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ORIGINAL PAPER

Donor motives, public preferences and the allocation of UK foreign aid: a discrete choice experiment approach

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Abstract
This paper develops a prescriptive model for the inter-country allocation of aid from the UK government. The model incorporates three broad motives for allocating aid: recipient need, donor interests and absorptive capacity (the ability of recipient countries to use aid effectively). To determine each motive's relative importance, a discrete choice experiment (DCE) involving more than 1600 members of the UK general population was conducted. Absorptive capacity is the most important motive, and recipient need and donor interests are equally but much less important. Current UK aid allocations are compared with those prescribed by the model. Some countries, including China, India and Indonesia, would receive much more if aid were allocated according to the model; other countries, including Afghanistan, Ethiopia and Pakistan, would receive much less. Cluster analysis reveals that the political parties voted for by DCE participants at the 2015 general election are, *inter alia,* related to their aid preferences.

Keywords Foreign aid · Discrete choice experiment (DCE) · Cluster analysis · UK

JEL Classification F35 · H50 · C90

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1 Introduction

The amount of foreign aid is at a record global high. Measured as Official Development Assistance (ODA), OECD countries contributed $142.6 billion in 2016,[1] a doubling in real terms since 2000. The UK has scaled-up its ODA considerably, providing more than $18 billion in 2016, and is currently the world's third largest donor after the US and Germany. The UK is one of only a handful of countries to have reached the long-standing United Nations' target of net ODA equal to 0.7% of a country's Gross National Income (OECD 2017). In 2015 a law was passed that committed the UK government to maintaining this level of assistance.

The rise in UK ODA has increased the politicisation of foreign aid in the UK. The media and surveys of public attitudes have focused on whether the government is providing an appropriate amount of ODA, with some UK newspapers citing examples of aid being 'wasted' and arguing that 'charity should begin at home'. Far less attention has been paid to how UK aid is allocated across developing countries—which is surprising given that people's feeling about the level of aid could be very different to their preferences with respect to which countries are supported and the amount of aid received.[2]

Anecdotally, it is clear that governments consider multiple objectives when allocating aid across developing countries. Though donor agencies' objective statements emphasise the humanitarian role of aid in reducing global poverty, it is not the case that the countries most in need receive the most aid. For example, in 2015 Tuvalu, an upper-middle-income country in the Pacific, received more than $4500 per person from the international community, whereas Niger, one of the world's poorest countries, received less than $44 per person; on a per capita basis, Syria receives nearly 12 times more aid than Sudan (World Bank 2018). With respect to aid from the UK government, Lebanon, an upper-middle-income country in the Middle East, received almost $26 per capita, whereas Togo, one of the least developed African countries, receives less than one cent per capita (World Bank 2018).

As well as humanitarian objectives, national interests and political and strategic goals also play a role in government aid allocations. Security concerns partly explain the high levels of aid currently going to countries like Afghanistan, Pakistan and Syria. Such motives are sometimes stated in donor agencies' objective statements. For example, the mission of the United States Agency for International Development (USAID), is "to end extreme poverty and promote resilient, democratic societies while advancing our security and prosperity" (USAID 2017). The UK's Department

1 All dollar amounts reported are US dollars.

2 An exception is Lightfoot et al. (2016) which draws on one specific survey question to examine public preferences for using aid to advance national interest versus allocating it to those most in need: The specific survey question was: "Some people say that Britain's foreign aid should simply be distributed to the countries which are most in need of help. Others say that we should put our own national interests first when deciding how to distribute foreign aid in the developing world. On a scale from 0 (according to need) to 6 (according to our national interests), which number best represents your view about how aid should be distributed?" Responses from the survey question in both 2010 and 2015 indicate an almost equal balance between the two preferences.

for International Development (DFID) states that it "leads the UK's work to end extreme poverty… Our work is building a safer, healthier, more prosperous world for people in developing countries and in the UK too." (DFID 2017).

Following an influential study that found aid is more effective in countries with sound macroeconomic policies (Burnside and Dollar 2000), international donors have increasingly sought to allocate aid to countries capable of putting it to good use. The macroeconomic policy environment is one of many factors that donors need to consider in getting the most 'bang for their buck', as further discussed below.

This paper develops a model for the allocation of UK government aid that prescribes how aid *ought* to be allocated, in contrast to most earlier studies that explain how aid *has been* allocated.[3] Such prescriptive allocations (how aid *ought* to be allocated) depend on the relative importance, or 'weight', attached to the motives ascribed to aid allocation. Earlier studies have struggled with determining valid and reliable weights. In this paper, a discrete choice experiment (DCE) involving more than 1600 members of the UK general population is used to ascertain their weights for the three broad motives introduced above (and discussed in greater detail in the next section): recipient need, donor interests and the ability to use aid effectively.

The prescriptive facet of the paper is supported with reference to the 'median voter theorem', which implies that foreign aid programmes should reflect the preferences of voters (e.g. Mayer and Raimondos-Møller 2003). This is the case even if other factors, such as group lobbying, influence foreign aid programmes and if the political institutions created by modern democracies provide a degree of autonomy in policy formulation (Kapstein 2005). As aid levels increase, the greater is the median voter's interest in foreign aid spending and the more important it is that aid programmes reflect the preferences of the public, who rightfully demand greater accountability for their taxes.

Applying the three broad motives and their weights from the DCE, the model determines how much aid each country should receive from the UK government, given its budget constraint. These allocations are compared with how much aid each country actually receives. Finally, a cluster analysis is performed to identify any 'clusters' of DCE participants with similar patterns of weights, including investigating the extent to which such clusters are related to participants' socio-demographic and background characteristics.

The remainder of the paper is structured as follows. Section 2 develops the model of UK government aid allocation, which is strongly informed by the academic literature. Section 3 discusses the data and the DCE used to elicit the weights of the UK general population and the results. Section 4 presents the country allocations of UK government foreign aid based on the model and DCE results and compares it to current actual allocations. Section 5 presents the results of the cluster analysis. Section 6 discusses the paper's conclusions and their implications.

[3] Other prescriptive models of aid allocation include Llavador and Roemer (2001), Collier and Dollar (2001, 2002), McGillivray et al. (2002), Cogneau and Naudet (2007), Wood (2008) and McGillivray and Clarke (2018).

2 A prescriptive model of UK government aid allocation

When developing a model for how UK government aid ought to be allocated, it is important to justify the motives for such allocations to be included in the model. Also, the model must incorporate the fact that aid budgets are limited. This paper bases the motives included in the model on a careful review of the aid allocation (and effectiveness) literature. This extensive literature reveals that humanitarian concerns (the development needs of a country) and donor interests (geopolitical, strategic and commercial) are two important motives for allocating aid (e.g. Maizels and Nissanke 1984; Alesina and Dollar 2000; Alesina and Weder 2002; Neumayer 2003; Berthélemy and Tichit 2004; Feeny and McGillivray 2008; Dreher et al. 2011). The literature confirms these motives also exist for UK aid specifically (Bowles 1987; McGillivray and Oczkowski 1991, 1992; Hoeffler and Outram 2011).

It is also clear from their policies of recipient selectivity that donors prefer allocating aid to countries that can use aid effectively. This is evident in the performance-based aid allocation models and formulae of multilateral development institutions, including the World Bank and the Asian Development Bank (ADB). Aid is allocated according to need—proxied by per capita income—but also 'performance', measured using Country Policy and Institutional Assessment (CPIA) scores (in the case of the World Bank) and Country Performance Ratings (CPR) (in the case of the ADB).

The motive for allocating aid to countries capable of using the money best has its roots in one of the most robust and important findings from the aid-effectiveness literature: the existence of diminishing and eventually negative returns to foreign aid (e.g. Hansen and Tarp 2000, 2001; Dalgaard and Hansen 2001; Lensink and White 2001; Hudson and Mosley 2001; Dalgaard et al. 2004; Asra et al. 2005; Feeny and McGillivray 2011). The relationship between the level of aid and its incremental impact on growth (or alleviation of poverty) takes the form of an inverted-U shape, which implies that, beyond a certain level, aid's incremental impact starts to fall.[4] Diminishing returns to aid arise due to the absorptive capacity constraints of recipient countries—i.e. factors limiting the ability of recipient countries to put aid to good use.[5]

Thus, based on the academic literature as well as existing donor practices, these three motives for allocating UK government aid are included in the model developed in this paper: (i) recipient need (relating to humanitarian concerns), (ii) the ability to use

[4] Not all aid effectiveness studies have detected a relationship between aid and growth (e.g. Roodman 2007; Rajan and Subramanian 2008). However, numerous surveys of the aid literature (Morrissey 2001; McGillivray et al. 2006; Clemens et al. 2012; Glennie and Sumner 2014) as well as recent meta-analyses of foreign aid and growth (Mekasha and Tarp 2011, 2018) have confirmed (on average) a positive relationship between foreign aid and growth.

[5] Not all studies test for diminishing returns to aid. Those that do usually include a quadratic (aid squared) term and commonly find an inverted U-shaped relationship between aid and growth, implying there are diminishing and eventually negative returns to aid. Note that modelling a nonlinear relationship between aid and growth by using a quadratic term is restrictive because this does not allow for the 'big push' theory which suggests that aid has increasing returns.

aid effectively (based on levels of absorptive capacity), and (iii) donor interests (relating to political, strategic and commercial considerations).

Roodman (2009) argues that McGillivray et al. (2002) adopts the most sophisticated approach to modelling aid allocation and one which is well suited to prescribing aid amounts according to multiple criteria. A variant of this model is adopted for the present paper; thus, the objective function for UK aid policy-makers is specified as:

$$U = \sum_{j=1}^{n} \left\{ W_1 RN_j^s POP_j^{\beta} \left(\frac{A_j}{A_i}\right)^{\alpha} + W_2 AC_j^s POP_j^{\beta} \left(\frac{A_j}{A_i}\right)^{\alpha} + W_3 DI_j^s POP_j^{\beta} \left(\frac{A_j}{A_i}\right)^{\alpha} \right\}, \quad 0 < \alpha < 1,\ 0 < \beta < 1, \tag{1}$$

where RN_j^s is a scaled composite indicator of developing country j's need for aid, POP_j is j's population size, AC_j^s is a scaled composite indicator of the country's absorptive capacity, DI_j^s is a scaled composite indicator of the UK's interests in j, A_j is the amount of aid allocated to j, and A_i is the total amount of aid available for distribution across n countries. W_1, W_2 and W_3 are the weights reflecting the relative importance of recipient need, absorptive capacity and donor interests respectively. Finally, α is a coefficient indicating diminishing marginal returns to aid and β implies that there are also diseconomies in population scale; these two parameters imply that all foreign aid will not be provided to a single country.

RN_j, AC_j and DI_j are defined as:

$$RN_j = \sum_{k=1}^{m} w_k rn_{k,j}^s, \quad AC_j = \sum_{q=1}^{m} w_q ac_{q,j}^s, \quad DI_j = \sum_{r=1}^{m} w_r di_{r,j}^s, \tag{2}$$

where $rn_{k,j}^s$, $ac_{\mathrm{q},j}^s$ and $di_{r,j}^s$ specify indicators of recipient need, absorptive capacity and donor interests respectively, and w_k, w_q and w_r are weights representing the relative importance of these variables (discussed below). The total amount of aid, A_i, is treated as predetermined, as is typically the case in practice.

Equation (1) is therefore maximised subject to the budget constraint:

$$\sum_{j=1}^{n} A_j = A_i \tag{3}$$

The constrained optimization problem can be solved using a Lagrangian function to determine the share of aid that should be allocated to individual developing countries that maximises utility. Thus, maximising Eq. (1) subject to Eq. (3) via a Lagrangian and various substitutions yields:

$$\frac{A_{i,j}}{A_j} = \frac{\left\{ \left(W_1 RN_j + W_2 AC_j + W_3 DI_j\right) POP_j^{\beta} \right\}^{\frac{1}{1-\alpha}}}{\sum_{z=1}^{n} \left\{ \left(W_1 RN_z + W_2 AC_z + W_3 DI_z\right) POP_z^{\beta} \right\}^{\frac{1}{1-\alpha}}}, \tag{4}$$

where $i = 1, \ldots n$ and $z = 1, \ldots n$.

Aid allocations consistent with this share are obtained by multiplying Eq. (4) by A_i.

Finally, an important normative attribute of aid is population-scale neutrality (McGillivray and White 1994). Scale neutrality requires that if recipient countries have the same levels of recipient need, absorptive capacity and donor interests but different populations, they should receive the same amount of aid per capita. This condition may be written as:

$$\frac{A_{i,j}}{POP_j} = \frac{A_{i,z}}{POP_z} \quad \text{if} \quad RN_{i,j} + AC_j + DI_j = RN_z + AC_z + DI_z \tag{5}$$

According to McGillivray and White (1994), population-scale neutrality is obtained if $\beta = 1 - \alpha$.

It is acknowledged, however, that the assumption of population-scale neutrality, which heavily conditions the aid amounts prescribed by the model, might be viewed as restrictive. A small country bias, whereby smaller countries receive more aid per capita, is well established in the literature (Doucouliagos and Paldam 2007). Isenman (1976) discusses several reasons why smaller countries are likely to receive more aid per capita, including: donors using aid to secure a vote at the United Nations or other international fora; donors providing an amount of aid that does not appear derisory; smaller countries requiring greater financing of imports due to greater trade openness; and the impacts of aid being observed more easily in smaller countries. There are also fixed costs in providing aid which are spread across fewer people in smaller countries, resulting in higher levels of aid per capita.

The caveats above mean that the prescribed allocations from the model and their interpretation should be regarded as being demonstrative rather than definitive. The issue of the model's interpretation is returned to later, in Sect. 5, when the sensitivity of the application of the population-scale neutrality condition is examined.

Information on each country's need, absorptive capacity and donor interests (discussed below) is mostly available, whereas information on α (capturing diminishing marginal returns to aid) and β (the population bias parameter)—both used to calculate the prescribed aid allocations—is unavailable. Given the population neutrality constraint, the value of α is easily calculated once β is specified (i.e. as above, $\alpha = 1 - \beta$).

This paper adopts Collier and Dollar's (2001) estimate of $\beta = 0.32$, which was arrived at via trial-and-error to ensure that the correlation between modelled aid and GDP and log population respectively was the same as the correlation with respect to actual aid (i.e. so that the modelling exercise preserved the observed population bias in aid allocations). Other values of β are experimented with in order to examine how sensitive results are to different degrees of population bias. As discussed in the results section below, most countries' modelled aid allocations are quite robust in this respect.

Table 1 The 25 largest recipients of UK Official Development Assistance (ODA) in 2015

Country	Net UK ODA ($ million)
Pakistan	571.10
Ethiopia	517.62
Afghanistan	458.25
Nigeria	401.35
Syrian Arab Republic	393.75
Sierra Leone	332.63
South Sudan	317.79
Tanzania	312.98
India	283.54
Bangladesh	250.11
Kenya	237.70
Democratic Republic of the Congo	218.06
Uganda	188.46
Somalia	186.14
Myanmar	174.02
Rwanda	154.76
Lebanon	152.08
Zimbabwe	141.93
Nepal	134.77
Malawi	130.73
Yemen	125.36
Ghana	92.63
Jordan	87.77
Iraq	84.70
Sudan	83.42

3 Data and methods

The group of UK aid recipients is defined by the Development Assistance Committee of the OECD.[6] According to ODA data for 2015 (the latest year available), the UK provided over $6.9 billion in country-programmable aid. Table 1 reports the 25 largest UK ODA recipients, where, as can been seen, Pakistan ($571.1 million) is top of the list, followed by Ethiopia, Afghanistan and Nigeria (more than $400 million each). The importance of these four countries provide further *prima facie* evidence in support of both security concerns and recipient need being motives for ODA from the UK government.

[6] The DAC updates its list of eligible ODA recipients every three years. The list includes all low- and middle-income countries based on Gross National Income per capita as defined by the World Bank, and all the Least Developed Countries as defined by the United Nations (see OECD 2018).

In order to be able to apply the model developed in Sect. 2, recipient need, absorptive capacity and donor interests need to be measured. Absorptive capacity, in particular, has been poorly measured in earlier studies. According to Benyon (2003), notwithstanding having been largely overlooked, absorptive capacity is of major importance to aid allocation models.

Following Feeny and de Silva (2012), this paper adopts a Composite Index of Absorptive Capacity (CIAC) to measure absorptive capacity. The CIAC recognises that a number of absorptive capacity constraints, often in combination, might limit the ability of recipient countries (and donor agencies) to use aid effectively, including: (i) human and physical capital constraints, (ii) governance/policy and institutional constraints, and (iii) deficiencies in how the international donor community delivers its foreign assistance. The CIAC is calculated for individual countries using data and variables capturing these multiple dimensions of absorptive capacity from the World Bank (2018); details are in Table 7 of the "Appendix".

Income per capita is used to represent recipient need. Although the headcount poverty index or other direct measures of poverty would be desirable, data availability issues prevent them being used. Income per capita is highly correlated with these other measures of poverty.

Three variables are included to measure the extent of UK donor interests in each recipient country. Political and strategic interests are captured by whether or not a recipient is in the same geographic region (Europe) as the UK. Former colonies of the UK are specially identified via a binary variable. Finally, the strength of commercial ties is represented by the value of UK exports to the recipient country, based on IMF (2017) data. To ensure scale equivalence, all three variables are scaled to the range 0–1.

Finally, weights (W_1, W_2, and W_3) representing the relative importance of recipient need, absorptive capacity and donor interests need to be assigned. Determining valid weights, representing donors' preferences, has been the greatest challenge facing the (prescriptive) aid allocation literature. Earlier researchers have imposed arbitrary weights. Instead, arguably, the weights should reflect the preferences of UK ODA funders (taxpayers). The main contribution of this paper is the use of a DCE to elicit these preferences from a sample of the UK general population.

3.1 Discrete choice experiment

A DCE is a common approach for modelling people's choices with respect to ranking the alternatives under consideration—in the present context, countries to be supported with UK government aid, where these countries are represented in terms of recipient need, absorptive capacity and donor interests. The DCE was undertaken using web-based software known as 1000minds (www.1000minds.com), which implements the PAPRIKA method (Hansen and Ombler 2008)—an acronym for Potentially All Pairwise RanKings of all possible Alternatives.[7] The

[7] This software and method have been used previously, *inter alia*, to measure preferences for the types of countries international development NGOs should allocate funds to (Hansen et al. 2014) and for how the New Zealand government should allocate bilateral aid (Cunningham et al. 2017). Both studies used university students as participants, with Cunningham et al. having a relatively small sample of 185.

Table 2 Attributes and mean part-worth utilities (n = 1642)

Attribute	Mean part-worth utility
Capacity to use aid effectively	
Low capacity	0
Medium capacity	0.27
High capacity	**0.46**
Political, strategic and commercial ties with the UK	
No ties	0
Some ties	0.15
Strong ties	**0.27**
Poverty	
Poor	0
Very poor	0.14
Extremely poor	**0.27**

The values in bold represent the relative weights of the attributes overall and sum to one

DCE survey was administered by a survey company that specialises in recruiting participants and running online surveys.

In the present context, the first stage of designing a DCE involves specifying the attributes corresponding to the three motives for allocating UK government aid included in the model, and their levels of ‘performance’. It is important to use everyday language that DCE participants are likely to understand and that is as succinct as possible—to minimise the responder burden associated with reading the attributes and levels in the form of the DCE questions (explained below). Thus, ‘recipient need’ is represented by the attribute ‘poverty, ‘absorptive capacity’ by ‘capacity to use aid effectively’, and ‘donor interests’ by ‘political, strategic and commercial ties with the UK’. These three attributes and their levels are presented in Table 2.

The PAPRIKA method for determining weights (known in DCEs as ‘part-worth utilities’) on the attributes and levels involves participants answering a series of questions based on choosing between pairs of hypothetical countries defined on two attributes at a time (where the third attribute is assumed to be the same) and involving a trade-off. An example of such a question (a screenshot from the 1000minds software) appears in Fig. 1.

The number of pairwise-ranking questions asked of each participant in the DCE depends on the number of attributes and levels included. Here, with three attributes, with three levels each, participants were required to answer ten questions on average.

Each participant’s answers also determine which questions, and how many, are asked. This question ‘path dependency’ arises from the adaptive nature of the PAPRIKA method: each time a participant answers a question, the method chooses another question for the participant to answer based on the preceding answer and all other preceding answers. Again based on how that question is answered, another question is presented, and then another, and another, and so on. This adaptivity

Fig. 1 An example of a pairwise-ranking question in the DCE

means that the PAPRIKA method is recognised as a type of adaptive DCE (or adaptive conjoint analysis).[8]

Each time a participant pairwise ranks a pair of hypothetical countries (i.e. defined on two attributes at a time; see Fig. 1 again), the method applies the transitivity property to immediately identify all other pairs of hypothetical countries that can be pairwise ranked. For example, if country *X* is ranked ahead of *Y* and also *Y* is ranked ahead of country *Z*, then, by transitivity, *X* must be ranked ahead of *Z*—and so the method eliminates this third pair and any other pairs implied by transitivity, thereby saving the participant from being asked any (redundant) questions pertaining to these implied rankings.

Thus, the participant has to answer only a relatively small number of questions (ten on average, as noted above). And yet all hypothetical countries defined on two attributes at a time end up being pairwise ranked, either explicitly or implicitly (by transitivity). The set of pairwise rankings defines an overall ranking of all hypothetical countries defined on the attributes. In addition, as a check of the 'quality' of each participant's answers overall, two questions are repeated at the end of the DCE as a test of the consistency (reliability) of their answers.

Finally, from each participant's answers to the pairwise-ranking questions, mathematical methods based on linear programming are used to calculate the participant's part-worth utilities, representing the relative importance (weights) of the attributes (motives); technical details are available in Hansen and Ombler (2008). As well as part-worth utilities (weights) for each individual participant, they are also averaged across participants.

[8] Discrete choice experiments are also sometimes referred to as conjoint analysis.

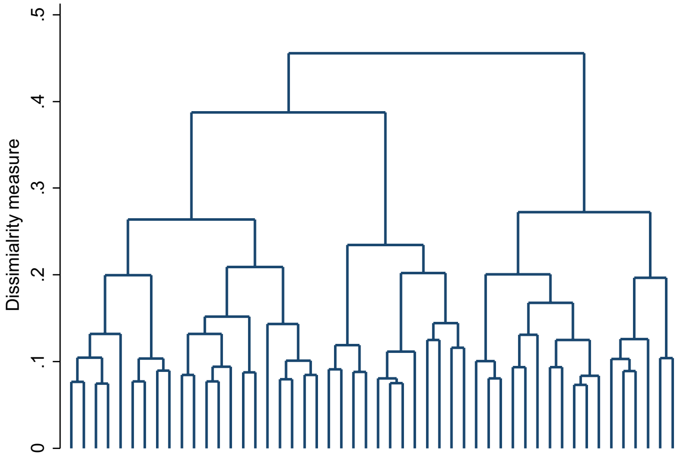

Fig. 2 Dendrogram for UK survey participants' part-worth utilities. *Notes*: hierarchical clustering based on the weighted average linkage method. Dendrogram truncated at 50 branches

3.2 Cluster analysis

Relative to other DCE methods which produce aggregated data only, an important advantage of the PAPRIKA method is that a set of weights is generated for each individual participant. Individual-level data enable cluster analysis to be performed to identify groups ('clusters') of participants with similar patterns of part-worth utilities. The results of the cluster analysis can then be used to investigate the extent to which the clusters are related to participants' socio-demographic and background characteristics. Thus, in addition to the DCE, participants were asked questions about their demographic and background characteristics: age, gender, education, and voting behaviour in the 2015 UK general election.

When performing cluster analysis, a fundamentally important choice by researchers is how many clusters to implement. A common approach is to use a graphical representation of hierarchical clustering known as a 'dendrogram' (see Fig. 2 in the next section) to help reach this decision.

As depicted in a dendrogram, hierarchical clustering starts from the 'bottom up' by initially pairing (clustering) each of the observations (i.e. individual sets of weights) with another observation that it is most like. These pairs are then successively agglomerated with other clusters or individual observations they are most like, which are themselves further agglomerated, and so on as the clustering algorithm proceeds up the hierarchy represented in the dendrogram. The vertical distances between successive levels in a dendrogram represent the degree of dissimilarity between the clusters at the lower level and are used to support the choice of how many clusters to implement.

Several agglomeration methods are available, each of which can generate a different dendrogram (and hence identifying different clusters). These five common methods were experimented with: single linkage, complete linkage, group average, weighted average and Ward's distance. Choosing the 'best' method to use involves selecting the results that most closely conform with the contextual and theoretical underpinnings of the underlying data.

In addition, as an alternative to hierarchical clustering that dendrograms are based on, the K-means clustering method was utilised. K-means clustering is an iterative procedure that partitions the observations into K groups, where K is set by the researcher. The approach partitions participants into different clusters each time it is run due to different starting values.

3.3 Aid allocations

For each country in receipt of UK ODA, the part-worth utilities are applied as the weights for the allocation model in Eq. (4) (Sect. 2) to determine the amount of aid each developing country should receive based on its need, absorptive capacity and donor interests. These 'model-prescribed' amounts are then compared to the actual aid the countries received, as discussed in the previous section.

4 Survey results

4.1 Discrete choice experiment

The DCE was completed by 2028 people, each of whom was required to answer 10 pairwise-ranking questions (including the two repeated ones) on average, taking most people less than 5 min in total. In response to being asked how easy or difficult they found answering the pairwise-ranking questions, 87% of participants indicated they did not find the questions difficult. With respect to the two repeated questions, 367 participants (18%) were excluded from further analysis because they answered one or both questions contradictorily (i.e. inconsistently).[9] This left 1661 participants; however, a further 19 participants were excluded because they were ineligible (not aged 18 or over or not a UK citizen). The socio-demographic and background characteristics of the remaining 1642 participants (that reported their characteristics) are summarised in Table 8 in the "Appendix".

Based on the 1642 participants, the mean weights for the attributes and levels are reported in Table 2. As can be seen in the table, 'capacity to use aid effectively' (i.e. absorptive capacity) is the most important attribute, followed by—in a tie for second place—'political, strategic and commercial ties with the UK' (donor interests) and 'poverty' (recipient need). The absorptive-capacity attribute has a mean weight of 0.46, whereas the two other attributes have mean weights of 0.27. Therefore, absorptive capacity is 1.7 times as important as donor interests or recipient need.

[9] The average part-worth utilities for the full sample were very similar to those for the restricted sample and make very little difference to the modeled aid amounts to individual recipients.

Table 3 Mean part-worth utilities by cluster (N = 1642)

Attribute	Recipient need cluster (n = 285)	Absorptive capacity cluster (n = 1162)	Donor interests cluster (n = 195)
Recipient need	0.50	0.22	0.19
Absorptive capacity	0.28	0.53	0.28
Donor interest	0.18	0.25	0.53

4.2 Cluster analysis

Three of the five agglomeration methods experimented with—complete linkage, group average and weighted average methods—yielded similar dendrograms, revealing three fairly distinct clusters. This ‘three cluster’ result accords with the design of the DCE with its three attributes relating to the three motives of the aid allocation model. The dendrogram produced by the weighted average method is reported in Fig. 2 and was used to identify the three clusters. The other dendrograms did not have an obvious interpretation.

Mean part-worth utilities for each of the three clusters are reported in Table 3. These utilities confirm that three clusters are plausible, as each cluster represents a group placing most weight on recipient need, absorptive capacity and donor interests respectively (and so the clusters are named accordingly). Moreover, tests based on pairwise comparisons of the means reveal that the difference in the part-worth utilities are statistically significant within each cluster. These findings are also confirmed using ANOVA.

Of particular interest is the large number of people—1162 (71%)—in the absorptive capacity cluster. This reinforces the point that for a significant majority of participants the ability to use aid effectively is substantially more important than the other two attributes; the mean part-worth utility on absorptive capacity for this cluster is 0.53. There are 285 people (17%) in the recipient need cluster and 195 (12%) in the donor interests cluster.

With respect to the K-means clustering method, informed by the dendrogram results and supported by the contextual and theoretical underpinnings of the underlying data as mentioned earlier, k = 3 was chosen. Similar to the dendrogram approach, K-means tended to yield clusters comprising participants with strong preferences for health, education and income respectively. However, cluster membership varied and findings from the multinomial logit regressions were unstable and not reproducible. The findings from the dendrogram approach to clustering are therefore preferred and emphasised here.

Based on the three clusters, multinominal logit regressions were run to determine whether participant characteristics are associated with the likelihood of belonging to a particular cluster. Participants needed to report all socio-demographic data in order to be included in the regressions. Marginal effects are presented in Table 4. The estimated marginal probabilities in each row sum to zero; if a change in a participant characteristic reduces the probability of membership to one cluster, the probability of membership to another cluster increases.

Table 4 Marginal probability of membership in each cluster from multinominal logit regressions (N = 1580)

	Recipient need cluster (n = 274)	Absorptive capacity cluster (n = 1123)	Donor interests cluster (n = 183)
Age	−0.0189**	0.0297**	−0.0108*
	(−2.73)	(3.60)	(−1.81)
Male	−0.000870	−0.0541**	0.0550**
	(−0.04)	(−2.34)	(3.33)
Married	0.0114	−0.0181	0.00663
	(0.57)	(−0.76)	(0.39)
Employed	0.00386	−0.0203	0.0165
	(0.18)	(−0.78)	(0.88)
Tertiary education	−0.0105	0.0388*	−0.0283*
	(−0.54)	(1.67)	(−1.73)
Conservative voter	−0.0688**	0.0630*	0.00586
	(−2.43)	(1.89)	(0.25)
Labour voter	0.0152	−0.00442	−0.0108
	(0.58)	(−0.14)	(−0.45)
UKIP voter	−0.0408	−0.00968	0.0505*
	(−1.10)	(−0.23)	(1.86)
Green voter	0.0241	0.00986	−0.0340
	(0.60)	(0.19)	(−0.82)
Liberal democrat voter	−0.0790*	0.139**	−0.0602
	(−1.70)	(2.50)	(−1.39)
n	1580	1580	1580

Clusters defined using the weighted average method

t statistics in parentheses

*$p < 0.10$; **$p < 0.05$

The results suggest that older participants are more likely to belong to the absorptive capacity cluster—i.e. they are more concerned with aid effectiveness and getting more impact for their aid dollar—and less likely to belong to the recipient need and donor interests clusters. Males are less likely to belong to the absorptive capacity cluster and more likely to belong to the donor interests cluster, whereas the reverse is true for tertiary-educated participants. There is no association between being married or employed and aid allocation preferences.

Interestingly, voting behaviour appears to be important.[10] People who voted for the Conservative and Liberal Democrat parties at the 2015 election are more likely to belong to the absorptive capacity cluster and less likely to belong to the recipient need cluster. Furthermore, those that voted for UKIP are more likely to belong to the donor interests cluster, possibly reflecting a desire to use aid to promote UK interests abroad.

[10] The omitted category for political parties is 'other' which includes voting for the Democratic Unionist Party, the Ulster Unionist Party, Sinn Fein, the Plaid Cymru Party of Wales, the Scottish Nationalist Party or the Social Democrats.

Table 5 The 10 largest gainers from modelled ODA

Country	UK ODA 2015 ($ million)	Increase in aid if allocated according to model ($ million)
India	283.5	2306.2
China	68.2	1262.7
Indonesia	30.4	206.5
Turkey	9.6	76.4
Brazil	31.9	76.2
Philippines	13.9	72.4
Iran, Islamic Republic	1.5	62.5
Vietnam	18.8	57.0
South Africa	29.2	51.4
Mexico	19.8	49.4

Table 6 The 10 largest losers from modelled ODA

Country	UK ODA 2015 ($ million)	Reduction in aid if allocated according to model ($ million)
Ethiopia	517.6	463.0
Afghanistan	458.3	442.1
Pakistan	571.1	410.4
Syrian Arab Republic	393.8	381.1
Sierra Leone	332.6	321.3
South Sudan	317.8	304.6
Tanzania	313.0	236.5
Kenya	237.7	177.2
Somalia	186.1	170.3
Congo, Dem. Republic	218.1	170.2

4.3 Aid allocations

The 'model-prescribed' amounts of aid each developing country should receive are presented and compared to the actual aid they received in the next section.

5 Aid allocations: model-prescribed versus actual

Tables 5 and 6 report the results from the modelling exercise in terms of the 10 countries most positively and negatively affected respectively if the UK government allocated its aid consistent with the model. Model-prescribed aid allocations for all recipient countries are provided in Table 9 in the "Appendix".

It was noted above that the aid amounts determined by the model are sensitive to its underlying assumptions and conceptualisation. The aid amounts determined by the model will depend on the functional form of the UK government's utility function as well as the choice of variables entering the vectors of need, donor interests and absorptive capacity.[11] Therefore, later in this section some of the assumptions underlying the aid allocation model are relaxed to examine how sensitive results are to such changes.

As can be seen in Table 5, India and China (the world's two most populous countries) would gain considerably if the UK government allocated its aid consistent with the model. ODA to these countries would increase by more than \$2.3 billion and \$1.2 billion respectively. Of course, in per capita terms these amounts are much smaller: for India, ODA would increase from 21 cents to \$1.96 per capita, and for China from 5 to 95 cents per capita. Also, Indonesia would receive more than \$200 million in additional UK ODA, and Turkey, Brazil and the Philippines would each receive more than \$70 million extra.

Table 6 reports the 10 countries that would lose the most UK ODA according to the allocation model. The biggest losers—losing more than \$400 million each—would be Ethiopia, Afghanistan and Pakistan. Other major losers of UK ODA would be Syria, Sierra Leone and South Sudan: decreases of more than \$300 million each. Interestingly, all these aid recipients are conflict-affected or post-conflict countries with relatively low absorptive capacity (as measured).

5.1 Sensitivity analysis

Several alterations to the aid-allocation model are introduced to check how sensitive model-prescribed aid allocations are to changes in assumptions and measurements. First, different values of β are used. As discussed in Sect. 2, β represents the population bias parameter which must be chosen by the researcher. The results presented above are based on $\beta = 0.32$. Changes in aid allocations to individual countries based on other values—i.e. $\beta = 0.5$ and $\beta = 0.7$—are provided in Table 9 of the "Appendix".

When the value of β increases, aid amounts to the largest countries vary the most. Modelled aid to China increases by more than \$150 million if $\beta = 0.7$. Modelled aid to Brazil and Indonesia also increases substantially. On the other hand, the increase in modelled aid to India falls: instead of an additional \$2306 million, India would receive an additional \$1691 million. A higher value of β also implies that the reduction in modelled aid is less for Ethiopia and Pakistan, but there is a greater reduction for modelled aid to Nigeria. In general, the changes in modelled aid due to changes in β are small relative to the total UK aid budget.

It is recognised that absorptive capacity is a difficult concept to measure. Other studies have used the World Bank's CPIA scores as a proxy. Unfortunately, the CPIA's coverage for the developing countries included in the analysis of this paper

[11] For example, as noted by an anonymous referee, countries rather than territories might be favoured by donors due to their sovereignty. Countries with a larger land mass might present greater opportunities for resource exploration and extraction, and countries with larger GDPs might be favoured due to their potential for access to larger exports markets.

is far from complete. As an alternative, the paper adopts the World Bank's 'rule of law' governance indicator as another proxy for absorptive capacity. Again, with two exceptions, there is little change to the model-prescribed aid amounts when this measure is used. The exceptions are India, which would receive an additional $400 million relative to the model using the composite index of absorptive capacity, and China, which would receive $200 million less. Results are provided in the penultimate column of Table 9 in the "Appendix".

The final column of Table 9 provides the allocations from the model when donor interests are omitted and recipient need and absorptive capacity are re-weighted accordingly. Findings from this model indicate that, relative to the base model, Bangladesh, Brazil and Indonesia would receive much more aid, whereas China, India and Nigeria would receive much less.

As noted in Sect. 2, if the population-scale neutrality condition written in (5) holds, all countries will receive the same amount of aid per capita, if their relative need, absorptive capacity and donor interests are the same. Yet it could be that donors might want to give more aid per capita to larger countries *ceteris paribus*, given their greater importance as represented by their size. This possibility would mean that the population-scale neutrality condition should not be imposed as it might result in aid allocations that are not consistent with donor preferences.[12]

Therefore, additional sensitivity analysis was performed, allowing β (the population parameter) to be greater than $1-\alpha$ (α captures diminishing marginal returns to aid); specifically, β was increased to 0.5 while maintaining $\alpha=0.68$. Under this scenario, the world's two largest countries would receive the lion's share of the UK's aid budget: India and China would receive over 81% of total ODA from the UK; correspondingly, ODA to all other countries would be less relative to if population-scale neutrality held. Although the countries included in the top gainers and biggest losers changes a little bit (see Tables 10 and 11 in the "Appendix"), the ranking of countries remains largely unchanged compared to the model in which population neutrality holds (Spearman's rank correlation coefficient = 0.99).

Finally, notwithstanding this paper arguing that foreign aid is unlikely to yield high returns when absorptive capacity is low (given the importance of human capital and governance for the success of aid interventions), aid can be provided through channels other than the government when donors are worried about the public sector's absorptive capacity. Further sensitivity analysis was performed: all countries with absorptive capacity index scores of below 0.25 were adjusted to this minimum 'floor' and the model re-run[13]; this implies low levels of absorptive capacity become less binding in these countries as donors can use alternative aid delivery mechanisms. Although countries with the lowest absorptive capacity index scores exhibited slightly smaller reductions in ODA, the ten largest gainers and losers of ODA remained unchanged and the ranking of countries overall remained virtually unchanged (Spearman's rank correlation coefficient = 0.99).

[12] Thank you to an anonymous reviewer for this insight.

[13] The absorptive capacity index score was adjusted for these 26 countries: Afghanistan, Bangladesh, Burkina Faso, Burundi, Cambodia, Central African Republic, Chad, Cote d'Ivoire, Democratic Republic of Congo, Ethiopia, Guinea, Haiti, Kenya, Liberia, Mali, Mozambique, Myanmar, Niger, Peoples Democratic Republic of Korea, Sierra Leone, Somalia, South Sudan, Sudan, Tanzania, Uganda and Yemen.

6 Conclusion

This paper developed a model for how UK government aid ought to be allocated across recipient countries based on three broad motives: recipient need, donor interests and absorptive capacity. Previous prescriptive aid allocation models applied arbitrary weights to the motives for providing aid. In contrast, this paper used a discrete choice experiment involving more than 1600 members of the UK general population to determine weights for the three motives. Absorptive capacity (the ability of recipient countries to use aid effectively) is the most important motive, and recipient need and donor interests are equally but much less important. This finding implies that the UK general population is most concerned with issues of aid effectiveness—in other words, that aid is put to good use and not wasted.

Because the model (and the way it is operationalised) requires a number of assumptions, the inter-country allocated aid amounts should be viewed as indicative rather than definitive. With this caveat in mind, comparing the model-prescribed amounts of aid to actual allocations from the UK government's aid budget in 2015 revealed that some countries, including China, India and Indonesia, would receive much more if aid were allocated according to the model, whereas other countries, including Afghanistan, Ethiopia and Pakistan, would receive much less. These results are largely robust to changes in assumptions and how key variables are measured.

These results highlight the countries for which the UK government should examine how much aid it gives, based on public preferences. Where differences between actual and modelled aid allocations are large, the government should consider the extent to which other important considerations are able to justify the discrepancy.

Three distinct groups were identified by the cluster analysis, centred on a dominant preference for recipient need, donor interests and absorptive capacity respectively as the most important attribute for choosing countries to support with aid. Voting behaviour in the 2015 UK general election was found, *inter alia*, to be important in explaining people's preferences: voters for the Conservative party or Liberal Democrats are more likely to belong to the cluster favouring absorptive capacity, UKIP voters are more likely to belong to the cluster favouring donor interests, and voters for all three parties are less likely to belong to the cluster favouring recipient need.

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Appendix

See Tables 7, 8, 9, 10 and 11.

Table 7 The composite index of absorptive capacity

Component	Measurement	Source	Year
Capital			
Human capital	(i) Number of doctors per 1000 people	World Bank (2018)	Latest available
	(ii) Number of nurses per 1000 people		
	(iii) Number of primary school teachers per 1000 people		
	(iv) Number of secondary school teachers per 1000 people		
	(v) Adult illiteracy		
Infrastructure	(i) Paved roads (% of total)	World Bank (2018)	Latest available
Governance			
Policy/institutional	(i) Voice and accountability	World Bank (2018)	2016
	(ii) Political instability		
	(iii) Government effectiveness		
	(iv) Regulatory quality		
	(v) Rule of law		
	(vi) Control of corruption		
Donor			
Donor practices	(i) Ratio of the number of DAC donors to the log of government expenditures.	OECD (2011)	Latest available
	(ii) Ratio of fragmentation (number of donors accounting for less than 10% of Country Programmable Aid (CPA) to the log of government expenditures.		

Table 8 Descriptive and summary statistics of variables used in the multinominal logit regressions

Variable	Coding definition	Mean	SD	Min. value	Max. value
Age	1 if 18–24 years old, 2 if 25–34, 3 if 35–44, 4 if 45–54, 5 if 55–64, 6 if 65 or over	3.68	1.56	1	6
Male	1 if male, 0 otherwise	0.45	0.50	0	1
Married	1 if married, 0 otherwise	0.53	0.50	0	1
Employed	1 if employed either full-time or part-time, 0 otherwise	0.68	0.47	0	1
Tertiary educated	1 if tertiary qualification, 0 otherwise	0.55	0.50	0	1
Conservative	1 if voted for the Conservative party at the last general election, 0 otherwise	0.30	0.46	0	1
Labour	1 if voted for the Conservative party at the last general election, 0 otherwise	0.27	0.44	0	1
UKIP	1 if voted for the Conservative party at the last general election, 0 otherwise	0.11	0.32	0	1
Green	1 if voted for the Conservative party at the last general election, 0 otherwise	0.06	0.23	0	1
Liberal Democrat	1 if voted for the Conservative party at the last general election, 0 otherwise	0.07	0.26	0	1

Table 9 Modelled UK ODA

Country	UK ODA (2015)	$\beta=0.32$	$\beta=0.5$	$\beta=0.7$	AC = Rule of Law	No DI
Afghanistan	458.25	−442.1	−435.5	−431.4	−444.3	−431.5
Angola	1.98	15.4	20.4	23.2	10.6	26.3
Albania	1.01	3.5	3.1	2.9	2.9	2.8
Argentina	2.41	10.0	18.5	24.6	2.6	17.8
Armenia	1.81	1.0	1.3	1.4	0.5	2.9
Antigua and Barbuda	0	0.1	0.1	0.1	0.1	0.0
Azerbaijan	3.74	5.9	6.7	6.9	2.0	11.9
Burundi	0.31	6.2	8.0	9.0	5.9	10.5
Benin		9.4	10.6	11.2	10.5	15.6
Burkina Faso	0.13	13.5	16.2	17.6	18.2	22.5
Bangladesh	250.11	−149.5	−121.8	−106.4	−127.4	−83.9
Bosnia and Herzegovina	6.77	−1.7	−2.0	−2.2	−2.1	−2.5
Belarus	1.34	16.0	13.7	12.4	6.7	14.1
Belize	1.75	−1.1	−1.2	−1.2	−1.4	−1.2
Bolivia	1.26	5.7	7.5	8.5	3.1	10.3
Brazil	31.91	76.2	114.7	137.5	80.0	130.0
Bhutan	0.12	0.7	0.8	0.8	1.2	1.3
Botswana	1.61	1.6	1.4	1.3	2.8	1.1
Central African Republic	27.93	−25.3	−24.5	−24.0	−26.4	−23.5
Chile	7.11	−1.6	1.9	4.3	10.6	1.7
China	68.21	1262.7	1376.8	1423.5	1046.0	936.5
Cote d'Ivoire	1.07	15.0	18.8	20.8	18.3	25.6
Cameroon	9.51	8.4	11.6	13.2	5.4	20.1
Congo, Dem. Rep.	218.06	−170.2	−156.7	−149.2	−188.1	−138.7
Congo, Rep.		4.4	5.0	5.3	2.8	7.3
Colombia	61.59	−32.0	−23.7	−19.0	−29.4	−13.2
Comoros	0.01	1.1	1.0	1.0	0.6	1.8
Cape Verde	0.18	0.5	0.5	0.5	0.8	1.0
Costa Rica	1.68	0.2	1.1	1.8	1.2	1.4
Cuba	2.03	6.2	8.0	8.8	1.6	11.7
Djibouti	0.03	0.6	0.8	0.8	0.5	1.0
Dominica	0.75	−0.6	−0.6	−0.6	−0.6	−0.6
Dominican Republic	2.23	5.4	7.0	7.8	2.6	10.4
Algeria	4.09	35.9	39.0	40.2	15.6	61.5
Ecuador	0.48	9.5	12.3	13.9	4.2	16.1
Egypt, Arab Rep.	18.53	48.8	63.3	71.0	46.3	88.6
Eritrea	0.46	3.6	4.1	4.3	1.4	6.4
Ethiopia	517.62	−463.0	−444.3	−433.4	−415.6	−427.6
Fiji	1.93	−0.5	−0.6	−0.7	−0.9	−0.6
Micronesia, Fed. Sts.		0.1	0.1	0.1	0.1	0.2
Gabon		1.1	1.4	1.6	0.8	1.8
Georgia	4.36	1.1	0.8	0.5	0.4	4.7

Table 9 (continued)

Country	UK ODA (2015)	$\beta=0.32$	$\beta=0.5$	$\beta=0.7$	AC = Rule of Law	No DI
Ghana	92.63	−43.6	−49.6	−52.7	−24.9	−50.1
Guinea	0.48	7.8	9.8	10.9	6.7	13.3
Gambia, The	14.58	−11.1	−11.5	−11.7	−11.5	−11.6
Guinea-Bissau	0.03	1.5	1.7	1.8	0.9	2.6
Equatorial Guinea		0.4	0.7	0.8	0.1	0.7
Grenada	0.07	0.0	0.1	0.1	0.0	0.0
Guatemala	1.63	10.2	12.7	14.0	5.4	18.0
Guyana	3.4	−2.2	−2.3	−2.4	−2.5	−2.4
Honduras	0.28	7.6	8.6	9.1	4.8	12.8
Haiti	5.88	1.8	3.4	4.3	0.0	6.8
Indonesia	30.35	206.5	232.5	244.0	170.4	356.2
India	283.54	2306.2	1893.9	1690.6	2739.8	1730.3
Iran, Islamic Rep.	1.52	62.5	72.9	78.1	29.2	104.4
Iraq	84.7	−61.3	−55.1	−51.6	−76.2	−46.4
Jamaica	11.78	−5.6	−6.8	−7.3	−7.9	−6.1
Jordan	87.77	−70.7	−73.0	−74.2	−66.1	−72.8
Kazakhstan	8.29	5.5	7.9	9.1	−0.5	14.3
Kenya	237.7	−177.2	−177.8	−178.7	−159.8	−189.5
Kyrgyz Republic	4.13	2.0	2.4	2.6	−0.3	6.0
Cambodia	4.25	5.5	8.2	9.7	5.5	12.0
Kiribati	0.02	0.1	0.1	0.1	0.1	0.2
Kosovo	7.16	−4.0	−4.4	−4.6	−4.8	−4.4
Lao PDR	3.57	0.9	2.0	2.6	0.7	3.9
Lebanon	152.08	−149.6	−148.5	−147.7	−150.5	−148.1
Liberia	16.3	−12.8	−12.2	−11.8	−12.8	−10.5
Libya	15.94	−12.4	−11.3	−10.6	−15.1	−10.1
St. Lucia	0.27	0.1	0.0	0.0	0.1	0.1
Sri Lanka	37.61	−8.4	−9.7	−10.6	0.9	−13.6
Lesotho	0.66	3.9	3.1	2.7	3.9	3.5
Morocco	5.46	23.2	27.6	29.8	33.6	41.2
Moldova	1.97	5.1	4.0	3.4	4.0	4.4
Madagascar	2.04	19.6	22.3	23.6	20.2	33.8
Maldives	0.28	0.3	0.2	0.2	0.0	0.2
Mexico	19.75	49.4	72.8	86.4	32.4	88.5
Marshall Islands		0.1	0.1	0.1	0.0	0.1
Macedonia, FYR	3.28	0.6	0.0	−0.2	−0.5	0.1
Mali	−9.48	19.5	22.8	24.6	24.2	26.1
Myanmar	174.02	−101.9	−104.9	−107.0	−125.3	−114.3
Montenegro	1.54	−0.4	−0.6	−0.6	−0.7	−0.6
Mongolia	0.97	1.4	1.8	2.0	1.4	3.0
Mozambique	77.13	−59.6	−54.6	−51.9	−54.7	−48.0
Mauritania	0.18	3.3	3.8	4.1	2.8	5.6

Table 9 (continued)

Country	UK ODA (2015)	$\beta=0.32$	$\beta=0.5$	$\beta=0.7$	AC = Rule of Law	No DI
Mauritius	1.19	0.8	0.6	0.5	1.1	0.5
Malawi	130.73	−99.8	−103.4	−105.3	−94.4	−103.7
Malaysia	8.56	38.0	34.6	32.6	37.3	28.7
Namibia	0.45	2.0	2.2	2.2	2.5	3.6
Niger		13.5	16.9	18.7	20.2	22.4
Nigeria	401.35	−127.8	−146.2	−157.5	−202.4	−180.3
Nicaragua	0.24	8.9	8.3	7.9	7.4	7.5
Nepal	134.77	−110.2	−106.8	−105.2	−109.7	−94.0
Nauru		0.0	0.0	0.0	0.0	0.0
Pakistan	571.1	−410.4	−387.1	−376.0	−427.9	−309.6
Panama	2.86	−1.9	−1.2	−0.6	−1.9	−1.4
Peru	3.3	14.7	20.4	23.7	13.1	26.4
Philippines	13.93	72.4	84.6	90.5	77.4	127.2
Palau		0.0	0.0	0.0	0.0	0.0
Papua New Guinea	1.45	10.9	9.9	9.3	7.6	9.1
Korea, Dem. People's Rep.	1.13	13.1	17.6	20.3	6.9	22.5
Paraguay	0.75	4.9	5.7	6.1	3.0	8.7
West Bank and Gaza	78.58	−74.9	−74.3	−74.1	−75.1	−72.5
Rwanda	154.76	−144.5	−143.1	−142.5	−136.7	−137.6
Sudan	83.42	−38.7	−37.5	−37.4	−50.8	−48.2
Senegal	1.67	11.9	13.5	14.3	18.2	20.8
Solomon Islands	0.79	0.1	0.0	0.0	0.1	0.0
Sierra Leone	332.63	−321.3	−322.2	−322.7	−322.6	−323.0
El Salvador	0.73	4.7	5.4	5.7	3.1	8.2
Somalia	186.14	−170.3	−169.8	−169.7	−180.8	−173.7
Serbia	5.83	4.7	3.9	3.5	4.0	3.0
South Sudan	317.79	−304.6	−304.0	−303.9	−310.9	−307.5
Sao Tome and Principe		0.2	0.2	0.2	0.1	0.3
Suriname	0.05	1.1	0.9	0.8	0.3	1.8
Swaziland	0.26	2.2	1.9	1.7	1.8	2.0
Seychelles	0.49	−0.4	−0.4	−0.4	−0.4	−0.4
Syrian Arab Republic	393.75	−381.1	−378.2	−376.7	−388.1	−372.8
Chad		9.6	11.9	13.2	8.0	16.0
Togo	0.05	6.9	7.7	8.0	6.0	11.5
Thailand	5.75	44.9	54.9	60.0	45.9	74.1
Tajikistan	18.43	−11.6	−10.4	−9.8	−13.1	−7.0
Turkmenistan	0.7	3.4	4.2	4.7	0.2	6.1
Timor-Leste	0.1	1.2	1.3	1.3	0.6	2.0
Tonga	0	0.3	0.2	0.2	0.2	0.2
Tunisia	9.64	0.4	1.7	2.2	1.9	7.0
Turkey	9.61	76.4	80.0	81.0	57.6	46.9

Table 9 (continued)

Country	UK ODA (2015)	$\beta=0.32$	$\beta=0.5$	$\beta=0.7$	AC = Rule of Law	No DI
Tuvalu	0.04	0.0	0.0	0.0	0.0	0.0
Tanzania	312.98	−236.5	−239.9	−242.3	−211.4	−249.8
Uganda	188.46	−130.9	−133.7	−135.5	−111.6	−140.7
Ukraine	43.76	42.2	29.2	22.7	8.9	32.5
Uruguay	2.33	−1.4	−0.8	−0.3	−0.7	−0.9
Uzbekistan	2.3	36.7	36.5	36.1	13.0	62.4
St. Vincent & Grenadines	0.17	0.1	0.0	0.0	0.0	0.1
Venezuela, RB	2.15	4.7	10.6	15.2	−2.0	9.1
Vietnam	18.83	57.0	68.6	74.1	71.4	105.3
Vanuatu	3.74	−3.2	−3.3	−3.3	−3.2	−3.2
Samoa		0.3	0.3	0.3	0.5	0.3
Yemen, Rep.	125.36	−110.2	−105.2	−102.3	−112.1	−100.2
South Africa	29.18	51.4	46.5	43.4	67.1	32.4
Zambia	77.15	−48.3	−51.8	−53.7	−44.8	−51.9
Zimbabwe	141.93	−117.9	−119.6	−120.6	−127.5	−121.6

Table 10 The 10 largest gainers from modelled ODA ($\beta=0.5$, $\alpha=0.68$)

ODA recipient	UK ODA (2015) ($ million)	Increase in ODA ($ million)
India	283.5	3636.9
China	68.2	1997.5
Indonesia	30.4	113.7
Brazil	31.9	25.9
Iran, Islamic Rep.	1.5	18.6
Turkey	9.6	17.2
Philippines	13.9	17.2
Mali	−9.5	10.8
Thailand	5.8	8.8
Mexico	19.8	8.4

Table 11 The 10 largest losers from modelled ODA (β = 0.5, α = 0.68)

ODA recipient	UK ODA (2015) ($ million)	Reduction in ODA ($ million)
Ethiopia	517.6	498.04
Pakistan	571.1	488.60
Afghanistan	458.3	455.10
Syrian Arab Republic	393.8	392.02
Sierra Leone	332.6	331.70
South Sudan	317.8	316.36
Tanzania	313.0	293.49
Nigeria	401.4	263.81
Kenya	237.7	223.42
Congo, Dem. Rep.	218.1	203.24

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