mid-1990s when there was a levelling off.

Government ODA features prominently in Atkinson’s identification model: it influences the living standards of the recipients with whom the donor identifies, reducing the marginal impact of a donation on the welfare of the recipient. This provides another possible source of crowding-out, leading to lower donations.[4] Alternatively, ‘crowding in’ can be expected if increases in ODA raise donors’ perceptions of need by drawing attention to problems of developing countries. The UK government’s prominent commitment in the late 1990s to increase ODA and its continued pledge to sustain development assistance might be seen in this light. Finally, some donors may of course be unaware of ODA levels or changes. The scale of official assistance in relation to private donations demands that we include ODA as an explanatory variable in our empirical model.

An empirical model that focuses on development charities needs to recognise emergency relief as an important influence on giving. A major humanitarian crisis can have an immediate and large impact on the donor perceptions of need that are at the heart of the identification model. The period we consider includes two such crises: the Ethiopian famine in 1984-85 and the Asian Tsunami of Christmas 2004. Both saw huge responses from private donors which we seek to measure.

Finally, in a major departure from previous practice, we initially allow for a general dynamic model. Whereas previous studies used lagged regressors to avoid endogeneity

[3] Andreoni and Payne (2011) present evidence that the observed crowding out in studies using US data operates largely via changes in the fundraising behaviour of charities which receive grants.

[4] However, Atkinson (2009) notes that ODA and private donations may not be perfect substitutes. Were they to fund different, complementary activities, ODA would encourage donations. He offers the example of ODA funding school construction while donations fund textbooks.

(Khanna et al. 1995; Okten and Weisbrod, 2000), we begin with a general dynamic model including contemporaneous and lagged regressors, including lagged donations. There are good institutional reasons for such a specification. Many individuals make donations through bank standing orders, which they fail to adjust each year as their circumstances change. Consider a charity that hires fundraisers to find new donors among high street shoppers. Donors typically sign up to give indefinitely and the charity's fundraising expenditure in that year produces a continued stream of income. The specification we use allows us to separate out the persistence found in the donations data that is due to an unobserved charity-specific effect from that due to the effect coming via lagged donations. The lagged dependent variable also allows us to separate the long-run from the short-run effects of the explanatory variables, albeit in a restricted way.

Taken together, our approach allows us to control simultaneously for the characteristics of donors, the characteristics of charities, the environment in which donations are made, and potential dynamics determining donations.

# 3 Data

Our data come from the Charity Trends reports published by the Charities Aid Foundation (CAF) from 1978 to 2006, covering donations to 2004.[5] The reports document the annual revenues and expenditures of the leading UK fundraising charities. We obtain our donations variable by subtracting the figure for legacies from the total reported 'voluntary income', the variable on which the CAF rankings are based. CAF first included the top 200 fundraising charities, increasing coverage to the top 300 in 1985, the top 400 in 1986, and the top 500 from 1991. There was no report in 1995 and we did not have access to the report from 1981. We assign observations to a calendar year by applying the rule that where the charity's reporting year finishes before June 30th the observation is assigned to the previous calendar year.

[5] The last report in this series was published in 2007 but the information for donations is not consistent with that in earlier reports. Khanna et al. (1995) and Khanna and Sandler (2000) also used CAF data but just for eight years.

The resulting panel is unbalanced and has gaps. The gaps appear for various reasons including changing accounting years, duplicate data used by CAF from one year to the next, the unavailable CAF reports, or because a charity drops out of the rankings for a year.[6] Where a gap of a single year appears we linearly interpolate the missing values by using the observations for the preceding and following years.[7] We test the sensitivity of results to the exclusion of these filled-in observations.

Although the charities for which we have data represent only a small fraction of the roughly 160,000 registered UK charities, they form a large share of the economic activity of the charitable sector. The largest 500 charities by donated income account for about half of all such income (Charities Aid Foundation, 2004: ix, 21 and 40). The great bulk of donations come from individuals; a small part comes from the corporate sector and grant-making charitable trusts but these donations cannot be separated in the data.

Our focus is on the development charities. We include both the charities under this heading in the CAF reports and the 'religious international' charities that are separately identified. The development charities include a number that serve domestic as well as overseas development e.g. the Red Cross and Save the Children. The dataset contains 70 development charities that appear in Charity Trends at least once during the period, of which we drop two – see below – leaving 68. We lose a further 12 (only 35 charity-years in total) as there must be at least three consecutive observations for our estimation method (see Section 4).

In terms of aggregate giving for development, there was a striking rise in the real value of donations across the period we consider, with an average annual growth rate for development charities among the top 200 fundraisers of nearly 7.5 per cent, a little above that for charities as a whole. This growth far outstripped the 2 per cent average annual growth in

[6] Charities sometimes neglected to respond to CAF's requests for their financial reports. Rather than exclude them charities from the rankings, CAF would use the data from the previous year. We have identified and removed these duplicate observations. Full details of our assembly and cleaning of the panel are given in Atkinson et al. (2008).

[7] In two cases (Actionaid and UNICEF) we know the charity existed and was large enough to enter the rankings in the first years they were compiled but they were excluded by CAF for some reason. In these two cases we apply the average growth rate over the three subsequent years (1981-1983) to fill in the missing data for 1978-1981.

real after-tax household income. It was also far larger than the rise in the UK government's ODA, which grew unevenly in real terms by a factor of just 1.5. 1984-85 saw a spike in development donations due to the response to the Ethiopian famine. This was in part stimulated by Bob Geldof, who organised the Band Aid Christmas single in 1984 and the Live Aid concerts in 1985. Geldof's Band Aid Trust was the charity with the most donations in the UK in 1985 – among all causes – with £122m (2007 prices). We exclude this charity from our analysis since it was not founded to engage in annual fundraising. Its removal still leaves a spike in the two years. For example, Oxfam had a record year in 1984, with its £109m of donations (2007 prices) nearly double the level of the year before.[8] We also exclude Comic Relief which raises funds with a telethon and associated events every two years, so it does not raise funds each year like other charities.[9] The median year of entry is 1989 and the median number of observations is 12 years.

Table 1 gives summary statistics for the continuous variables entered in our model. The unit of analysis in the top panel (A) is the charity-year. Mean annual donations received by development charities is £11.7m (2007 prices). Fundraising statistics are conditional on fundraising being recorded as positive – information is missing or is recorded as zero for 11 per cent of cases. The absence of positive values for fundraising is not easy to understand – these are all charities that are among the top 500 in terms of donated income and it does not seem likely that this status can be attained without spending money on raising funds. Following Tinkelman (2004), we exclude observations with zero recorded or missing fundraising expenditure information and we test the sensitivity of our results to their inclusion. The percentage of zeros or missing data are substantially higher for government grants, 39 per cent, for which the statistics are also based on positive values. Zeros or missing values for government grants are easier to understand – many charities do not get such grants. We include all observations, with a dummy variable to capture the impact of zero grant income relative to positive grant income. Only three observations have

[8] Given Oxfam's anomalous size, we test the robustness of our results below to its exclusion.

[9] We exclude the Priory of St John (St John Ambulance), which was included among development charities by CAF, and missionary charities.

zero non-voluntary income.[10] The second panel (B) summarises the aggregate variables common to all charities: total household income, the Gini index for household income, and ODA. ODA figures include grants paid to charities, so we use the values net of these grants (they constitute only a small part of the total – about 5 per cent in 2004).

**[Table 1 about here]**

Following Tinkelman (2004) and Okten and Weisbrod (2000) we use the natural logarithm of all the continuous variables in our model, except the Gini. The model also includes dummy variables for zero grant income (noted above), the years 2000-2004 (to allow for the effect of Gift Aid), for 1984 and 1985 to capture the impact of the Ethiopian famine, and for 2004 given the Asian Tsunami. The last of these takes the value 1 for charities whose financial year ended in the first half of 2005. These charities are assigned to 2004 according to our rule outlined above. However, their financial reports will capture at least some of any increase in donations that arose from the Boxing Day Tsunami at the end of 2004. This applies to seven charities.

# 4 Specification, estimation and results.

We start with a first order auto-regressive distributed lag mode (ARDL(1)):

$$y_{it} = \gamma y_{it-1} + \sum_{k=0}^{1} z'_{it-k}\vartheta + \sum_{k=0}^{1} x'_{t-k}\beta + D'_{it}\eta + e_{it} \tag{1}$$

where $i$ and $t$ index charities and years respectively, $y_{it}$ is the charity's (log) donations, and $e_{it} = \alpha_i + \varepsilon_{it}$ is a composite error term where $\alpha_i$ is a charity-specific unobservable (possibly correlated with the included regressors) and $\varepsilon_{it}$ is an *iid* idiosyncratic error term.[11]

[10] The reporting of shop income in charity accounts changed in 1995. Prior to 1995, charities tended to reported the net profit of their shops. A change in the Charity Commission's 'Statement of Recommended Practice (SORP)' led charities to switch to reporting the gross value of goods sold. In the case of Oxfam, by far the largest earner of shop income on our data, we have adjusted the figures from 1995 onwards downwards by the ratio of the net profit to the gross value in 1995-1998 (obtained from Oxfam's annual reports).

[11] We test for serial correlation in the errors as part of our model specification tests.

The vector $z_{it}$ contains the charity-specific variables: log fundraising expenditure, log government grants, log non-voluntary income, and the log of the 'price' variable.[12]

The vector $x_t$ includes the aggregate household and the development-specific variables affecting the environment in which donations to development are made: the log of total household income, the Gini coefficient for household income and the log of ODA (net of grants paid). The vector $D$ includes dummy variables to capture the very large disasters that occurred during the observation period, the Ethiopian famine in 1984–85 and the 2004 Boxing Day Tsunami.

The current values of fundraising, non-voluntary income and grants may be correlated with the contemporaneous error term $e_{it}$. A positive shock to donations means that a charity can afford to spend more on fundraising. Such a shock could have positive or negative effects on the government grants it receives, depending on how these grants are allocated. If the correlation between $e_{it}$ and the regressors can be captured by the unobserved heterogeneity $\alpha_i$ the within-group (WG) estimator would be consistent.

However, if there is still correlation between the errors of the equation and the regressors after eliminating the $\alpha_i$, one can use the more efficient Generalised Method of Moments estimator (GMM) instead of the WG instrumental variable estimator. Since our panel has gaps we use the forward orthogonal deviation (FOD) transformation (Bover and Arellano, 1995) instead of first differencing the equation to eliminate the $\alpha_i$.[13] We then use tests for over-identification (Sargan, 1958 and Hansen, 1982)[14] and for first and second

[12] We do not include the age of each charity as in Tinkelman (1999, 2004) and Khanna and Sandler (2000) because in our within group approach age is equal to $\alpha_i$ plus a common time trend.

[13] Instead of subtracting the previous observation from the current, the FOD transformation subtracts the average of all future available observations. Formally, forward orthogonal transformation will transform $y_{it}$ to $\sqrt{\frac{T_{it}}{T_{it}+1}\left(y_{it} - \frac{1}{T_{it}}\sum_{s>t} y_{is}\right)}$. The weighting equalises the variances in the above transformation. This transformation eliminates $\alpha_i$ while preserving sample sizes in panel data with gaps as it is computable for all but the final observation. GMM estimates are obtained using *xtabond2* in Stata (Roodman 2009a). A more detailed discussion of GMM can be found in the online appendix to this paper.

[14] Both Sargan and Hansen tests for over-identification require non-rejection of the null hypothesis that the instruments are valid. Sargan test is robust to instrument proliferation (Roodman, 2009b) but not to heteroscedasticity. Hansen test, on the other hand is robust to heteroscedasticity but not to instrument proliferation. A large number of instruments can severely weaken the Hansen test producing questionably high $p$-values.

order serial correlations (Arellano and Bond, 1991)[15] to choose our preferred specification and the instrument set.

Our main results are presented in Table 2 with results of specification tests reported at the bottom of the table. Note that all the models in Table 2 were estimated using only those observations with positive values for fundraising. The grants effect is estimated using the positive values of grants as we include a dummy (not reported) to capture the zero reported grants income. Cluster robust standard errors are reported in parentheses (the charities are the clusters).

**[Table 2 about here]**

Column (1) presents the ARDL(1) model, estimated using GMM, treating all contemporaneous charity-specific regressors and the lagged donations as endogenous. This specification fails the Sargan test. Neither the lagged nor the contemporaneous effects are individually or jointly ($p$-value=0.93) significant at the 5 per cent level indicating that the model may be over-specified. In column (2) we exclude the lagged aggregate household characteristics and re-estimate the model using GMM, treating all the charity-specific regressors, including lagged donations, as endogenous. This model also fails the Sargan test. Of the lagged effects, only the lagged donations is significant. The other lags are not individually nor jointly significant ($p$-value=0.77). We further simplify the specification in column (3) where we estimate a partial adjustment model (with only the lagged dependent variable) using GMM, again treating all the charity-specific regressors, including lagged donations, as endogenous. This model performs well on all the specification tests. In column (4) we re-estimate the partial adjustment model using GMM, though here we treat only the lagged donations and the price (a function of lagged donations) as endogenous. In column (5), we estimate the partial adjustment model via WG using the sample used for the GMM.[16] In column (6) we re-estimate the partial adjustment model via WG using all

[15] White noise errors $\varepsilon_{it}$ would imply a MA(1) process for the $\Delta\varepsilon_{it}$, thus the specification test is passed by rejecting the null of no first order ($AR(1)$) serial correlation but not rejecting the null of no second order ($AR(2)$) serial correlation.

[16] The sample size is reduced as we use 3 period lags in the instrument set.

the observations with positive fundraising.

The WG estimator results are extremely similar to those obtained via GMM suggesting that *i*) the Nickell bias (Nickell, 1981) is mitigated by our large T and *ii*) the potential endogeneity of the charity-specific variables does not adversely affect the consistency of the WG estimator. We therefore proceed with the WG estimation and take the results in column (6) as our baseline.

We check for sensitivity of our results to the following specification and/or sample changes[17]: 1) adding observations with zero reported or missing fundraising data ($p$-value=0.71)[18]; 2) the use of year fixed effects in place of the aggregate household and development-specific variables ($p$-value=0.87)[19]; 3) the inclusion of a time trend ($p$-value =0.99); 4) the exclusion of Oxfam, far and away the largest development charity making up between a sixth and a third of total donations to development charities in a given year ($p$-value=1.00); 5) the exclusion of the filled in observations, discussed in Section 3 ($p$-value=0.12); 6) including only those observations among the 200 largest charities by donated income in each year ($p$-value=0.06); and using only those charities which first appear in the data prior to 1991 when CAF expanded to the top 500 ($p$-value=0.91). The full results for these robustness checks are presented in Table A.1 of the online appendix. We also check the robustness of the GMM results to different instrument sets (Table A.2). In general, the estimated coefficients vary little in terms of magnitude and significance over these different specifications demonstrating the robustness of the results in the baseline model (column (6), Table 2), on which the following discussion is based.

[17] We re-estimate the model using the listed specifications using the WG estimator. We then use Stata's seemingly unrelated regression module *suest* to perform a Wald test of the joint equality of the common variables in the alternative specification and our baseline. The reported $p$-values are from a Wald test of the null hypothesis that the coefficients from our baseline model and each alternative specification are equivalent.

[18] To do this we add a dummy variable to pick up observations with non-positive fundraising expenditure. In both this and our baseline case, the effect of fundraising on donations is estimated from the positive values only.

[19] In this instance, we test the joint equality of the charity-specific variables only.

# 5 Discussion

We estimate a short-run fundraising elasticity of 0.19 with a long-run effect equal to 0.37. The long-run effects are similar in magnitude to the partial fundraising elasticities from earlier work (Khanna and Sandler, 2000; Okten and Weisbrod, 2000; Tinkelman, 2004) which were necessarily interpreted as long-run effects. We discuss the estimated fundraising effect in greater detail below. Neither non-voluntary income nor grants have a significant effect – the latter means that we find no evidence of crowding in or out of donations from the expansion of government grants to the sector over the period. Both results are consistent with the findings in Khanna et al. (1995) and Khanna and Sandler (2000).

The coefficient on the price of giving is close to zero and statistically insignificant, as is the long-run price effect ($\hat{\beta}$=-0.07, se=0.33, $p$-value=0.83). However, when we estimate a static version of our model (not presented) the coefficient on the price effect is negative ($\hat{\beta}$=-0.80) and significant ( se=0.19, $p$-value<0.01), consistent with the general results in earlier work (e.g. Khanna et al., 1995; Khanna and Sandler, 2000; Okten and Weisbrod, 2000; Tinkelman, 2004). That the price becomes statistically insignificant in a partial adjustment specification suggests that the significant price effect estimated elsewhere may be driven by omitted variable bias from an otherwise unaccounted for autoregressive process in donations rather than a genuine responsiveness to changes in the severity of 'leakages' perceived by donors, i.e. the price. The direction of the omitted variable bias is consistent with $\gamma > 0$ and $\partial p_t / \partial D_{t-1} < 0$.[20]

The significance of the price effect generally found in the literature could lead charities to spend too little on fundraising as the total estimated fundraising effect will be diminished by the price effect. For example, Okten and Weisbrod (2000) conclude that the total fundraising effect, which takes into consideration the impact of the price, is not statistically different from zero. Such results may also lead charities to systematically under-report the amount they do spend on fundraising (Froehlich and Knoepfle, 1996) as they try to mitigate

[20] In Section 2 we defined our price variable as $p_t = 1/(1-f_{t-1})$ where $f = F/D$ so $\partial p_t / \partial D_{t-1} < 0$. As $\gamma > 0$, the omitted variable bias affecting the price variable in the absence of lagged donations would be $\left(\frac{\partial p_t}{\partial D_{t-1}}\right)\gamma < 0$.

the perceived negative price effect.

The estimated short-run household income elasticity of donations in column (6), Table 2 is 0.75 and we cannot reject the null hypothesis of a short-run unitary income elasticity ($p$-value=0.51). We also fail to reject a long-run unitary elasticity ($p$-value=0.55).

Evidence for the impact of the income distribution is mixed. The coefficient on the Gini index is statistically significant and of an economically important magnitude in columns (2), (3) and (5) of Table 2. While the same is true in column (6), the point estimate is no longer statistically significant at conventional levels. The significant effect in column (5) suggests that a one standard deviation increase in the Gini index leads to a 12 per cent decrease in donations to development, on average and *ceteris paribus*. This result conflicts with the prediction of Glazer and Konrad (1996), though their model has no development-specific component. It is difficult to draw conclusions from a weekly identified effect in our model and more work is needed in this area. We find no evidence that the change in Gift Aid in 2000 was associated with a change in donations to development charities.

The coefficient on ODA is not significant. We also estimated the model using alternative specifications of ODA (levels, share of GDP) but coefficients were consistently insignificant when the effect was assumed constant over time. The relationship between ODA and donations may not, however, be adequately described by such a restrictive specification. We find evidence of a change in the relationship following the Ethiopian famine of the mid-1980s (the effect of which we discuss below). In Figure 1 we plot the total donations made to development charities among the largest 200 fundraising charities in each year against the annual level of ODA, using log scales on both axes. The triangular markers and dashed line show the scatter plot and linear fit, respectively, for 1978-1983. The circular markers and solid line are the scatter plot and linear fit, respectively, for 1984 to 2004.

From 1978 to 1983, ODA may have 'crowded out' donations; as ODA fell (by 25 per cent from 1978 to 1983) total donations to development charities in the top 200 increased by 50 per cent. However, from the onset of the Ethiopian famine in 1984, there is a marked change in the relationship and the graphical evidence suggests 'crowding in'. To test this more rigorously we re-estimate our base line model adding a dummy for those years 1984 to 2004 and an interaction term between this dummy and the log of ODA, allowing the effect of ODA to differ between the two periods. The coefficient on the interaction term is significant, indicating that the effect of ODA does change between the two periods. The estimated effect of log ODA before 1984 is -0.40 ($p$-value=0.02). From 1984 onwards, the estimated effect (the linear combination of the coefficient on log ODA and that on the interaction term) is 0.38 ($p$-value=0.06), consistent with what we observe graphically. The severity of the crisis and the effect Live Aid had on popular culture (Street, 1997) seems to have affected a lasting change in the relationship between the state provision and the private provision of development assistance. The social psychology underpinning such a shift is, however, beyond the scope of this paper. Note the other coefficients were not qualitatively changed from our baseline model.

Both the Ethiopian famine and the Boxing Day Tsunami had a powerful, positive impact on giving for development. The Ethiopian famine saw donations to the development charities included in our panel increase, on average, by around a third in 1984. The insignificance of the 1985 dummy suggests that the continuation of the famine did not have an analogous impact in that year. In fact, several large development charities, e.g. Oxfam, saw donations fall from 1984 to 1985, presumably as donations were diverted to the Band Aid Trust, which we exclude from our panel as explained in Section 3. Total giving for development, including to Band Aid, actually increased by around a fifth from 1984 to 1985. The Boxing Day Tsunami had a similar impact on donations to development charities, seeing them increase by about 30 per cent.

We next turn our attention to two additional issues. First, we consider the distribution of the marginal fundraising effects. Second, we test for possible fundraising externalities.

## 5.1 The distributions of marginal fundraising effects

It has long been recognised that the objective function of charities might be inferred from the marginal effectiveness of fundraising expenditure (Weisbrod and Dominguez, 1986;

Steinberg, 1986). Charities maximising gross revenue will fundraise until the marginal pound spent brings in no additional funding. Those maximising net revenues (net of fundraising expenditure) will fundraise until the marginal pound spent brings in one pound of additional funds.

Conclusions about the objective functions of charities based on the estimated marginal effect of fundraising may depend on whether it is the marginal effect calculated at the mean characteristics or the mean marginal effect that is being interpreted (Tinkelman, 2004). The short-run marginal fundraising effect, calculated at the mean characteristics, for development charities is 0.97. Table 3 shows the distribution of the short- and long-run marginal effects of fundraising. [21]

Consistent with Tinkelman (2004) the mean effect is larger than the marginal effect calculated at the mean characteristics. This supports Tinkelman's claim that the mean effect can inadequately describe the behavior of the 'average' charity since the distribution of the effects can be skewed by extreme (low) values of fundraising expenditure. The extreme values also inflate the standard deviation of the distribution of marginal effects and so conclusions about the objective functions of charities can be sensitive to whether the analysis is of marginal effect calculated at the mean characteristics or of the mean marginal effect. In our case, the short-run marginal effect calculated at the mean values is about a quarter of the size of the the mean marginal effect. The median effect, being less sensitive to outliers, is similar in magnitude to the effect calculated at the mean characteristics in each column. We therefore consider the marginal effect calculated at the mean characteristics as it is more representative of the activities of the 'average' charity.

**[Table 3 about here]**

The results suggest that the 'average' development charity maximises net revenue in the short run as the short-run marginal effect (calculated at the mean characteristics) is not

[21] This was obtained by multiplying the coefficient on log fundraising (taken from Table 2, column (6)) by the ratio of the mean of donations to the mean of fundraising expenditure for the sample used in estimation. Alternatively, we can assume that the estimated elasticities are constant over charities and time and so calculate a charity-year specific marginal effect such that $mfx_{it} = \beta_{log\,fundraise} \times \frac{donations_{it}}{fundraising_{it}}$.

statistically different from one ($p$-value=0.94). In the long run the results suggest that the 'average' charity fundraises short of net revenue maximisation as the long-run marginal effect (calculated at the mean characteristics) is different from one at the 5 per cent level ($p$-value=0.02). This means that charities fundraise at an 'inefficiently' low level; charities could increase both fundraising expenditure and programme services. The reasons for this inefficiency are not immediately clear but may be a function of the perception that higher levels of fundraising reduce donations via the supposed price effect. However, we have shown here that, in the case of development charities, a reasonable observation rule for the price and controlling for serial correlation in donations, result in the price being statistically insignificant. Charities operating under the assumption that fundraising expenditure will have a negative impact on donations via the price will underestimate the revenue (net or gross) maximising level of fundraising and so fundraise too little.

## 5.2 Spillover effects of fundraising

To test for a fundraising spillover effect (see Section 2) among development charities we construct a new variable equal to the total fundraising expenditure of the five charities with the most fundraising expenditure in each year.[22] This construction is preferable to using the total fundraising of all other ($-i$) development charities as the number of development charities in the sample changes from year to year thus causing artificial changes in such a total.

We re-estimate our partial adjustment model including the log of this new 'spillover' variable. We present the estimated spillover effect in Table 4.

**[Table 4 about here]**

In columns (1) and (2) we estimate the model using the aggregate household characteristics, charity-specific and development-specific variables. The point estimate on the

[22] Our results below are not sensitive to ranking charities by donation income instead of fundraising expenditure.

spillover variable is positive but statistically insignificant. In column (2), where we exclude those charities among the five largest fundraisers (from which the spillover variable was constructed) the coefficient on household income (not reported) becomes insignificant, though the magnitude of the coefficient is not materially changed from our baseline model.[23] There is, however, a large ($\rho$=0.62) and significant ($p$-value<0.01) correlation between the spillover variable and household income. This collinearity may make identification difficult.

We therefore replace the aggregate household and development-specific variables with year fixed effects and re-estimate the model for all development charities in columns (3) and excluding the five largest fundraisers in column (4). The spillover effect remains positive, but now becomes more precisely estimated. This suggests that an increase in the fundraising expenditure of the largest fundraisers leads to an increase in donations to other development charities, on average and *ceteris paribus*. The point estimate on the spillover effect is similar in size to that on fundraising in our baseline model, 0.19. However, the magnitude of the effect is much smaller. Using the results in column (3), a one standard deviation increase in the fundraising expenditure of the very largest development charities increases average donations to other development charities by about 9 per cent. Whereas a one standard deviation increase in a charity's own fundraising will see donations increase by about a third.

# 6 Conclusions

We have modeled the determinants of donations received by overseas development charities in the UK, contributing to the relatively small literature on charitable giving that considers particular causes. We have used a newly constructed panel data spanning over 25 years and have drawn on recent theory on giving for development. Given the length of our panel, we are able to include controls for donor (household) characteristics, macro-level

[23] Neither the magnitude nor significance of the other coefficients were materially affected in any of the models in Table 4.

events that affect donations to development charities and a possible autoregressive process in donations. We summarise our results as follows:

- A partial adjustment specification best fits the data and improves on the static models previously used in the literature.
- Fundraising has a powerful effect on donations received by development charities with a short-run elasticity of 0.19 and a long-run elasticity of 0.37.
- The impact of the price faced by donors, as conventionally defined in the literature, is not a significant determinant of donations when we control for the autoregressive process driving donations.
- There is some evidence that the relationship between donations and the public provision of the public good in the form of ODA fundamentally changed following the Ethiopian famine of the mid-1980s. Prior to the famine, our results are consistent with ODA crowding out donations. After the famine, the evidence suggests the effect reversed.
- We cannot reject the hypothesis that giving to development has a unitary income elasticity in both the short and long run. We find no robust significant impact from changes in the inequality of household incomes, although there is some weak evidence suggesting that increased inequality decreases giving for development.
- Conclusions about the marginal effectiveness of fundraising and the objective functions of charities depend on whether the analysis considers the mean marginal effect or the marginal effect calculated at the mean characteristics.
- There is some evidence of a positive fundraising externality. The fundraising expenditure of the largest development charities increases the donations made to other development charities suggesting that there are positive fundraising spillovers.

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# Tables and figures

Table 1: Summary statistics

| Variable | Mean | Std. Dev. |
|---|---|---|
| **A: Charity specific** | | |
| Voluntary contributions (£'000s) | 11,713.49 | 18,287.28 |
| Fundraising (£'000s) | 2367.75 | 4095.00 |
| Zero fundraising reported | 0.11 | 0.31 |
| Grants (£'000s) | 8289.88 | 13,039.11 |
| Zero grants reported | 0.40 | 0.49 |
| Non-voluntary income (£'000s) | 8516.94 | 16,518.91 |
| Price | 1.25 | 0.31 |
| Observations | 868 | |
| **B: Macro level** | | |
| Household income (£ billions) | 511.53 | 94.80 |
| Gini | 0.31 | 0.03 |
| 2000-2004 dummy | 0.14 | 0.35 |
| ODA (£ billions) | 3.01 | 0.57 |
| Tsunami dummy | 0.01 | 0.12 |
| 1984 dummy | 0.02 | 0.15 |
| 1985 dummy | 0.03 | 0.16 |
| Observations | 27 | |

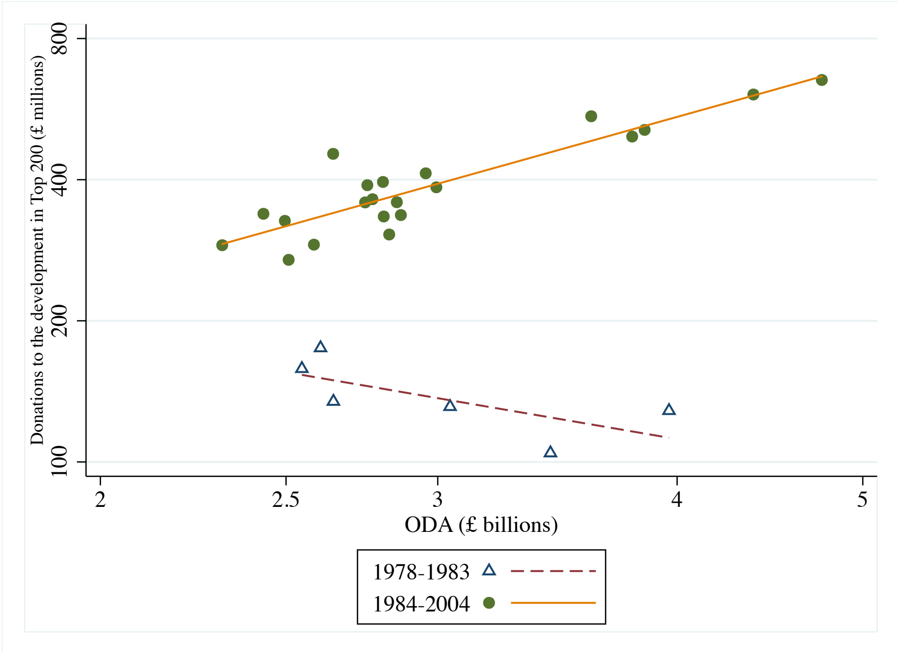
Notes: The statistics for fundraising and grants are based on the positive values only. The unbalanced panel contains 56 charities over the period 1978 to 2004. All monetary figures are in 2007 prices.

Table 2: Parameter estimates

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Estimator: | GMM | GMM | GMM | GMM | WG | WG |
| **Charity specific** | | | | | | |
| Lagged log donations | 0.203 | 0.427* | 0.583*** | 0.683*** | 0.498*** | 0.502*** |
| | (0.268) | (0.218) | (0.186) | (0.090) | (0.155) | (0.172) |
| Log fundraising | 0.064 | 0.074 | 0.152* | 0.119*** | 0.175*** | 0.186** |
| | (0.204) | (0.150) | (0.091) | (0.042) | (0.059) | (0.081) |
| t-1 | 0.099 | -0.049 | | | | |
| | (0.118) | (0.088) | | | | |
| Log non-voluntary income | -0.007 | 0.008 | 0.041 | 0.011 | 0.020 | 0.022 |
| | (0.049) | (0.044) | (0.037) | (0.026) | (0.041) | (0.038) |
| t-1 | 0.016 | -0.009 | | | | |
| | (0.042) | (0.030) | | | | |
| Log grants | -0.067 | 0.054 | 0.038 | 0.001 | 0.017 | 0.011 |
| | (0.091) | (0.039) | (0.031) | (0.013) | (0.016) | (0.016) |
| t-1 | -0.000 | -0.003 | | | | |
| | (0.054) | (0.017) | | | | |
| Log price | -0.849* | -0.219 | -0.180 | | -0.164 | -0.036 |
| | (0.465) | (0.297) | (0.251) | | (0.156) | (0.174) |
| t-1 | 0.106 | -0.159 | | | | |
| | (0.274) | (0.163) | | | | |
| | (0.240) | (0.161) | | | | |
| **Aggregate household** | | | | | | |
| Log household income | 0.095 | 1.777*** | 0.924*** | 0.613** | 1.167*** | 0.748* |
| | (3.744) | (0.677) | (0.358) | (0.240) | (0.348) | (0.378) |
| t-1 | 2.170 | | | | | |
| | (8.696) | | | | | |
| Gini | -5.324 | -5.036** | -3.697* | -1.749 | -3.947** | -1.964 |
| | (73.906) | (2.530) | (2.069) | (1.331) | (1.761) | (1.951) |
| t-1 | 1.257 | | | | | |
| | (37.051) | | | | | |
| Gift Aid dummy | -0.284 | -0.102 | -0.108 | -0.063 | -0.094 | -0.036 |
| | (0.428) | (0.071) | (0.080) | (0.058) | (0.083) | (0.070) |
| **Development specific** | | | | | | |
| Log ODA | -0.643 | 0.236 | 0.116 | 0.038 | 0.071 | 0.040 |
| | (0.982) | (0.258) | (0.156) | (0.092) | (0.190) | (0.139) |
| t-1 | -1.793 | | | | | |
| | (3.374) | | | | | |
| Tsunami dummy | 0.225 | 0.196 | 0.301*** | 0.345*** | 0.266*** | 0.298*** |
| | (0.520) | (0.144) | (0.096) | (0.082) | (0.095) | (0.091) |
| 1984 dummy | 0.333 | 0.339** | 0.698* | 0.356** | 0.336** | 0.381** |
| | (0.333) | (0.151) | (0.410) | (0.150) | (0.140) | (0.151) |
| 1985 dummy | 0.220 | 0.061 | 0.082 | 0.052 | 0.055 | 0.099 |
| | (0.357) | (0.125) | (0.105) | (0.068) | (0.086) | (0.083) |
| Observations | 566 | 566 | 633 | 633 | 633 | 684 |
| $R^2$ | | | | | 0.645 | 0.643 |
| Number of instruments | 25 | 25 | 25 | 18 | | |
| Lags used as instruments | 4 | 3 | 3 | 3 | | |
| AR(1) *p*-value | 0.039 | 0.005 | 0.010 | 0.032 | | |
| AR(2) *p*-value | 0.909 | 0.477 | 0.360 | 0.420 | | |
| Hansen *p*-value | 0.318 | 0.522 | 0.221 | 0.467 | | |
| Sargan *p*-value | 0.050 | 0.004 | 0.230 | 0.137 | | |

Notes: Standard errors are presented in brackets. Results in columns (1)-(4) were obtained via GMM. In column (1) we use four period lags in the instrument set and in columns (2)-(4) we use three period lags. In each case we collapse the instrument set following Roodman (2009b). In columns (1) to (3) we treat all contemporaneous charity-specific variables and lagged donations as endogenous. In column (4) we treat only lagged donations and the price as endogenous. The remaining results were obtained using the WG estimator. Results from specification tests are presented at the bottom of the table. ***, **, and * indicate $p$-value<0.01, $p$-value<0.05, and $p$-value<0.10, respectively.

Figure 1: ODA and giving for development




Notes: This figure plots the relationship between ODA and total donations made to development charities among CAF's top 200 in each year. The triangular markers and the dashed line are the scatter plot and linear fit, respectively, for the years 1978 to 1983. The circular markers and solid line are the scatter plot and linear fit, respectively, for the years 1984 to 2004.

Table 3: Distribution of the short-run and long-run marginal fundraising effects

| | (1) | (2) |
|---|---|---|
| | **Short-run** | **Long-run** |
| Minimum | 0.22 | 0.43 |
| $5^{th}$ percentile | 0.44 | 0.87 |
| $25^{th}$ percentile | 0.71 | 1.41 |
| Median | 1.15 | 2.27 |
| $75^{th}$ percentile | 2.31 | 4.54 |
| $95^{th}$ percentile | 7.49 | 14.25 |
| $99^{th}$ percentile | 101.03 | 163.22 |
| Maximum | 241.28 | 242.64 |
| Mean | 4.18 | 6.64 |
| SD | 17.06 | 22.18 |
| Between SD | 20.99 | 33.30 |
| Within SD | 7.23 | 9.27 |
| | | |
| Effect at mean characteristics | 0.97 | 1.84 |
| Observations | 684 | 684 |

Notes: The marginal effects are calculated using the estimated fundraising elasticity obtained in our baseline model multiplied by the ratio of donations to fundraising for each charity-year.

Table 4: Spillover effects of fundraising: parameter estimates

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Estimator: | WG | WG | WG | WG |
| | **Macro-level variables** | | **Year fixed effects** | |
| | **All** | **No Top 5** | **All** | **No Top 5** |
| Log Spillover | 0.076 | 0.144 | 0.191** | 0.300*** |
| | (0.163) | (0.186) | (0.075) | (0.087) |
| Observations | 684 | 554 | 684 | 554 |
| $R^2$ | 0.643 | 0.616 | 0.658 | 0.636 |

Notes: The spillover variable is equal to the log of the total fundraising expenditure of the five largest development fundraisers in each year. In column (1) and (2) we use the same specification as our baseline model, though the five largest fundraisers are excluded in column (2). In columns (3) and (4) we use year fixed effects instead of the macro-level variables in our baseline specification. We exclude the five largest fundraisers in column (4). ***, **, and * indicate $p$-value<0.01, $p$-value<0.05, and $p$-value<0.10, respectively.

# Online Appendix. Robustness of regression results to changes in the specification, sample selection and instrumentation

In Table A.1 we present our partial adjustment model estimated with zero reported or missing fundraising data (column (1)); the use of year fixed effects in place of the aggregate household and development-specific variables (column (2)); the inclusion of a time trend (column (3)); the exclusion of Oxfam (column (4)); the exclusion of the filled in observations (column (5)); including only those observations among the 200 largest charities by donated income in each year (column (6)); and using only those charities which first appear in the data prior to 1991 when CAF expanded to the top 500 (column (7)). None of the coefficients obtained in these models jointly differ from those from our baseline model at the 5 per cent level.

Table A.1 Robustness checks, selection biases

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Estimator: | WG | WG | WG | WG | WG | WG | WG |
| **Charity specific** | | | | | | | |
| Lagged log donations | 0.527*** | 0.500*** | 0.501*** | 0.502*** | 0.462** | 0.331* | 0.447** |
| | (0.165) | (0.167) | (0.172) | (0.174) | (0.196) | (0.190) | (0.178) |
| Log fundraising | 0.146** | 0.180** | 0.182** | 0.184** | 0.191** | 0.241** | 0.213** |
| | (0.073) | (0.080) | (0.081) | (0.081) | (0.088) | (0.093) | (0.086) |
| Log non-voluntary income | 0.023 | 0.023 | 0.022 | 0.023 | 0.012 | 0.063 | 0.036 |
| | (0.037) | (0.038) | (0.038) | (0.039) | (0.042) | (0.051) | (0.041) |
| Log grants | 0.012 | 0.015 | 0.012 | 0.011 | 0.024 | -0.009 | 0.022 |
| | (0.017) | (0.017) | (0.016) | (0.016) | (0.016) | (0.021) | (0.017) |
| Log price | 0.035 | -0.031 | -0.041 | -0.040 | 0.012 | -0.329 | -0.144 |
| | (0.165) | (0.174) | (0.175) | (0.177) | (0.175) | (0.197) | (0.182) |
| **Aggregate household** | | | | | | | |
| Log household income | 0.799** | | 0.703* | 0.775* | 1.137** | 0.725** | 0.663* |
| | (0.382) | | (0.350) | (0.389) | (0.484) | (0.354) | (0.388) |
| Gini | -1.921 | | -2.247 | -2.006 | -4.232* | -1.017 | -1.905 |
| | (1.981) | | (2.284) | (2.010) | (2.450) | (1.927) | (1.992) |
| Gift Aid dummy | -0.034 | | -0.044 | -0.036 | -0.097 | 0.027 | 0.016 |
| | (0.070) | | (0.076) | (0.073) | (0.085) | (0.060) | (0.061) |
| **Development specific** | | | | | | | |
| Log ODA | 0.046 | | 0.025 | 0.042 | 0.142 | 0.060 | -0.011 |
| | (0.138) | | (0.139) | (0.148) | (0.195) | (0.171) | (0.148) |
| Tsunami dummy | 0.287*** | | 0.295*** | 0.305*** | 0.243** | 0.247*** | 0.294*** |
| | (0.091) | | (0.092) | (0.100) | (0.104) | (0.086) | (0.105) |
| 1984 dummy | 0.381** | | 0.372** | 0.359** | 0.373** | 0.387** | 0.368** |
| | (0.151) | | (0.159) | (0.159) | (0.163) | (0.152) | (0.149) |
| 1985 dummy | 0.099 | | 0.096 | 0.101 | 0.102 | 0.099 | 0.096 |
| | (0.084) | | (0.085) | (0.085) | (0.104) | (0.085) | (0.083) |
| Observations | 701 | 684 | 684 | 658 | 613 | 548 | 606 |
| $R^2$ | 0.639 | 0.658 | 0.643 | 0.640 | 0.601 | 0.663 | 0.659 |

Notes: This table presents the robustness checks for our baseline results in column (5) of Table 2. Standard errors are presented in brackets. We vary the sample and/or specification by including those observation reporting 0 or missing fundraising expenditure (column (1)), replacing the aggregate household level and charity specific macroeconomic variables with year fixed effects (column (2)), including a time trend (column (3)), excluding Oxfam (column (4)), excluding those observations which were linearly interpolated using the data from previous and subsequent years ((column (5)), using only those observations among the 200 largest charities by donated income in each year (column (6)) and using only those charities which first appear in the data prior to 1991 when CAF expanded to the top 500 (column (7)). ***, **, and * indicate $p$-value<0.01, $p$-value<0.05, and $p$-value<0.10, respectively.

## Robustness of results to instrument proliferation and collapsing the instrument set

A practical problem with the GMM approach is that the number of instruments, which increases quadratically in $T$, can be numerous. Unlike in two-stage-least-squares (2SLS), where the estimation sample is restricted according to the choice of lags for the instrument, in standard applications of GMM a separate instrument is included for each time period. This approach can produce a large number of instruments which can lead to a finite-sample bias of the GMM estimator. Roodman (2009b) notes that 'simply by being numerous, instruments can over-fit instrumented variables, failing to expunge their endogenous components and biasing coefficient estimates toward those from non-instrumenting estimators.' (p. 139) Roodman proposes two methods to deal with the problem of instrument proliferation: (i) collapse the instrument set, and (ii) truncate the instrument set.

Roodman (2009a) suggests collapsing the instrument set to reduce the number of instruments used in GMM. The number of instruments in the collapsed instrument matrix, $Z_i$, increases linearly in $T$, rather than quadratically as in the uncollapsed set. However, the number of instruments can still be large and thus collapsing the instrument set may not sufficiently eliminate the finite-sample bias in of the GMM estimator.

We therefore test the sensitivity of our results to truncations of the instrument set, a second method recommended by Roodman (2009b) for limiting instrument proliferation. In practice this means limiting the number of lags of the endogenous regressors used in the instrument set. Alvarez and Arellano (2003) show that the Arellano–Bond estimator is consistent when the lag length of the instrument set is arbitrarily truncated. Alfaro (2008) undertakes a Monte Carlo study of GMM with large $T$ and finds that truncating the instrument set reduces efficiency, creating a trade-off between finite-sample bias and efficiency. Roodman (2009b) notes that the problems arising from instrument proliferation are most severe in the case of system GMM. Judson and Owen (1999) show in Monte Carlo simulations that when $T$ becomes large the one-step GMM estimator outperforms the two-step. We therefore use the one-step variant of difference GMM in our estimations.

In Table A.2, we check the robustness of the GMM results to changes in the lag depth of the instrument set. The size and significance of the coefficients are robust to changes in the instrument set. However, the GMM performs worse as the requisite specification tests are failed when we use varying lags in the instrument set (2, 5 or 10 lags).

Table A.2: Robustness checks, instrument set

| | (1) | (2) | (3) |
|---|---|---|---|
| Estimator: | GMM | GMM | GMM |
| **Charity specific** | | | |
| Lagged log donations | 0.601*** | 0.624*** | 0.554*** |
| | (0.165) | (0.176) | (0.158) |
| Log fundraising | 0.156 | 0.199*** | 0.198*** |
| | (0.106) | (0.069) | (0.072) |
| Log non-voluntary income | 0.047 | 0.041 | 0.036 |
| | (0.040) | (0.036) | (0.040) |
| Log grants | 0.027 | 0.041 | 0.021 |
| | (0.034) | (0.031) | (0.024) |
| Log price | -0.160 | -0.168 | -0.223 |
| | (0.251) | (0.237) | (0.231) |
| **Aggregate household** | | | |
| Log household income | 0.920** | 0.765** | 0.857*** |
| | (0.377) | (0.334) | (0.302) |
| Gini | -2.972 | -4.225** | -3.066* |
| | (2.051) | (2.075) | (1.729) |
| Gift Aid dummy | -0.137 | -0.130* | -0.113* |
| | (0.087) | (0.075) | (0.065) |
| **Development specific** | | | |
| Log ODA | 0.154 | 0.105 | 0.134 |
| | (0.163) | (0.129) | (0.137) |
| Tsunami dummy | 0.302*** | 0.321*** | 0.306*** |
| | (0.094) | (0.088) | (0.086) |
| 1984 dummy | 1.048* | 0.671** | 0.836*** |
| | (0.572) | (0.275) | (0.262) |
| 1985 dummy | 0.122 | 0.056 | 0.113 |
| | (0.112) | (0.098) | (0.089) |
| Observations | 633 | 633 | 633 |
| Number of instruments | 20 | 38 | 68 |
| Lags used as instruments | 2 | 5 | 10 |
| AR(1) $p$-value | 0.015 | 0.010 | 0.009 |
| AR(2) $p$-value | 0.382 | 0.370 | 0.375 |
| Hansen $p$-value | 0.770 | 0.021 | 0.000 |
| Sargan $p$-value | 0.300 | 0.139 | 0.066 |

Notes: This table presents the robustness checks for the GMM estimator in which we very the depth of the lags used in the instrument set. In each case we collapse the instrument set following Roodman (2009b). Standard errors are presented in brackets. Results from specification tests are presented at the bottom of the table. ***, **, and * indicate $p$-value<0.01, $p$-value<0.05, and $p$-value<0.10, respectively.

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