Introduction to the paper submitted for the methodology workshop (Gov 3009)

As will be clear, this is a chapter from my dissertation. It is one of the longest, and probably densest, chapters in the dissertation, for which my apologies. It is also not completely finished yet, although it is getting close.

One of the important things that still needs changing is the presentation of the results and associated effects (first differences, fitted values, whatever). I don't think the effects currently being presented are all that useful. A note in the text provides my own thoughts about how to make them better. In addition, there are some open or unaddressed questions, some of which I highlight in the outline for the conclusion.

This chapter represents my first attempt at developing and programming my own model. All other statistical work I have done until now has been in the form of largely uncritical use of programs written by others. I have thought a lot about various aspects of the model and its implementation, but it would not surprise me in the least if there are gaping holes left somewhere. Since I hope to send this chapter out into the job market fray, it would be quite helpful if I were able to plug those holes ahead of time.

Basically, any comments or thoughts about the contents of the chapter, the presentation of the model, methodological issues I should address but have not, etc. would be extremely welcome. Finally, since this chapter comes in the middle of my dissertation and takes a fair amount for granted, I thought it might be useful to include a brief dissertation abstract to help provide some context.

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Ideas and interests in foreign policy: The politics of official development assistance
Dissertation abstract

What motivates a government to aid foreign states or the citizens of those states? Despite half a century of foreign aid programs, the answer to this question remains elusive. Adding to the puzzle is the wide variation in aid policies we observe across states. Traditionally, the aid literature has focused on competing motivations of self-interest and altruism, with inconclusive and unsatisfactory results. I argue for the consideration of three additional types of motivation: prestige, obligation, and the pursuit of international public goods (in spite of the logic of collective action). The dissertation shows that the incorporation of these motivations into an overall conception of state preferences helps explain aspects of aid policy that until now were not well-understood or deemed idiosyncratic.

In order to incorporate several new goals into a model of foreign policy while retaining a coherent overall structure, I introduce a model of preferences as composed of seven different dimensions. Three of these — security, power, and wealth — encompass conventional understandings of self-interest; three more — enlightened self-interest, prestige, and obligation

— reflect the new categories I add; and the final dimension consists in humanitarian and altruistic motivations. I argue that the relative strengths of these objectives shape policy choice. Thus, a government which conceives of foreign aid primarily as an instrument to be used for its own economic benefit will exhibit a very different aid policy from a government which sees aid as a means to greater international influence or prestige, even if the material interests of the two states are the same.

To test this claim, I need a measure of the relative strength of different policy motivations. I argue that such a measure can be extracted from the rhetoric of legislators regarding the policy in question. Accordingly, I analyze the contents of parliamentary debates on aid in four countries — Belgium, Italy, the Netherlands, and Norway — at two- to three-year intervals over a period of more than forty years. By tallying the motivations for giving aid expressed by legislators, I derive a measure of the relative strength of the different dimensions of motivation in the different countries. The data suggest that legislators are indeed consistently concerned with enlightened self-interest, prestige, and obligation.

Statistical analysis shows that these same motivations are also important to aid policy itself. Both the factors determining aid volume and those relevant to the geographical distribution of aid include variables that ought not to matter if only self-interest and/or altruism were applicable. The legislative debate measures prove useful in distinguishing between different explanations that use the same independent variable as a proxy. By interacting my indicators of the strength of different motivations with such variables, I am able to explain why certain patterns in aid politics — such as a correlation between aid and trade — are not evident everywhere or all the time: the strength of the pattern fluctuates in tandem with the strength of the relevant motivation. In order to improve the statistical analysis of the allocation of aid, I develop a new two-stage, sample-selection model, allowing me to separate the selection of aid recipients from the decision of how much aid to give each. The results suggest that the recipient selection process is somewhat more idiosyncratic than are the decisions about allocation size, but also that considerations of prestige and obligation play an important role in many cases.

A detailed examination of the evolution and characteristics of aid policy over time in Belgium, Italy, the Netherlands, and Norway supports both my theoretical argument and the basic conclusions suggested by the statistical analyses. Belgium's development assistance policy is characterized by a conception of aid as an obligation resulting both from Belgium's history as a former imperial power and from its current status as an advanced industrial state. However, accepting that aid has to be given, Belgians have attempted to derive as much economic benefit from it as possible. In Italy, the same interest in the economic benefits of aid is evident. However, it is paired not with a sense of obligation but rather with an interest in the reputational possibilities of giving aid. Reputational aspects have been important in Norway too, but, more than most other donor states, Norway has also subscribed to a vision of aid as an essential instrument for the promotion of international peace and stability. In the Netherlands, finally, a number of different motivations come together to produce a policy characterized by an interest in simultaneously obtaining influence and prestige, and in simultaneously fulfilling an obligation and promoting international stability and global development.

The dissertation contributes to ongoing attempts to re-conceptualize international relations theory so as to provide a richer model of the choices actors face and make. It also advances the subject literature through an exhaustive study of legislative debates on aid policy, and the quantitative literature by deriving a new two-stage, sample-selection model to help explain the process of making aid allocation decisions. Most importantly, however, my findings about the importance to the shaping of aid policy of enlightened self-interest the pursuit of prestige and the fulfillment of perceived obligations have intriguing implications for the study of other issue areas in international relations (and policy-making more generally), showing that preferences often are neither materialistic nor exogenous and suggesting some additional motivations to take into account.

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CHAPTER 5

SELECTING THE RECIPIENTS OF AID: A TWO-STAGE, SAMPLE-SELECTION MODEL

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(Draft — not for citation)

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Abstract

The geographical distribution of ODA has been the subject of considerable attention in the academic literature as well as in political debates. Many findings have been flawed or inconclusive, often due to methodological problems. I develop a new statistical model to analyze the distribution of aid by Belgium, Italy, Norway, and the Netherlands. Allocation decisions are modeled as a two-stage process, the first modeled with ordered probit, the second with a limited dependent variable OLS model. The results obtained using this model show the presence of substantial cross-national differences in the factors considered in aid allocation. They also suggest that the selection process is rather more idiosyncratic than decisions regarding the amount of aid to grant to the selected recipients. Interaction of measures of the strength of different motivations with conventional explanatory variable contributes some valuable additional insights into the factors that shape allocation decisions by eliminating problems of overdetermination and clarifying causal pathways. In particular, the results suggest that considerations of prestige, and obligation do play an important role in one or both of the stages of the allocation process, in particular in Belgium, the Netherlands, and Norway. Evidence for the impact of enlightened self-interest is also present, albeit more weakly.

CHAPTER 5

SELECTING THE RECIPIENTS OF AID: A TWO-STAGE, SAMPLE-SELECTION MODEL

> Criteria for the choice of main recipient countries must be taken seriously!
> — Article title, *Norkontakt*[1]

> ODA is determined not by the needs of developing countries, but by the fluctuating goodwill of the people and their parliaments in the rich countries. As a result, it is largely ad hoc and unpredictable.
> — *Human Development Report,* 1992[2]

Few aspects of aid policy attract more attention, in political debates as well as in academic circles, than the distribution of development assistance across recipient countries. Studies of the determinants of aid allocation date back to the early 1960s and continue to account for the bulk of the aid literature today.[3] I discussed in chapter two, such studies have, over time, touched upon the influence of a large number of different explanatory variables. However, there has been relatively little cumulation of findings, in part due to methodological problems in systematic analyses of aid allocation data, and in part due to a lack of consistent cross-national comparisons of results. This chapter aims to address both of these weaknesses, by developing a new statistical model of the decision-making process of aid allocation, and by applying this model to aid allocation data for the four different donor states that are the focus of this study.

Allocation decisions are modeled as a two-stage process, the first modeled with ordered probit, the second with a limited dependent variable OLS model. The results obtained using this model show the presence of substantial cross-national differences in

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1 *Norkontakt* 1983: nr. 2:10.

2 UNDP (1992:45).

the factors considered in aid allocation. They also suggest that the selection process is rather more idiosyncratic than are decisions regarding the amount of aid to grant to the selected recipients. Interacting my measures of the strength of different motivations with conventional explanatory variable contributes some valuable additional insights into the factors that shape allocation decisions, by eliminating problems of overdetermination and clarifying causal pathways. In particular, the results suggest that considerations of prestige, and obligation do play an important role in one or both of the stages of the allocation process, in particular in Belgium, the Netherlands, and Norway. Evidence for the impact of enlightened self-interest is also present, albeit more weakly.

The chapter proceeds in four stages. First, I introduce the dependent variable, and describe the empirical variation observed across donor states as well as over time. Next I review the hypotheses introduced in chapter two, and discuss the different explanatory variables. The statistical model is developed in the third section, which also discusses the model's particular implementation in the present context. The results of applying the model to the geographical distribution of aid in Belgium, Italy, the Netherlands and Norway follow in the fourth section. A fifth section, finally, discusses the findings and suggests some open questions that remain to be addressed in the case study chapters that follow.

Geographical patterns in aid flows

Several measures of overall aid flows are recorded by the Development Assistance Committee. Disbursements are a measure of the actual transfers from donor to recipient.

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[3] For early studies, see, for example, Kirschen (1964) and Levitt (1968). Two recent studies are

Net disbursements subtract repayments of principal from earlier loans from the gross disbursements figure. Finally, repayments of interest are subtracted from net disbursements to arrive at the figure of net ODA. In addition to these three measures the DAC also keeps track of aid commitments. These are the sums that donors promise to make available to recipients, i.e. from which disbursements are drawn. The preferred measure for our purposes is the one donor states are most likely to use as their own decision variable.[4]

There are plausible reasons for focusing on either commitments or disbursements as the decision variable. On the one hand, disbursements are affected by the actions of the recipient states. Some recipients may not succeed in proposing enough projects to consume all the funds committed to them by a donor. Conversely, sudden emergencies such as famines or political upheaval may result in additional supplies of aid over and above committed levels. In view of these factors, one could argue, as Dudley and Montmarquette do, that disbursements are "more likely to represent the results of a compromise between the aid demand of recipient countries and the aid supply of donor countries" (1976:138).

On the other hand, there is evidence that donors systematically commit more funds than they are intending to spend.[5] Indeed, the ratio between commitments and net ODA can at times exceed two to one.[6] In some cases, excess commitments are saved in a

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Schraeder, Hook, and Taylor (1998), and Meernik, Krueger and Poe (1998).

4 Using any other variable would imply introducing measurement error into the dependent variable.

5 Japan, for example, has at times managed to get considerable mileage out of promising to increase its aid budget dramatically without ever doing so.

6 The ratio got as high as 2.8 in Italy in 1978 and 1979. On the other hand, it has also been as low as 0.5 in Belgium in 1985 and Norway in 1988.

reservoir for future use,[7] but often they revert to the general state budget. In either situation, it appears likely that decision-makers are cognizant of these possibilities and, at least roughly, of the sums involved. Similarly, donor states are likely to take into account expected repayments by recipients. Indeed, it is not uncommon for donors to provide new aid in order to help recipients make payments on earlier loans. In other words, anticipated repayment is factored into the decision process. Finally, the data used most often by domestic and international observers to evaluate the donor state's policies are net ODA figures, providing one more reason for governments to use these as their primary decision variable, and hence for us to use it here.

Another decision to consider is whether to scale the aid flows by the populations of the recipient states. Many studies have used per capita aid as the dependent variable, in part because doing so makes sense in terms of assessing the degree to which aid addresses the humanitarian needs of LDC populations.[8] However, it seems implausible that aid allocation decisions are made on this basis. From a purely pragmatic point of view, it is quite difficult to calculate allocations per capita for different recipients in such a way as to satisfy an overall budget target or constraint. Nor does the data appear to support per capita aid as the decision variable. In particular, the smallest states are systematically over-represented by this metric. India and China, with enormous populations, always receive far less in per capita aid than do tiny recipient states such as Dominica or Grenada, even though the standard of living in the latter is considerably

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[7] The presence of a reservoir, in turn, will bias commitments downwards since expected disbursements from the reservoir will be taken into account in the decision-making process. This is yet another reason to look at actual aid flows rather than commitments.

[8] E.g. Maizels and Nissanke (1984) and Bowles (1989).

higher.[9] The data make rather more sense if we look at the total aid received by each state, where India receives about 200 times as much aid as does Dominica.[10]

It remains possible, of course, that aid decisions are targeted at supra-national, regional levels, or sub-national, local levels. Thus, there have been regular initiatives by some donor states to allot aid funds at a regional level, leaving it to the recipient states in different regions to compete against one another for the available funds. Indeed, DAC statistics list categories such as 'Latin America, unallocated,' and some of these regional groupings do account for considerable sums. As is standard practice, I assume that 'unallocated' and 'undecided' disbursement categories in the official statistics are not systematically related to the distribution of those funds for which the national destination is known. Aid could also be allotted at a sub-national level, to specific projects or programs. The fact that many larger and more visible aid projects take several years to complete suggests the possibility that national aid allotments result from choices not among countries but rather among projects. More often than not, however, the initial selection of a project is made possible by an initial allocation to a recipient state. The possibility of project-based decision-making, then, can usually be captured by considering decisions for previous years.[11]

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9 For example, in 1997 the Netherlands gave Dominica, with its 73800 citizens, ODA equivalent to $2 per capita, compared to a mere $0.03 per capita for the 960 million citizens of India. It seems unlikely that the Netherlands really values Dominicans 66 times higher than it does Indians. Similarly, it is hard to imagine that a conscious decision-making process resulted in aid allocations of $0.005 to Korea, $0.0054 to Cuba, and $0.0058 to Libya (referring, again, to 1997 Dutch aid flows). (OECD 1999b)

10 Of course, given that total aid is a more plausible decision variable, it becomes advisable to include population as an explanatory variable.

11 Nonetheless, we shall see in the case study chapters that it is not altogether unusual for donor state firms to propose large, prestigious projects before aid allocation decisions are made. In such cases, the project decision really is causally prior to both aid commitments and actual flows.

DAC	**1960**		**1970**		**1980**		**1990**		**1997**
India	16.47	India	14.11	Bangladesh	6.57	Egypt	7.61	Egypt	4.63
Algeria	9.36	Indonesia	7.88	Egypt	6.32	Indonesia	4.62	China	3.80
Pakistan	7.09	Pakistan	6.47	Indonesia	5.11	China	3.54	India	2.87
Korea	6.98	Viet Nam	5.85	India	5.02	Israel	3.37	Indonesia	2.44
Viet Nam	5.37	Korea	3.93	Israel	4.85	Kenya	2.84	Mozambiq.	1.92
Egypt	3.35	Turkey	3.16	Turkey	3.90	Philippines	2.77	Thailand	1.86
Taiwan	3.08	Brazil	2.79	Tanzania	3.43	India	2.71	Viet Nam	1.81
Turkey	3.06	Papua N.G.	2.48	Pakistan	2.33	Bangladesh	2.59	Tanzania	1.76
Israel	3.04	Colombia	2.19	Sudan	2.17	Turkey	2.09	Philippines	1.75
Indonesia	2.33	Algeria	1.98	Zaire	1.73	Tanzania	2.02	Madagascar	1.70
Total	*60.12*	*Total*	*50.83*	*Total*	*41.43*	*Total*	*34.17*	*Total*	*24.54*

TABLE 5.1. Top aid recipients over time, DAC donors.

Table 5.1 shows the evolution over time in the set of most favoured aid recipients, and the percentage of total bilateral ODA each receives, for all DAC donors combined.[12] Table 5.2 shows the same data for Belgium, Italy, the Netherlands and Norway. [13] The well-known preference for former colonies among donor states emerges clearly. Thus, in the early years of development assistance, present or former colonies received the bulk of aid. The concentration of aid has fallen considerably since then, as the table shows. Nonetheless, Belgium, in particular, has continued to target a large share of its total aid at Zaire, Rwanda, and Burundi.[14] Similarly, in the case of the Netherlands, Indonesia remained a prominent recipient through 1990. In 1992, however, Indonesia informed the Netherlands that it did not wish to receive any further development assistance, because it

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12 These tables and the ones that follow are derived from the OECD's annual publication *Geographical Distribution of Financial Flows*. The percentages listed are shares of total bilateral aid to LDCs. It is worth noting the presence of several states that most people would not immediately think of as LDCs, such as Taiwan, Turkey, and Israel.

13 The presence of unallocated sums in the statistics explains why not all of these figures sum to 100%, even when no other recipients are identified.

14 Democratic Republic of Congo is the new name for Zaire, so its position as Belgium's favourite aid target has not changed in recent years.

felt the latter was too openly critical of its domestic political situation.[15] Its place at the top is now occupied by the Netherlands Antilles, self-governing Dutch territories.

Belgium	**1960**		**1970**		**1980**		**1990**		**1997**
Zaire	82.56	Zaire	54.19	Zaire	37.11	Zaire	16.84	Congo, DR	7.03
Burundi	8.72	Rwanda	12.15	Rwanda	7.86	Rwanda	7.67	Malagasy	5.62
Rwanda	8.72	Burundi	10.54	Burundi	6.02	Burundi	6.98	Rwanda	4.78
		Indonesia	3.98	Indonesia	4.63	Tanzania	2.53	Benin	4.06
		Tunisia	3.44	Philippines	3.76	Uganda	1.87	C. d'Ivoire	3.55
		Pakistan	2.26	Tunisia	3.63	Senegal	1.79	Burk. Faso	2.84
		Turkey	2.15	Morocco	3.08	Bangladesh	1.75	Morocco	2.59
		Morocco	1.94	China	2.26	India	1.61	Ecuador	2.21
		Chile	1.61	Turkey	2.24	Somalia	1.41	Vietnam	1.77
		India	1.18	Niger	2.19	Tunisia	1.38	Senegal	1.77
Total	*100.0*	*Total*	*93.44*	*Total*	*72.78*	*Total*	*43.83*	*Total*	*36.21*

Italy	**1960**		**1970**		**1980**		**1990**		**1997**
Somalia	41.47	Egypt	23.58	Somalia	21.73	Ethiopia	7.94	Uganda	16.17
Egypt	24.03	Indonesia	14.00	Indonesia	7.53	Zaire	6.69	Ethiopia	6.98
Ethiopia	23.64	Yugoslavia	10.33	Ethiopia	6.42	Tanzania	5.36	Albania	6.81
Yugoslavia	7.36	Ethiopia	6.74	Libya	5.55	Somalia	5.09	Malta	4.90
Sudan	0.39	Mexico	5.84	Yugoslavia	3.65	Mozambiq.	4.91	Mozambiq.	4.49
		Tanzania	4.57	Mozambiq.	2.54	Egypt	4.14	Zambia	4.14
		Turkey	4.34	Zimbabwe	2.14	Argentina	3.75	Cameroon	4.13
		Guinea	4.19	Thailand	1.59	Peru	3.69	Kenya	4.03
		India	4.12	Morocco	1.51	Tunisia	3.24	Egypt	3.68
		Somalia	4.04	Tanzania	1.43	Poland	3.21	Algeria	3.30
Total	*96.90*	*Total*	*81.74*	*Total*	*54.08*	*Total*	*48.02*	*Total*	*58.63*

Netherl.	**1960**		**1970**		**1980**		**1990**		**1997**
Indonesia	83.91	Indonesia	29.88	India	11.65	Indonesia	11.25	N. Antilles	5.11
Suriname	13.03	Suriname	15.83	Suriname	9.28	India	9.26	Bos&Herz.	3.94
Chile	0.77	N. Antilles	15.64	Indonesia	7.02	Tanzania	4.68	Suriname	3.04
N. Antilles	0.38	India	9.92	N. Antilles	6.95	Kenya	3.63	Bangladesh	2.98
		Pakistan	2.67	Tanzania	6.65	Bangladesh	3.52	Bolivia	2.80
		Chile	1.46	Bangladesh	4.21	Mozambiq.	3.20	Tanzania	2.46
		Nigeria	1.40	Sudan	3.70	Sudan	3.08	Yemen	2.46
		Kenya	1.14	Kenya	3.65	Zambia	2.99	Afghanist.	2.01
		Colombia	0.89	Jamaica	2.62	N. Antilles	2.61	Iraq	2.01
		Cameroon	0.83	Peru	2.61	Suriname	2.24	Mozambiq.	2.00
Total	*98.08*	*Total*	*79.66*	*Total*	*58.34*	*Total*	*46.46*	*Total*	*28.81*

15 This illustrates once more the potential influence of recipients on the geographical distribution of aid flows, in this case affecting both commitments and disbursements.

Norway	**1960**		**1970**		**1980**		**1990**		**1997**
India	58.33	Pakistan	21.23	Tanzania	15.55	Tanzania	13.53	Mozambiq.	5.976
Korea	41.67	India	17.81	Bangladesh	8.23	Zambia	7.26	Tanzania	5.562
		Kenya	17.81	India	7.88	Mozambiq.	6.87	Palest. AA	4.472
		Tanzania	9.59	Kenya	7.42	Bangladesh	5.77	Bos&Herz.	4.459
		Uganda	6.85	Pakistan	5.80	Nicaragua	4.61	Zambia	4.064
		Zambia	4.79	Botswana	4.50	India	3.36	Bangladesh	3.533
		Nigeria	3.42	Sri Lanka	4.01	Ethiopia	3.35	Ethiopia	3.103
		Turkey	3.42	Turkey	3.76	Zimbabwe	3.17	Uganda	3.036
		Tunisia	2.05	Mozambiq.	3.69	Sri Lanka	2.97	Angola	2.674
		Ethiopia	1.37	Zambia	3.69	Kenya	2.96	S. Africa	2.161
Total	*100.0*	*Total*	*92.47*	*Total*	*64.54*	*Total*	*53.84*	*Total*	*39.04*

TABLE 5.2. Top aid recipients over time, Belgium, Italy, Netherlands, and Norway.[16]

A few states appear to be favourites of all donors. Tanzania is an oft-cited case, but Zambia, Mozambique and Bangladesh are other examples. It is also worth noting that these four donor states display a far greater emphasis on LDCs in Africa than do the DAC donors as a group. It has been argued that this pattern results from an explicit division of labour among DAC donor states, with Japan concentrating on Asian recipients and the United States on Latin America. It is likely that historical ties, as well as the disproportionate presence within Africa of the poorest LDCs, also play a role in creating an African bias, however. The final column in tables 5.1 and 5.2 shows the aid allocation of these donor states for 1997, the most recent year for which data are available. These data highlight the rise to prominence of some states that were not previously candidates for aid, such as Bosnia-Herzegovina, the Palestinian Administration Areas, and South Africa.[17]

16 In 1970, Norway gave the same amount of aid to Ethiopia (10th place), Ghana, Korea, and Madagascar (not listed). The total percentage figure includes the 3*1.37% added by the latter three.

17 On the whole however, the overall geographical distribution of aid flows appears to have been influenced relatively little by the presence of new potential recipients such as the aforementioned states and the many former Soviet republics.

Finally, it is worth noting the decline in concentration of aid flows among the top recipients. All donor states give aid to much larger number of countries than are on their official lists of ‘target’ or ‘program’ recipients. For example, in 1997 Norway allocated over 1% of its aid budget to each of 20 recipients. Another 50 recipients received between 0.1% and 1% of Norway's total ODA each, 19 more received between .025% and 0.1, and 17 countries received less than 0.025% (1/40 of 1%). Nor is the pattern much different for other donors. Even Italy, in the throes of severe budget cut-backs, and with a degree of concentration on its top recipients considerably higher than that of the other three states considered here, gave aid to a total of 81 countries (25 received more than 1%, 32 0.1-1%, 12 0.025-0.1%, and 12 more less than 0.025%). Not surprisingly, the countries at the bottom of these lists are rarely the subject of explicit deliberation, whether in the legislature or within the aid administration. Indeed, the size of the flows to these countries is more likely to reflect the cost of the one or two ‘token’ projects sponsored there than any explicit decision regarding the amount that country ought to receive.

Causal factors of aid allocation

What features of recipient states influence how much (if any) aid they receive? The literature on the allocation of aid suggests a long list of possible factors, some of which were described in chapters one and two. Here I limit myself to considering those that appear most directly related to a particular type of motivation.[18] We can distinguish three broad categories: descriptive measures of the bilateral relationship between donor and recipient, characteristics of the recipient that may make it of interest to the donor, and characteristics of the recipient that reflect its need for aid. I discuss them in the context of the types of motivation they are likely to be associated with, as shown in table 5.3, which presents the hypotheses introduced in chapter two regarding the distribution of aid flows.

Category	Predictions	Relevant variables
Security	Friendly regimes, states encircling enemies	Regime-type & location, UN voting agreement
Power	Allied states, countries with military or economic potential, ex-colonies	UN voting agreement, GDP, population, colonial status
Wealth	Trading partners, countries with economic potential	GDP, trade with recipient
Enlightened self-interest	Unstable, high-population states States with great environmental patrimony	Population, stability, area
Prestige	Friendly regimes, visible (popular) recipients	UN voting agreement, total aid receipts
Obligation	Visible (popular) recipients, ex-colonies, trading partners	Total aid receipts, colonial status, (trade with recipient)
Humanitarian	Poorest states, most basic human needs, states with good rights records	GDP/capita, mortality, literacy, polit. & civil rights

TABLE 5.3. Basic hypotheses about the relationship between motivations and aid policy.

Two explanatory variables are hypothesized to supply indirect measures of a recipient's interest to a donor state concerned with security. The first is proximity to a Communist state. This variable has been widely accepted in the literature as an indication of a recipient's importance in the Cold War, anti-Communist struggle. Most authors have found it to be relevant primarily for the United States as a donor state, and less so for other donors.[19] Nonetheless, in so far as donor states explicitly express an interest in development assistance as an instrument for pursuing security goals, this variable may

18 After all, it makes little sense to add variables merely in the hope of obtaining statistically significant effects, if no causal explanation of their importance to decision-making on aid is available.

19 E.g. Kato (1969), Wittkopf (1972), McKinlay and Mughan (1984).

have some explanatory power. I use a dummy variable with a value of 1 for a non-Communist state bordering on a Communist state and 0 otherwise.[20]

The second variable commonly used as an indicator of a recipient's 'security value' to a donor state is its voting behaviour in the United Nations. The argument here is that allies will vote alike on issues of international security and stability, and that aid may be used to reward or strengthen the degree to which the recipient's international stance matches that of the donor state. Again, evidence suggests that this is a consideration more for the United States than for most other donor states.[21] In addition, a shared international posture may be a signal of a more general affinity between donor and recipient, regardless of the security value of one to the other. Indeed, donors may value recipients siding with them at the UN simply from the perspective of the status or reputational effects this may have. Or they may believe that this increases their international influence. In other words, UN voting patterns may be relevant not only to security concerns, but also to an interest in power or prestige.[22]

To measure UN voting agreement, I use the indicator S proposed in Signorino and Ritter (1999). To calculate S, average the difference between the votes of states A and B (where 0 represents agreement and 1 opposition) over all UN votes in a given year, to get a summary value between 0 (all votes identical) and 1 (all votes diametrically opposed). This result is then rescaled to get a value in the interval [-1,1]. The formula for this

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20 The variable was constructed using the 1999 World Almanac and Book of Facts together with an atlas.

21 Levitt (1968) and Wittkopf (1973) both found some support for this measure as a factor shaping aid flows from the United States . Lebovic (1988) found similar results during Reagan's first term in office.

22 Both arguments are commonly made for the case of France. Some observers feel that France's interest in being the international leader of *francophonie* stems from the feeling that this will increase the weight of its contribution in international fora. Others, however, argue that French expenditures on *francophonie* (e.g. the use of aid to reward or promote voting with France in the UN) serve largely to satisfy its own desire for (or sense of) grandeur.

calculation is given below, where N is the number of votes, and v_{Ai} and v_{Bi} are the votes of country A and country B respectively.[23]

$$S(A,B) = 1 - \frac{1}{N}\sum_i |v_{Ai} - v_{Bi}|$$

In addition to UN voting agreement, three other variables can be considered relevant to an interest in international influence. The first is a recipient's status as a former colony. To the degree that the former metropolis succeeds in portraying itself as the international voice of its former colonies, its power may be expected to increase. This has been argued to be one reason why France continues to lavish aid on its former colonies, for example.[24] Colonial status is represented by a dummy variable with a value of 1 if a state is a former territory (including UN trust territories) of the donor, and 0 otherwise. The other two variables to consider here are more straightforward measures of the potential strength of the recipient: its GDP and population. Both measures were obtained from the World Bank's 1999 CD-ROM *World Development Indicators.*[25] Note, however, that GDP can also be taken to reflect the economic potential of a recipient country and can thus be expected to be of interest to states interested in using aid to further their trade and investment goals.

The conventional measure of the value of a recipient to a donor interested in using aid to pursue greater wealth is the strength of the trading relationship between donor and

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23 There should really be a factor of 2 outside the sum, and a factor of 1/2 inside it, but since the latter is constant over all votes, the two cancel one another out. Assigning values to votes of 1 for against, 2 for abstention and 3 for in favour, the difference between the two votes is at most 2. Summing this over all votes gives a value of at most 2N, which divided by N gives a value of at most 2, to bring the final value of S in the range [-1,1].

24 E.g. Schraeder, Hook, and Taylor (1998).

recipient. The argument here is twofold. First, aid serves to stabilize the domestic political situation in recipients whose products and consumption are of importance to the donor's domestic industries. Second, aid can be used to make the products of domestic firms more affordable to the recipient, or to create an infrastructure that makes it more attractive for domestic firms to invest in the recipient state. Of course, measures of existing commercial relations cannot capture the potential value of greater future commerce. Indeed, assuming two recipients that are otherwise equal, it is just as plausible that a donor will decide to give to the recipient that it trades with *less*, to promote and foster increased commerce.[26] This possibility suggests the value of including the GDP of the recipient as a measure of economic potential in addition to the trade data, which measure only current value. Trade data were obtained from the IMF's *Direction of Trade Statistics* dataset (ICPSR #7628).

The next category of motivations to consider is that of enlightened self-interest, or a belief in the value of contributing to international public goods. Here, we look at three different measures. First is the population of the recipient state. The greater a state's population, the higher the costs of potential instability in that state (including but not limited to the production of an international refugee population).[27] Next, we would like to have a measure of the likelihood that a recipient will generate international upheaval, either through domestic instability or through internationally destabilizing activities. An imperfect yardstick for this concept can be argued to be the recipient's level of

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25 GDP at market prices was selected from among several possible measures of GDP, since it had the fewest missing values and is thought to be the measure that has traditionally been most widely available to decision-makers.

26 E.g. McGillivray and Oczkowski (1992).

27 As noted in the discussion of power interests, the source for the population data is the World Bank's *World Development Indicators* CD-ROM.

democracy, which simultaneously captures the ideas that democratic states are more peaceful internationally — at least amongst themselves[28] —and that they are less likely to suffer from domestic instability resulting from repression, coups, succession crises, etc. Aid can be used to promote the stability of democratic regimes, and thus to pursue the systemic interest in global peace and stability. I use the measure of democracy provided in the Polity III dataset (ICPSR #6695), which ranges from 0 to 10, with 10 being the most democratic. Finally, in recent years development assistance has increasingly been viewed as potential instrument to protect the world's environmental resources. For lack of a better measure of environmental diversity or patrimony, I use the surface area of a state, which is provided as part of the World Bank's *World Development Indicators.*

Next are motivations of prestige in the selection of aid recipients. I have already argued that voting along with a donor state at the United Nations may be seen to increase the donor's international reputation. As another measure of the potential of a particular recipient to add to the donor's prestige, I include the total amount of aid a recipient receives. The argument here is that aid will do little for one's status if it is not observed. And the more visible the aid recipient within the donor and broader international communities, the more visible the donor's actions there.[29] The DAC provides two aggregate measures of aid receipts: from all DAC donors and from all aid donors. Since the prestige sought by the donor states studied here is more likely to be the respect of their DAC peers than that of Comecon or Arab League donors (the two main other donor groupings), I use the former.

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[28] This idea is exhaustively studied in the democratic peace literature (c.f. e.g. Maoz and Russett 1993).

[29] A similar argument is offered by Bowles (1989), who posits a bandwagoning effect, whereby states compete as aid givers to the most popular recipient countries. See also McGillivray and Oczkowski

A similar argument can be made for including aid receipts from DAC donors as a measure of a recipient's value to a donor interested mostly in fulfilling a perceived obligation to provide aid. If development assistance is seen as something that one has to provide if one wants to be perceived as an advanced, industrialized country, for example, it stands to reason that the more visible the aid is, the better. The other characteristic that may promote a country's selection as an aid recipient for a state concerned with its international duties is its status as a former colony or trust territory of the donor. Here the obligation is more specific, as guilt over past exploitation and a sense of shared history combine to create a special feeling of obligation with respect to these states or territories.

In addition to these two explanatory factors, I include two more variables that might be relevant to countries that provide development assistance out of a sense of obligation. If a general sense of obligation is all that motivates a donor, there is likely to be little domestic interest in or control over or the fulfillment of this duty. Hence, private interest groups may be well-placed to capture the aid program and mold it to their interests. In this case, the same considerations are likely to come into play as with states interested in pursuing wealth, namely existing commerce and economic potential. For this reason, I also interact the strength of feelings of obligation with the recipients' GDP and trade ties with the donor.

The final category to consider is that of humanitarian considerations. The standard indicator here is GDP per capita, a measure of the relative need of the recipient population. Also relevant will be total population, since a greater number of people will have a greater total need. In addition, it is worth including some non-financial measures

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(1992). Wittkopf (1972) expects the opposite effect to be evident, as a result of burden-sharing among donor states.

of human need. The most widely available are probably infant mortality, an indicator of health, and illiteracy, an indicator of education. Both are found on the *World Development Indicators* CD-ROM. In addition, development assistance may be used to promote or reward human rights. Indeed, human rights have become an increasingly salient feature in domestic debates about aid policy over the past two decades, along with an interest in good governance. As a measure of these concepts, I use Freedom House's data from its annual survey *Freedom in the World.* In this survey, rights are divided into political rights and civil liberties, each on a scale of 1 to 7. I sum the two, to get a scale from 2 to 14.

All together, I test a total of 14 independent variables, some of which are relevant to more than one type of motivation. All have been readily available to decision-makers throughout the period being studied. The quality of the data is not always optimal, in part since the reporting by developing countries often leaves a lot to be desired. However, this problem does not affect the present analysis. Since we are studying the decision-making process of donor state governments, the main concern is that we model the "crude rules of thumb" they can be expected to use,[30] with the same data they are likely to have access to, regardless of its accuracy. Table 5A.1 in the appendix provides basic descriptive statistics for each of the variables. The appendix also discusses the universe of recipient states and the years for which the different variables are available.

30 Gulhati and Nallari (1988).

Modeling the decision-making process

As I suggested in chapter two, the methodological validity —and hence the substantive results —of much of the literature on the geographical distribution of aid is highly questionable. For example, many studies have followed Maizels and Nissanke (1984) in testing separately for the influence of donor interests and recipient needs, introducing serious specification errors.[31] Others have considered only a specific subset (e.g. a region) of aid recipients, without considering whether aid allocations to that subset are independent of those to other potential recipients.[32] Perhaps the most significant problems, however, result from the treatment of states receiving zero aid.

To begin with, since one cannot logically provide negative aid,[33] it makes sense to treat aid receipts as a limited dependent variable truncated at zero. More importantly, countries receiving no aid are unlikely to be a random subset of all potential recipients. Therefore, it is important to include them in the analysis.[34] Next, it seems highly likely that the decision whether or not to offer development assistance is correlated with the decision regarding the amount to provide. One possible model is the Tobit estimator, which combines these two decisions, providing unbiased estimates for truncated variables. However, assuming that the factors determining selection as a recipient are identical to those determining the amount of aid offered is a rather strong assumption. A

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31 See McGillivray and White (1993:38-39) for a replication of their results combining the two sets of variables, the results of which suggest that Maizels and Nissanke's conclusions are tenuous at best.

32 E.g. Schraeder, Hook and Taylor (1998).

33 Actually, negative aid flows do get recorded occasionally. As noted earlier, these are the result of recipient state repayment on loans granted in previous years. However, such occurrences still imply that the donor did not see fit to make a *net* allocation to the recipient, i.e. it can be considered to have given zero aid.

more realistic approach would be to model the two decisions separately, an approach originated in Heckman (1976).[35] Lee and Maddala (1985) describe a two-equation model in this vein and derive an associated likelihood function.[36] Their approach uses probit to model the selection decision, and a truncated linear regression model for the amount decision.

However, empirical evidence suggests that a number of countries receive sums that can best be described as ‘token’ aid — small amounts that cover just one or two projects. These recipients do not warrant separate headings in the annual reports on the donor state’s development efforts, nor does the latter select the projects funded within the framework of an overall country program for the recipient. Such aid flows may be initiated as a result of a visit by dignitaries from the recipient to the donor (or v.v.) or out of a desire of the donor to establish a ‘presence’ in the recipient without getting too involved. The presence of such aid flows introduces a problem for the modeling process. On the one hand, it appears likely that the exact sum allocated is less a result of an explicit decision by the donor than determined by the specific one or two projects funded. Accordingly, McGillivray and Oczkowski (1992) argue that such inconsequential flows can be considered decisionally equivalent to no aid. On the other hand, however, although the sums may be negligible, it seems unlikely that the decision to provide them is similarly meaningless. Instead, it appears plausible that donor states consciously distinguish between those states that deserve at least a token aid contribution, and those

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34 If they are excluded, as is sometimes done, we are no longer studying the geographical allocation of aid over all countries, but rather only over the subset that has *already* been selected as recipients of aid.

35 See and Meernik, Krueger, and Poe (1998) for an application of this model to U.S. aid allocations.

36 See also Greene (1993:706-714). McGillivray & Oczkowski (1992) apply a version of this model to a study of British aid. However, their model appears seriously flawed. Their log-likelihood expression

that do not.[37] Moreover, I assume that the decision to give token aid lies on a continuum between no aid and substantial aid, suggesting the use of an ordered probit model.[38]

The second decision within the process concerns the amount of aid to provide to countries that have been selected as recipients of substantial aid flows. [39] This can be modeled using a truncated linear regression model. Rather than truncating at zero, however, truncation takes place at the level (T) below which aid can be considered a 'token' contribution. This can be taken to signify that the donor state would never establish a substantial aid program with a recipient unless it were planning to spend at least T.[40] In addition to the truncation at T, censoring takes place based on the first stage of the decision-making process: if the eligibility decision is not to provide a substantial amount, we do not observe the outcome of the amount decision. Instead, we observe either 0 or a small, arbitrary amount below the threshold T (depending on the outcome of the eligibility decision). The model can be expressed as follows:

$$\begin{aligned}
&y^* = z\gamma + \varepsilon \\
&y = 0 \quad if \qquad z\gamma + \varepsilon \leq 0 \\
&y = 1 \quad if \quad 0 < z\gamma + \varepsilon \leq \tau \\
&y = 2 \quad if \qquad z\gamma + \varepsilon > \tau \\
&w^* = x\beta + \sigma u \quad w^* > T \\
&\quad w = 0 \qquad if \quad y = 0 \\
&\; 0 < w \leq T \quad if \quad y = 1 \\
&w = x\beta + \sigma u \quad if \quad y = 2
\end{aligned} \tag{1}$$

adds the term ρJ(*u*) rather than subtracting it. Moreover, they simplify this term to $\rho\mu/\Phi((x\beta-T)/\sigma)$, which is incorrect. These errors call into question the validity of their results.

37 To argue otherwise is to suggest that donor states randomly select some countries from among those they have decided not to aid and then give this subset some aid after all.

38 It is conceivable, although it does not seem likely, that a multinomial model would work better.

39 The actual contribution in the case of token aid is assumed to be arbitrary (e.g. drawn from a uniform density function from 0 to T).

where y* is the unobserved underlying eligibility variable, y represents the observed eligibility decision, z and x are vectors of independent variables and γ and β are their parameters (i.e. the coefficients to be estimated). I assume that ε is standard normal distributed (mean 0, variance 1),[41] and that w* is normal truncated at T.

The presence of σ in the equation turns *u* into a standard normal truncated variable. The density function of a truncated normal variable (over the observed range)[42] needs to be scaled by a factor 1/Φ((xβ–T)/σ), so that it still integrates to one.[43] The density function for w* is thus given by:

$$g\left(w^*\middle|x,z\right)=\frac{1}{\sigma}*\varphi\left(\frac{w^*-x\beta}{\sigma}\right)\Big/\Phi\left(\frac{x\beta-T}{\sigma}\right) \qquad (2)$$

where ϕ and Φ are the standard univariate normal density and distribution functions, respectively.[44] We can derive analogous density and distribution functions for the error term *u*, using the substitutions *u* = (w-xß)/ σ and d*u* = (1/σ)dw:[45]

$$g(u|x,z)=\varphi(u)\Big/\Phi\big((x\beta-T)\big/\sigma\big) \text{ and} \qquad (3)$$

$$G\left(u\middle|x,z\right)=\left(\Phi(u)-\Phi\left(\frac{T-x\beta}{\sigma}\right)\right)\Big/\Phi\left(\frac{x\beta-T}{\sigma}\right),\quad u>T-x\beta/\sigma \qquad (4)$$

Since the considerations that enter into the eligibility and amount decisions are likely to be related, the error terms in the equations for y* and w* are not independent. This

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40 One can think of it in terms of the administrative overhead of starting a new country program. Such an additional cost is worth incurring only if the actual aid expenditure will be non-negligible.

41 There is no information on the scale of y*, so we can let the variance be 1 without loss of generality.

42 Outside the observed range it is zero, of course.

43 The scaling factor is equivalent to the probability of getting a result over the threshold T in the non-truncated distribution. See Greene (1993:684).

44 Greene (1993:689).

45 Lee and Maddala (1985:7) omit the second term in the dividend, which leads to an invalid distribution function G with incorrect lower and upper bounds.

situation can be modeled using a standard bivariate normal distribution (B), with correlation coefficient ρ. However, since the truncation affects the moments of *u*, we need to apply a transformation first, to turn it into a standard normal variable. We can do so by applying the inverse normal distribution function to G.[46] Call this transformation J = Φ^{-1}G, and let the correlation between ε and J(*u*) be ρ. The bivariate distribution for *u* and ε, then, becomes H(ε,*u* |x,z) = B(ε,J(*u*)|x,z). Using the formula for a bivariate normal distribution, the joint density function is: [47]

$$\begin{aligned} h(\varepsilon,u,\rho|x,z) &= b(\varepsilon,J(u),\rho|x,z) \\ &= \frac{1}{2\pi\sqrt{(1-\rho^2)}} e^{-\frac{\varepsilon^2+J^2(u))-2\rho\varepsilon J(u)}{2(1-\rho^2)}} \\ &= \frac{1}{\sqrt{(1-\rho^2)}}\varphi(\varepsilon)\varphi(J(u))e^{-\frac{\rho(\varepsilon^2+J^2(u)))-2\rho\varepsilon J(u)}{2(1-\rho^2)}} \\ &= \frac{1}{\sqrt{(1-\rho^2)}}\varphi(\varepsilon)g(u|x,z)e^{-\frac{\rho(\varepsilon^2+J^2(u)))-2\rho\varepsilon J(u)}{2(1-\rho^2)}} \end{aligned} \tag{5}$$

where, to replace the term $\varphi(J(u))$, I make use of the following:

$$\begin{aligned} J(u) &= \Phi^{-1}\left(\frac{\Phi(u)-\Phi((T-x\beta)/\sigma)}{\Phi((x\beta-T)/\sigma)}\right) \Rightarrow \\ \frac{dJ(u)}{du} &= \frac{1}{\varphi(J(u))}\frac{\varphi(u)}{\Phi((x\beta-T)/\sigma)} = \frac{1}{\varphi(J(u))}g(u) \end{aligned} \tag{6}$$

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46 Since G is the correct distribution function for the variable *u*, it provides a valid input to the inverse normal distribution function.

47 See Greene (1993:661). Note the appearance of the scaling factor. This is a result of differentiating the formula for the joint distribution with J(μ) in it to get the density function. See also Lee and Maddala (1985:7) for a different expression of the same function which includes the density functions of μ and ε as marginal distributions.

Given this joint density function, finally, we can derive a density function for the observed variable w, conditional on y=2. Note first that, given that y=2, we know that u=(w-xβ)/σ. The joint density function for (w|not truncated,y=2) can be expressed in terms of the joint density function for ε and u given above, by integrating with respect to ε over the range of values of ε for which y=2, i.e. from τ-zγ to positive infinity:

$$\begin{aligned}\psi(w,2|x,z) &= \frac{1}{\sigma}\int_{\tau-z\gamma}^{\infty} h(\varepsilon,u|x,z)d\varepsilon \\ &= \frac{1}{\sigma}\frac{\partial}{\partial u}H(z\gamma-\tau,u|x,z) \\ &= \frac{1}{\sigma}\frac{\partial B(z\gamma-\tau,J(u)|x,z)}{\partial J(u)}\frac{\partial J(u)}{\partial u} \\ &= \frac{1}{\sigma}\frac{\partial B(z\gamma-\tau,J(u)|x,z)}{\partial J(u)}\frac{1}{\varphi(J(u))}g(u)\end{aligned} \tag{7}$$

This expression can be simplified using some algebra:[48]

$$\begin{aligned}&\frac{\partial B(x_1,x_2)}{\partial x_2} = \varphi(x_2)\Phi\left(\frac{x_1-\rho x_2}{\sqrt{(1-\rho^2)}}\right) \Rightarrow \\ &\frac{\partial B(x_1,x_2)}{\partial x_2}\frac{1}{\varphi(x_2)} = \Phi\left(\frac{x_1-\rho x_2}{\sqrt{(1-\rho^2)}}\right)\end{aligned} \tag{8}$$

to get:

$$\psi(w,2|x,z) = \frac{1}{\sigma}\Phi\left(\frac{z\gamma-\tau-\rho J(u)}{\sqrt{(1-\rho^2)}}\right) * \frac{\varphi(u)}{\Phi\left(\frac{x\beta-T}{\sigma}\right)} \tag{9}$$

After substituting in (w-xβ)/σ for u, the log-likelihood function can be expressed as:

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48 This follows from the formulas for conditional and marginal distributions for a bivariate normal distribution. See Greene (1993:69,73).

$$L = \sum_{i,y=0} \ln \Phi(-z_i\gamma) + \sum_{i,y=1} \ln\left(\Phi(\tau - z_i\gamma) - \Phi(-z_i\gamma)\right) +$$
$$\sum_{i,y=2} \left\{ -\ln\sigma + \ln\Phi\left(\frac{z_i\gamma - \tau - \rho J\left(\frac{w_i - x_i\beta}{\sigma}\right)}{\sqrt{(1-\rho^2)}} \right) + \ln\varphi\left(\frac{w_i - x_i\beta}{\sigma}\right) - \ln\Phi\left(\frac{x_i\beta - T}{\sigma}\right) \right\}$$

(10)

where the first two terms follow from the likelihood function for a normal ordered probit model. To get the maximum likelihood estimates, we need to maximize not only over the unknown parameters β and γ, but also the additional model parameters ρ, σ, and τ. I do so using a numerical optimization algorithm for maximum likelihood estimation provided by the statistical program Stata.[50]

Implementing the model

Given the log-likelihood equation above, it remains to specify the contents of xβ and zγ. As I argued in chapter five, aid decisions tend to be made for the coming year using data from the preceding year, suggesting a 2-year lag. Those variables representing judgements (by the decision-makers or others), such as the presence of democracy and the degree of political and civil rights, need only a one-year lag, as they will presumably be based on assessments at the time policy is being set. The same goes for the geographical data: sharing a border with a Communist state and a recipient's total surface area. Lagging the variables helps eliminate the potential problem of simultaneity

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[49] Cf. Greene (1993:696). Note: there are 2 small errors in Lee and Maddala (1985:6-8) at this point. First, they miscode their dummy variable I, setting it to 0 when it should be 1 and *vice versa*. Second, they use y when they mean w in the derivation of the log likelihood function.

between the dependent variable and some independent variables. For example, total ODA receipts by a recipient state include those provided by the donor state being studied. Moreover, exports from the donor to the recipient are likely to be funded in part by aid funds, and GDP per capita figures are boosted by aid receipts.[51] Fortunately, since current aid cannot affect any of these factors in previous years, it cannot have a causal influence on the lagged variables.

It remains possible for error terms to be correlated over time, however. To address this issue, I also include a lag of the dependent variable on the explanatory-variable side. Doing so simultaneously solves the main problem associated with pooling data from multiple years. For the purpose of estimation, it is extremely valuable to increase the number of observations. However, pooling multi-year data introduces autocorrelation (which might be caused, for example, by bureaucratic inertia and by the prevalence of multi-year projects within aid programs).[52] The inclusion of a lagged value of the dependent variable helps resolve the most serious aspect of this problem.[53]

We also need to take into account the fact that aid budgets rise and fall over time independently from the characteristics of the recipient countries. In other words, countries may receive more aid from one year to the next, simply because the overall aid budget

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50 Stata code available from the author upon request.

51 In addition, it is often impossible to tell to what degree aid creates new exports, or rather just helps pay for exports that the recipient country would have bought in any case.

52 In addition, familiarity with the recipient state makes the latter more 'visible' from the point of the view of the donor when decisions about the next year's allocations are made. Similarly, current recipients can exploit their contacts in the aid bureaucracy to plead their case for continued or increased aid in future years.

53 This does assume that it is the realization of the dependent variable that has an influence on its new value, as opposed to the expectation. Since the actual value of aid flows is likely to be readily available to decision-makers (and those who evaluate them) at budget time, such an assumption appears reasonable.

has increased, not due to any changes in their own situation. By using a recipient's relative aid share — the percentage of the donor's total aid disbursements it receives — I bypass this problem. Finally, it stands to reason that there will be a lot of countries receiving relatively small aid shares, with just a few receiving a lot — in other words, the distribution of aid shares declines exponentially. Hence it makes sense to take the log of aid shares as the actual dependent variable. The same process — calculating relative aid shares, and then taking the log — is applied to the explanatory variable representing the total amount of aid received from all DAC donors.[54]

Similar issues enter into the scaling of the explanatory variables. Many of them, in particular those that are a function of the size of the recipient, are exponentially distributed, and hence are logged. In addition, there are year-to-year changes in the variables that do not affect the relative standing of different recipients. For example, economic growth has generated a secular trend towards greater GDP per capita and more international trade. Even logged, what was once a reasonably high GDP per capita might now seem low, and what once seemed like a significant amount of trade may now be almost negligible. Similarly, there has been an increasing trend with respect to rights and the level of democracy in developing countries over the past few decades. Yet it seems likely that donor states do not use such trends as an argument for increased (or reduced) aid, but rather just rescale their 'rules of thumb' used to assess a recipient's needs and its value to the donor. The approach I adopt is to standardize all these variables (i.e. subtract

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54 Values of zero prior to logging are handled as follows: for the dependent variable, they are simply assigned a value of –999. (The form of the likelihood function means that these values are not used in the calculation.) For the total DAC aid variable, I add the negligible value of 1*10-8 prior to logging.

the mean and divide by the standard deviation) on a year-by-year basis, over the universe of potential aid recipients.[55]

A final issue to resolve before performing the regression is the choice of the threshold for a 'token' aid allocation. A reasonable threshold was deemed to be an aid share of 0.025%, which corresponds, roughly, to 1/25 of the amount each recipient would get if a donor were to divide its aid evenly across all potential aid recipients.[56] Small though this amount might seem to be, a significant number of countries was judged to receive only token aid by this standard. For example, Belgium provided no aid to 57 countries, token aid to 40, and substantial aid to 85 more in 1995; in other words, over 20% of aid recipients received a share of less than 0.025% each of Belgium's total bilateral aid.[57]

Regression analysis

In this section, I provide the results of two sets of regressions: a basic model including the explanatory variables introduced above, and a model interacting measures

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55 There is a related problem in that this universe of recipients has not been constant over time; consider, for example, the recent addition to DAC aid lists of the Asian former Soviet Republics. In part, this problem is resolved simply by the fact that data for these recipients prior to their independence are likely to be missing, and hence the states in question will not be included in the regression for earlier years. However, this, in turn, distorts the analysis, as the range of potential recipients changes over time. It would be worthwhile to consider the applicability of models from the economics of new goods to this problem by using shadow values for newly independent countries to derive an implicit supply of aid to these countries in earlier periods when they were not yet 'available' as recipients. See e.g. Berry (1994) and Hausman (1997).

56 This choice is, of course, arbitrary. Assuming the basic concept of token aid is valid, it is quite possible that the cut-off is somewhat higher or lower. Moreover, it may vary from donor to donor, as well as within donors over time. I experimented with values for the threshold that were slightly higher or lower, as well as with thresholds that varied over time, and results were substantially the same.

of the strength of different types of motivations for aid with those same explanatory variables. The model used in the first four regressions is:

$$y^*_{it} = \gamma_1 y^*_{it-1} + \gamma_2 UNvotes_{it-2} + \gamma_3 CommBorder_{it-1} + \gamma_4 GDP_{it-2} + \gamma_5 Pop_{it-2} + \gamma_6 ExColony_i + \gamma_7 Exports_{it-2} + \gamma_8 Imports_{it-2} + \gamma_9 Democracy_{it-1} + \gamma_{10} Area_{it-1} + \gamma_{11} totalODA_{it-2} + \gamma_{12}(GDP/capita)_{it-2} + \gamma_{13} Mortality_{it-2} + \gamma_{14} Literacy_{it-2} + \gamma_{15} Rights_{it-1} + \varepsilon_{it}$$

$$w^*_{it} = \beta_1 w^*_{it-1} + \beta_2 UNvotes_{it-2} + \beta_3 CommBorder_{it-1} + \beta_4 GDP_{it-2} + \beta_5 Pop_{it-2} + \beta_6 ExColony_i + \beta_7 Exports_{it-2} + \beta_8 Imports_{it-2} + \beta_9 Democracy_{it-1} + \beta_{10} Area_{it-1} + \beta_{11} totalODA_{it-2} + \beta_{12}(GDP/capita)_{it-2} + \beta_{13} Mortality_{it-2} + \beta_{14} Literacy_{it-2} + \beta_{15} Rights_{it-1} + \sigma\mu_{it}$$

where y* is the eligibility decision and w* is the decision as to the amount of aid to provide, as in the derivation of the model above. The results are shown in table 5.4 on page 30.[58] In addition to the estimated coefficients, the bottom of the table provides a number of additional pieces of information. The number of countries and years in the regression is listed, as well as the total number of observations, which is disaggregated into observations for which the eligibility value is 0 (no aid), 1 (token aid), or 2 (substantial aid). The table also lists predictions for the two dependent variables when each explanatory variable is held at its mean. The first column lists the probabilities that eligibility will be 0, 1, or 2. Next to the first of those values, the second column shows the

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57 Similar breakdowns for Italy and Norway were given earlier. In fact, the incidence of token aid donations is increasing. Whereas the fraction of donations falling in this category is roughly 10% for the whole dataset, it has been over 15% in recent years.

58 Full details on each of these regressions are provided in appendix B at the end of the chapter. The number of observations for which we have data on all independent variables is affected most by the variables for literacy and rights, and to a lesser extent by the measure of democracy. I reran the model dropping these three variables, which increased the number of observations from about 1750 to close to 3000. The results were substantially similar, although a few more explanatory variables attained statistical significance. Where relevant, such additional findings are reported in footnotes. Full results of this extra set of tests are available from the author.

actual predicted $z\gamma$ for all variables at their mean, which is used to calculate these probabilities. Next, the value of $x\beta$, again for all variables at their mean, is shown, together with the associated value for predicted aid share (in percentage points), which is obtained by raising e to the power $x\beta$ (since the dependent variable is a log).

Finally, I show the predicted value for the log of the aid share, as well as the associated aid share, immediately underneath. It is important to note that we cannot simply take $x\beta$ as the fitted value for the aid shares, as both the selection and the truncation processes have an impact on the expectation of the dependent variable. Specifically, the change in the value of the expected aid share resulting from a change in x is *not* equal to β. Instead, it is a function of both $x\beta$, as a result of the truncation process, and of $z\gamma$, as a result of the selection process. The truncation tends to result in an attenuation of β (i.e. its effect is closer to 0 than the coefficient would suggest), whereas it is impossible to predict the effect of $z\gamma$ *ex ante* (it could go so far as to change the sign on the effect!).[59] Appendix C discusses this issue in more detail, and outlines how to calculate the expected value of the aid share, given a set of values for the independent variables.

To assess the validity of the model, I provide some measures in addition to the Wald test-statistic provided by the maximum likelihood estimation program.[60] First, I calculate

59 Cf. Greene (1993:710), who notes that this point is generally overlooked in the empirical literature. Indeed, neither of the two studies in the aid literature that have used selection models (McGillivray & Oczkowski 1992 and Meernik, Krueger & Poe 1998) take it into account.

60 The Wald statistic is asymptotically distributed as $\chi^2(n)$. Stata reports n as the number of independent variables for which coefficients are estimated, whereas the number of coefficients estimated is 2n+3. Even if we take the latter figure for n, the Wald statistic is statistically significant at vanishingly small levels (on the order of 10^{-50}).

a measure of the goodness of fit for each of the two individual equations estimated. For the aid share equation, I use r^2, the squared correlation coefficient between the fitted and actual aid shares, taking into account the truncation and the censoring imposed by y=2.[61] As table 5.4 shows, the values for r^2 are not tremendously high, but they are respectable compared to the other studies in the literature, with the regression for Italy having the weakest result.

For the eligibility equation, I calculate the fraction of observations predicted correctly, where the predicted value for y is taken to be the value for y with the highest estimated probability. Here, the results are quite impressive, with about 80% of the observations predicted correctly in each regression. Next, I test the model's assumption that the eligibility and aid amount decisions are separate, by comparing it to a tobit-like model. This is done by calculating a likelihood ratio $LR = -2(\ln L_r - \ln L)$, where $\ln L_r$ is the log-likelihood for the restricted model, in which $\gamma = \beta/\sigma$ and $\rho = 0$. In the restricted model, eligibility is seen as being simply a result determined by the amount decision (which is still truncated, of course). The likelihood ratio is distributed as $\chi^2(n)$, where n is the number of restrictions, i.e. the number of independent variables in both equations plus 1 (for the restriction on ρ). The likelihood ratios are given at the bottom of the table, with the χ^2 values in parentheses in the next column. Clearly, we can reject the hypothesis that aid allocation is a one-stage process. In addition, the estimated correlation between the two stages is statistically significant (and quite high) in at least two of the four

61 The r^2 measure is calculated only for the subset of data that has been selected for substantial aid (i.e. the eligibility decision is 2). The figure obtained from using xß as the prediction is, in fact, slightly higher in most (but not all) regressions. I am not quite sure of the cause of this difference; presumably it is related to the degree of impact of the selection and truncation processes on the observed values.

regressions presented here, supporting the hypothesis that the two decisions are not independent.[62]

The *Change* column in table 6.4 shows the estimated effect of increasing that variable by 1 standard deviation, holding all others at their means.[63] *** Note: this is not a very useful fitted value to provide, as the standard deviation of a logged and/or standardized variable has no intuitive meaning. Instead, add a column specifying the change. For the logged variables, give instead the effect of doubling the variable from its pre-log, pre-stdized mean. For mortality, give mean and an increase of (say) 10 infant deaths per 1000 births. For illiteracy, give mean and an increase of 5 percentage points in the rate. For democracy and rights, state mean and give result of an increase by 1 point on the 0-10 and 2-14 scales. (Need to review discussion of results as appropriate.) ***

Variable	Belgium		Italy		Netherl.		Norway	
	Coeff.	Change	Coeff.	Change	Coeff.	Change	Coeff.	Change
Eligibility, lag	1.241	43.94	0.947	4.99	1.285	42.64	1.075	40.71
UN votes, std.	0.112	3.87	0.036	0.57	0.029	1.07	-0.029	-0.77
Comm. Border	-0.759	-20.10	-0.371	-7.45	-0.194	-7.02	-0.004	-0.10
GDP, std.log.	0.840	32.04	-1.156	-33.67	0.068	2.58	2.477	75.65
Popul., std.log	-0.591	-16.05	1.016	8.18	0.261	10.10	-2.190	-18.45
Colony	3.435	73.36			-0.886	-25.71		
Exports, std.log.	-0.005	-0.18	0.217	3.06	-0.138	-5.01	0.045	1.21
Imports, std.log.	-0.050	-1.65	0.078	1.21	0.040	1.49	-0.163	-4.01
Democracy, std.	-0.119	-3.86	0.113	1.71	-0.069	-2.52	0.017	0.46
Area, log	0.092	9.25	0.128	4.58	-0.002	-0.20	0.002	0.16
DAC aid share	0.039	10.30	0.029	3.02	0.038	10.85	0.022	4.61
GDP/cap, std.log.	-0.667	-17.49	0.361	4.60	-0.344	-11.85	-2.017	-18.37
Mortality, std.	0.028	0.94	-0.049	-0.83	0.235	9.04	-0.006	-0.15
Illiteracy, std.	0.005	0.17	0.014	0.23	-0.156	-5.65	-0.053	-1.38
Rights, std.	-0.242	-7.55	0.032	0.52	-0.305	-10.64	-0.218	-5.25
constant	-1.212		-1.757		-0.074		-0.732	

62 I also estimated the simpler model of a binary probit. This changes the dependent variable being modeled, and hence cannot be compared to the present model using a likelihood ratio test, I believe. The results are quite similar to those presented here, but in both cases — the ‘token’ recipients can be added either to zero aid recipients or to those receiving substantial aid — the overall fit appears to be slightly worse. Results available from the author.

63 In the case of discrete independent variables, the change, instead, is from 0 to 1, for Communist border and ex-colony, or 1 to 2, for lagged eligibility. Means and standard deviations are provided in Appendix B, where the results of each regression are also provided in more detail.

Aid share, lag	-0.001	0.001	-0.001	-0.001	0.000	0.00	0.001	0.001
UN votes, std.	0.098	0.024	-0.112	-0.065	-0.208	-0.119	-0.451	-0.138
Comm. Border	-0.138	0.327	0.231	0.273	0.120	0.146	0.773	0.338
GDP, std.log.	1.848	1.340	0.650	0.870	2.333	1.741	-0.551	-0.721
Popul., std.log	-0.949	-0.039	-0.700	-0.566	-1.723	-0.759	0.550	1.402
Colony	3.714	3.237			1.363	1.174		
Exports, std.log.	-0.089	-0.044	0.745	0.343	0.135	0.128	0.441	0.157
Imports, std.log.	-0.259	-0.112	-0.270	-0.152	-0.265	-0.151	-0.194	0.039
Democracy, std.	-0.025	0.026	-0.128	-0.102	0.000	0.027	0.156	0.051
Area, log	0.120	0.140	0.418	0.617	0.213	0.365	0.130	0.144
DAC aid share	0.051	0.161	0.060	0.160	0.110	0.444	0.130	0.362
GDP/cap, std.log.	-0.935	0.027	-0.848	-0.495	-2.256	-0.513	-1.277	1.291
Mortality, std.	0.162	0.080	0.112	0.071	0.072	-0.033	-0.703	-0.232
Illiteracy, std.	0.277	0.151	-0.092	-0.047	-0.311	-0.086	0.117	0.077
Rights, std.	-0.002	0.086	-0.421	-0.195	-0.306	-0.004	-0.010	0.139
constant	-3.223		-6.571		-4.258		-3.337	
tau	1.085		0.577		1.054		0.673	
sigma	1.364		1.499		1.187		1.560	
rho	0.585		0.454		0.234		0.170	
P(y=0)	0.305	0.510	0.028	1.910	0.243	0.697	0.588	-0.222
P(y=1)	0.412		0.063		0.397		0.227	
P(y=2)	0.283		0.909		0.361		0.186	
Xß	-2.136	0.118	-2.252	0.105	-2.488	0.083	-2.252	0.105
E[aid share]	-1.709	0.181	-1.588	0.204	-1.966	0.140	-1.529	0.217
# countries	96		97		96		89	
# years	23		23		23		23	
N	1707		1679		1694		1297	
N(y=0)	261		357		222		491	
N(y=1)	293		189		223		174	
N(y=2)	1153		1133		1249		632	
r^2	0.29329		0.16655		0.42393		0.32148	
% predicted	82.0152		79.4521		85.4191		79.6453	
Wald	901.73	(1E-166)	748.39	(5E-136)	825.94	(8E-151)	747.78	(6E-136)
LR (tobit)	123.227	(1.3E-18)	106.04	(9.2E-16)	171.819	(3.6E-28)	65.3266	(3E-08)

TABLE 5.4. Basic regressions, all four donor states.
Significance levels: single underline 0.05, double underline 0.01.

For the eligibility decision, the effect shown is the increased estimated probability that a country will be selected for a substantial aid allocation (i.e. y=2), in percentage points. This can be added to the corresponding mean estimated probability given at the bottom of the table to obtain a predicted probability of aid. For the amount decision, this column shows the predicted marginal effect of increasing the variable in question by a single standard deviation — in other words, the updated 'coefficient' for that variable, taking into account the estimated effect of the truncation and selection processes, as discussed above.[64] It is worth noting that in most cases the absolute value of this adjusted coefficient is smaller than the estimated β. More interestingly, in a few cases (including one where the estimate of β is statistically significant — imports in the case of Norway), the estimated sign even changes! Of course, the fact that the marginal effect of different variables depends greatly on the starting point (i.e. on the values of the other independent variables) as well as on the size of the change, makes it rather more difficult to interpret the results of the regression.[65] Nonetheless, a number of quite striking effects are worth noting.

Consider, first, the eligibility decision. Not surprisingly, in all four cases, the status of the recipient in the preceding year has the largest impact on its eligibility for aid the next year. Neither of the two security-related variables appears to function in the way the literature predicts they should. The degree to which a potential recipient votes along with the donor states is statistically significant only in the case of Belgium, and even there the predicted increase in the likelihood of receiving substantial aid is relatively small. Sharing a border with a Communist state is statistically significant in both Belgium and Italy, but in each case the effect is the opposite of that expected: such states are *less* likely (considerably less likely, in fact) to be considered candidates for aid from these two donors. The variables related to the size of a country are significant only in the case of Norway, with states with larger GDPs considerably more likely to receive substantial aid. However, this effect is counteracted by the fact that states with larger populations, as well

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64 To get the predicted change, one would have to multiply this corrected coefficient by the size of the change in x. That information is provided in appendix B.

65 Indeed, it is not quite clear what the statistical significance of the updated coefficients should be taken to be. For the sake of simplicity, I assume that a significant estimate for ß also implies that the updated coefficient can be considered statistically significant, but this is unlikely to be entirely correct.

as those with higher GDP per capita, are rather less likely to be selected as aid recipients.[66] Indeed, as footnote 66 shows, holding population constant, the combined effects of changes in GDP and GDP/capita result in a country become less likely to be selected as a recipient. In other words, for a given country size, Norway is more likely to select the poorer country.

The other measure of a country's size, its area, is significant in the regressions for Italy and Belgium, suggesting that these two states prefer to give aid to larger recipients. The impact of being a former colony is somewhat indeterminate in the eligibility decision. No estimate was generated for Italy, since its lone territory, Somalia, dropped out of the regression due to missing values for some of the explanatory variables. In the case of Belgium, the effect is extremely large but dwarfed by an even larger standard error. In the case of the Netherlands, finally, the effect is statistically significant, but negative. This surprising result can be attributed to political disagreements between the Netherlands and two of its former territories, Indonesia and Suriname, disagreements which have repeatedly led to the freezing or cancellation of aid flows, as was described earlier in the chapter.

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[66] Calculating the combined effect of these three coefficients is cumbersome, but relatively straightforward. Holding population constant an increase in ln(GDP) implies the same increase in ln(GDP/cap). The descriptive statistics in appendix A show that the standardization process will divide the former roughly by 2.18 and the latter by 1.34 (their respective standardizations. Properly divided by these factors, the two effects can be added. Conversely, holding GDP constant, an increase in ln(population) implies an equivalent reduction in ln(GDP/cap). The former will be divided by 2.06, and will then operate in the opposite direction from the change in ln(GDP/cap) divided by 1.34. Note that these values are approximate only, as standardization is done on a year-by-year basis, not over the entire pool of data. To work through an example, in the case of Norway, a doubling in a potential recipient's GDP (holding other variables constant) corresponds to an increase in the log of the recipient's GDP by ln(2) • 0.69. The increase in the standardized variable is 0.69/2.18 • 0.32; the increased in the standardized per capita variable, similarly, is 0.69/1.34 • 0.52. Multiplied by their

The impact of trade on selection as an aid recipient appears to be less than is often suggested in the literature, except in the case of Italy, where important export partners are indeed more likely to receive substantial aid than other developing countries. Conversely, in Norway, countries from which Norway imports a lot are *less* likely to be selected as aid recipients. This suggests that another mechanism is at work: aid is not given to ensure good relations with important mineral suppliers, but instead it is withheld from countries that have products that compete with domestic suppliers, such as textiles.

The most interesting result in the eligibility regressions is the importance of a recipient's aid share from all donors combined. A clear bandwagoning effect appears to be at work in three of the four countries. Belgium, the Netherlands, and to a lesser extent Italy, are all more likely to select a country as an aid recipient if it also receives substantial aid from other donors. *** However, the effect is less powerful than the table would lead one to suspect. A doubling of a country's overall aid share makes it just 1 percentage point more likely to be selected as a recipient by Belgium. *** The remaining variables show fewer interesting patterns. Countries with a high mortality rate — i.e. poor health conditions — are relatively more likely to receive aid from the Netherlands, suggesting a humanitarian concern. More difficult to interpret is the fact that the Netherlands, as well as Belgium and Norway, are less likely to give aid to countries with good political and civil rights situations. This could be interpreted to imply that aid is *not* given to reward good governance, but rather to help improve the situation in countries

respective coefficients, we get an increase of 0.79 added to a reduction of 1.04, so the net effect is to make the country *less* likely to be selected as an aid recipient.

with questionable regimes.[67] Whether this is indeed the case is a question to be examined in the case study chapters.

Next, consider the equation for the relative aid share. One immediate, striking result here is that the lagged value of the dependent variable has almost no impact. It appears that, once a country has been selected to be a recipient, its aid share in a previous year tells us little about its aid allocation in a subsequent year that is not already found in the other explanatory variables. Second, it is interesting to note that where UN votes and a Communist border mattered to Belgium and Italy in the eligibility decision, they appear to play a role in the other two countries at the amount determination stage. Here, both the Netherlands and Norway give *less* aid to countries that vote with them more in the UN, suggesting that security concerns are unlikely to figure very strongly in their decisions. On the other hand, Norway does give more aid to countries bordering on Communist states.

Where GDP, GDP per capita, and population mattered in Norway's selection of aid recipients, in the Netherlands they affect the amount of aid given. As was the case in Norway, the negative coefficient on GDP/capita outweighs the positive estimate for GDP, if we take the effect of standardization into account.[68] In other words, an increase in GDP, other things equal reduces the amount of aid a country can expect to receive. Similarly, the GDP/capita coefficient outweighs the impact of the population parameter, *ceteris*

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67 Or, to take the cynical approach, one might suspect that donors prefer to deal with dictators rather than with possibly more chaotic and less reliable (as trading partners) democracies. However, it must be noted that there is a strong *negative* correlation between democracy and rights in the dataset, which may negatively affect the significance of the estimate for the democracy variable. In other words, the impact of governance and rights remains an open question.

68 The effective, 'non-standardized' coefficients are 2.333/2.177•1.07 for GDP and –2.256/1.341•-1.68 for GDP per capita.

paribus, so holding GDP constant, an increase in population is associated with greater aid receipts.

The interpretation of the coefficients on status as an ex-colony is more straightforward, and as expected: both the Netherlands and Belgium give more to their ex-colonies, other things being equal. The coefficients on exports and imports suggest, much more so than was the case in the eligibility decision, the economic motives *do* play a role in the decision-making regarding the size of aid flows: Italy, the Netherlands, and Norway all tend to give more aid to more important export partners, while giving less to important sources of imports.[69] Countries with a greater area are likely to receive more aid from Belgium, Italy, and the Netherlands. More interestingly, the bandwagoning effect already introduced above is in significant evidence here too, with all four countries tending to give more to LDCs that are important recipients of overall DAC aid.

Turning to the humanitarian variables, Norway favours recipients where health conditions are already fairly good. Similarly, the Netherlands gives more to recipients where illiteracy rates are relatively low. In contrast, Belgium — which, as we shall see later, has long prioritized education in its aid program — concentrates its funds on recipients with higher illiteracy rates. LDCs with relatively good governance, finally, as likely to receive relatively smaller sums from Italy and the Netherlands, the same pattern that was evident for the latter, Belgium, and Norway in the eligibility decision.

What do all these results imply about the relative importance of different motivations for giving aid and, in particular, of the considerations central to my argument? The bandwagoning effect is strong evidence in favour of the presence of prestige- or obligation-related preferences among donors. Neither direct self-interest nor humanitarianism predicts such an effect.[70] Indeed, humanitarianism might predict the opposite effect, since the net impact of an aid donor is likely to be greatest where there are fewest alternative aid sources. The importance of the colonial variable in the amount decision further strengthens the case for obligation as a consideration. As for the third type of motivation I emphasize, the persistent importance of area (beyond the effects of GDP and population) suggests that some form of enlightened self-interest might also be at work. There is little consistent evidence for a concern with security or power, and humanitarianism appears to play a role only in the allocation decisions of Netherlands and Norway. Wealth, finally, emerges as a concern that is relatively unimportant in the selection of aid recipients, but that clearly makes itself known in the decision regarding how much each recipient ought to receive.[71]

The interaction of expressed motivations and explanatory variables

The results of the basic regression models appear to match the rhetoric in the different donor states relatively well. For example, humanitarian considerations are strongest in legislative debates in the Netherlands and Norway, and the associated explanatory variables matter most in these donor countries. Similarly, wealth is a dominant concern to Italian legislators, and Italy is the only country for which export ties make a country significantly more likely to be selected as an aid recipient. Finally, prestige and

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69 The latter effect, again, is most likely due to protectionist considerations.

70 Self-interest might be argued to predict it if the favoured recipients were primarily large, economically and militarily powerful states. While table 5.1 shows that this is true to some degree, it certainly does not hold across the board. Moreover, the inclusion of variables directly measuring size ought to reduce the extent to which overall aid share represents those characteristics.

71 This result illustrates the value of separating the eligibility and amount decisions.

obligation, which matter to representatives in all four donor states considered here, appear to be reflected in the significant bandwagoning effect evident in table 5.4

Now it is time to see whether combining the motivations of legislators with the various independent variables can provide us with any additional explanatory leverage in understanding the aid allocation process. The connections between those variables and the different categories of motivation is laid out in table 5.3. The model for the regression featuring interaction effects between measures of the strength of the different motivations and the various independent variables is:

$$y^*_{it} = \gamma_1 y^*_{it-1} + \gamma_2 Sec^*UN_{it-2} + \gamma_3 Sec^*Comm_{it-1} + \gamma_4 Pow^*UN_{it-2} + \gamma_5 Pow^*GDP_{it-2} + \gamma_6 Pow^*Pop_{it-2} + \gamma_7 Pow^*Col_i + \gamma_8 Wea^*GDP_{it-2} + \gamma_9 Wea^*Exp_{it-2} + \gamma_{10} Wea^*Imp_{it-2} + \gamma_{11} ESI^*Pop_{it-2} + \gamma_{12} ESI^*Democ_{it-1} + \gamma_{13} ESI^*Area_{it-1} + \gamma_{14} Glo^*Pop_{it-2} + \gamma_{15} Glo^*Col_i + \gamma_{16} Glo^*ODA_{it-2} + \gamma_{17} Dut^*Col_i + \gamma_{18} Dut^*ODA_{it-2} + \gamma_{19} Dut^*Exp_{it-2} + \gamma_{20} HumGDPcap_{it-2} + \gamma_{21} Hum^*Mort_{it-2} + \gamma_{22} Hum^*Illit_{it-2} + \gamma_{23} Hum^*Rights_{it-1} + \varepsilon_{it}$$

$$w^*_{it} = \beta_1 w^*_{it-1} + \beta_2 Sec^*UN_{it-2} + \beta_3 Sec^*Comm_{it-1} + \beta_4 Pow^*UN_{it-2} + \beta_5 Pow^*GDP_{it-2} + \beta_6 Pow^*Pop_{it-2} + \beta_7 Pow^*Col_i + \beta_8 Wea^*GDP_{it-2} + \beta_9 Wea^*Exp_{it-2} + \beta_{10} Wea^*Imp_{it-2} + \beta_{11} ESI^*Pop_{it-2} + \beta_{12} ESI^*Democ_{it-1} + \beta_{13} ESI^*Area_{it-1} + \beta_{14} Glo^*Pop_{it-2} + \beta_{15} Glo^*UN_i + \beta_{16} Glo^*ODA_{it-2} + \beta_{17} Dut^*Col_i + \beta_{18} Dut^*ODA_{it-2} + \beta_{19} Dut^*Exp_{it-2} + \beta_{20} HumGDPcap_{it-2} + \beta_{21} Hum^*Mort_{it-2} + \beta_{22} Hum^*Illit_{it-2} + \beta_{23} Hum^*Rights_{it-1} + \sigma\mu_{it}$$

where Sec(urity), Pow(er), Wea(lth), ESI (enlightened self-interest), Glo(ry), Dut(y), and Hum(anitarianism) are the binned values (ranging from 0 to 4) representing the strength of each dimension of motivation, as introduced in chapter three. The variables with which these measures are interacted are the same as in the basic regressions discussed above. Table 5.5 presents the results of this, more complicated regression, in the same format as that of table 5.4.[72] It should be noted that the interpretation of the fitted values is slightly different in this second table. It did not seem very informative to show the anticipated effect of a change in the interacted variable, since there is no real substantive interpretation of a standard deviation in the interacted value. Instead, the expected impact is shown for a change in the interaction term from 0 to one standard deviation above the mean of the un-interacted explanatory variable. We can see this as the expected effect of a change in the weight of a particular motivation in the donor state's decision-making process (from 0 to 1) for a recipient whose characteristic remains constant at one standard deviation above the characteristic's mean in the overall population.[73] *** The same concern applies here as for table 5.4: replace the listed change by one that is more intuitively meaningful (i.e. use the same changes as in that table). ***

The overall fit of these regressions is less strong than was the case for the basic regressions. This should not be surprising, however, since we have to handle a considerable reduction in the number of observations, combined with an increase in the number of parameters to be estimated.[74] Nonetheless, the r^2 values are still considerable for the Netherlands and Norway, and reasonable for Belgium. Only for Italy is it disappointingly low. Again, eligibility decisions are predicted quite well, and both the overall Wald statistic and the comparison against a restricted Tobit-like model show strong statistical significance.

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72 Again, full results of each regression are presented in appendix B.

73 This is not the only possible interpretation, of course.

74 *** It might be worth dropping some of the highly correlated variables here, to reduce multicollinearity and (one hopes) increase the statistical significance of some estimates. In any case, although there are relatively few statistically significant effects, there are fortunately quite a few more estimates significant at the 1% level than would be expected for an arbitrary model. ***

	Belgium		Italy		Netherl.		Norway	
Variable	Coeff.	Change	Coeff.	Change	Coeff.	Change	Coeff.	Change
Eligibility	1.363	43.97	1.051	36.15	1.360	44.66	1.242	43.06
Sec*UN	-0.123	-4.28	0.338	13.20			0.419	14.42
Sec*Comm	-0.741	-21.07	-0.594	-19.44			-0.086	-2.54
Pow*UN			0.070	2.66	0.766	29.69	0.325	10.94
Pow*GDP			-0.348	-12.08	0.015	0.55	-0.005	-0.16
Pow*Pop			0.238	9.21	-0.229	-7.97	0.043	1.33
Pow*Col					-3.510	-35.81		
Wea*GDP	-0.092	-3.21	0.016	0.61	-0.052	-1.90	-0.448	-11.29
Wea*Exp	-0.035	-1.23	0.030	1.14	-0.217	-7.56	0.292	9.75
Wea*Imp	0.026	0.92	0.044	1.68	0.031	1.14	-0.165	-4.70
Esi*Pop	-0.092	-3.21	0.008	0.31	0.085	3.17	0.048	1.50
Esi*Democ	0.034	1.21	-0.009	-0.32	0.012	0.45	0.002	0.06
Esi*Area	0.009	4.22	-0.001	-0.40	0.020	10.44	-0.007	-2.95
Glo*Pop	0.242	9.08	0.189	7.26	0.349	13.46	0.209	6.82
Glo*UN	0.082	2.97	-0.011	-0.40	-0.276	-9.45	-0.086	-2.52
Glo*ODA	0.023	1.21	-0.007	-0.35	0.038	2.13	-0.023	-0.84
Dut*Col	2.098	64.17			2.424	65.15		
Dut*ODA	-0.010	-0.49	0.020	1.11	0.019	1.05	-0.001	-0.04
Dut*Exp	0.009	0.33	0.056	2.14	0.171	6.46	-0.130	-3.75
Hum*GDP/cap	-0.096	-3.33	-0.031	-1.16	-0.126	-4.49	-0.164	-4.66
Hum*Mortal	-0.008	-0.30	0.018	0.69	0.082	3.06	-0.035	-1.07
Hum*Illit	-0.052	-1.83	-0.021	-0.77	-0.072	-2.61	0.055	1.70
Hum*Rights	-0.041	-1.47	-0.066	-2.43	-0.085	-3.07	-0.108	-3.17
constant	-0.514		-0.468		-0.035		-0.878	
Aid share (lag)	-0.002	-0.003	-0.002	-0.002	0.000	0.000	-0.001	-0.001
Sec*UN	0.435	0.247	-0.583	-0.294			-0.288	-0.204
Sec*Comm	-0.185	-0.001	1.222	0.652			2.204	1.519
Pow*UN			0.012	0.001	-0.113	-0.233	-1.097	-0.590
Pow*GDP			0.058	0.081	0.348	0.192	-1.232	-0.560
Pow*Pop			0.596	0.325	-0.685	-0.196	0.516	0.305
Pow*Col					0.923	1.957		
Wea*GDP	0.015	0.006	0.059	0.027	-0.177	-0.069	0.668	0.439
Wea*Exp	0.026	0.014	0.047	0.021	-0.004	0.091	-0.247	-0.171
Wea*Imp	-0.139	-0.076	-0.036	-0.021	-0.137	-0.082	-0.809	-0.341
Esi*Pop	0.188	0.104	0.170	0.083	0.640	0.358	-0.093	-0.058
Esi*Democ	-0.055	-0.030	-0.029	-0.013	0.035	0.014	0.102	0.057
Esi*Area	0.003	0.029	0.000	0.000	-0.019	-0.249	0.022	0.179
Glo*Pop	0.284	0.187	0.101	0.042	0.588	0.264	0.118	0.047
Glo*UN	-0.145	-0.078	-0.070	-0.032	-0.316	-0.021	-0.144	-0.062
Glo*ODA	0.060	0.060	0.001	0.002	0.081	0.066	0.030	0.029
Dut*Col	1.255	1.029			0.852	0.357		
Dut*ODA	-0.013	-0.009	0.068	0.057	0.070	0.061	0.030	0.025
Dut*Exp	0.008	0.005	0.431	0.220	0.027	-0.043	0.350	0.216
Hum*GDP/cap	0.004	0.000	-0.032	-0.012	-0.264	-0.075	-0.448	-0.185
Hum*Mortal	0.120	0.068	0.187	0.091	0.033	-0.011	-0.138	-0.069
Hum*Illit	0.057	0.030	-0.064	-0.028	-0.084	-0.014	-0.003	-0.009
Hum*Rights	0.026	0.014	-0.037	-0.011	-0.055	0.005	-0.074	-0.022
constant	-1.629		-1.620		-1.442		-1.651	
tau	1.053		0.509		1.274		0.689	
sigma	1.710		1.781		1.229		1.614	
rho	0.867		0.789		0.171		0.590	
P(y=o)	0.276	0.594	0.433	0.168	0.190	0.876	0.517	-0.041
P(y=1)	0.401		0.200		0.464		0.251	
P(y=2)	0.323		0.367		0.345		0.233	
Xß	-1.835	0.160	-2.030	0.131	-2.563	0.077	-1.813	0.163
E[aid share]	-1.486	0.226	-1.524	0.218	-1.956	0.141	-1.416	0.243

# countries	96		97		96		86	
# years	9		9		9		9	
N	678		668		674		516	
N(y=0)	100		143		79		194	
N(y=1)	111		64		87		70	
N(y=2)	467		461		508		252	
r-squared	0.191		0.118		0.369		0.318	
% predicted	81.858		81.437		87.240		78.488	
Wald	347.56	2.9E-49	297.94	3.5E-38	298.86	2.3E-38	294.09	1.8E-37
LRt(tobit)	76.88	1.3E-08	46.89	0.00152	69.18	8.9E-07	61.62	1.3E-05

TABLE 5.5. Interacted regressions, all four donor states.
Significance levels: single underline 0.05, double underline 0.01.

Selection:

Belgium: when security mattered, less to countries with communist border

Netherlands: when power matters: more to UN agreeers

Norway: when wealth matters, less to large GDP countries

Netherlands, Belgium, more to area with ESI

Three out of 4 states give more to larger countries when more interested in glory

Belgium, Netherlands, more to popular recipients when interested in glory

Netherlands and Norway *less* to good governance when interested in humanitarianism (interpret: help those in trouble)

Amount:

Near-nil influence of lag, as in basic regressions

Norway more to countries w. Communist border when security matters

Norway less to co- UN voters when power matters

Norway less to large GDP countries under wealth

Norway less to import partners under wealth

Netherlands, Belgium more to large population countries under ESI

Netherlands, Belgium more to large population countries under Glory

Netherlands, Belgium more to popular ODA recipients under glory

Belgium more to colonies under duty

Netherlands more to popular recipients under duty

Italy, Norway, more to export partners under duty

Netherlands, Norway less to high GDP/cap countries under humanitarianism

Netherlands less to high-literacy countries under humanitarianism ***

All in all, these results are in line with those from the basic regressions. Aid flows to countries with larger populations and countries that are popular targets of other donors both fluctuate in line with the weight attached to aid as an instrument for promoting international prestige by Belgian and Dutch legislators. Similarly, aid allocations favour large-population countries when enlightened self-interest is an important aspect of the reasons proffered for giving aid in these same countries. A sense of obligation in the Netherlands appears to be associated with a desire to make the fulfillment of that obligation quite visible (i.e. give to popular aid recipients) — not surprising given the consistent, simultaneous emphasis by Dutch legislators on both the duty to give aid and the importance of setting an example. Conversely, a sense of obligation in Italy and Norway appears to be associated with a desire to derive the maximum economic benefit from an unavoidable duty by giving more aid to important export partners.

Where the more conventional motivations regarding aid are concerned, finally, the Dutch tend to select as aid recipients those countries that vote in accordance with it at the United Nations when the relative importance of power objectives is stronger. On the opposite end of the spectrum, both the Netherlands and Norway are likely to give more aid to poorer countries as the influence of humanitarian motives gets stronger.

All in all, this second set of regressions makes two important contributions. First, it largely supports the conclusions from the first group of regressions, using a different set of variables. Second, and more importantly, it enables us to distinguish between different motivations that could plausibly generate an effect for the same independent variable. For example, we find that UN votes, at least to the Dutch, are more relevant to power objectives than to considerations of prestige. Conversely, population size appears to be more relevant to the prestige-related goals — give to important, visible countries — than to power considerations in the process of selecting recipients; in the process of determining how much aid to give, concerns about global instability also become important as motivations for giving more aid to countries with large populations.

Conclusion

*** Summarize, compare and contrast findings from all 8 regressions ***

*** Compare results from previous chapter about aid volume ***

*** Assess value of interaction variables (here and in previous chapter): intriguing and useful but not as strong as one might have hoped; discuss why not (too much noise in measurement? Conflation of importance of motivation to conception of aid and importance of motivation overall?) ***

*** Discuss success of hypotheses, things left for case studies (examine open questions, look at issue of dispersion / concentration of aid) ***

*** Discuss methodological issues, open questions, possibilities for further improvement of model

-> Problem of missing data and missing countries (real small ones), leading to loss of observations (will be able to address at least in part in the case studies)

-> Problem of not all recipients ‘available’ from the start; use economics of new goods on unbalanced dataset, rather than back-filling with zeros

-> Why does xb do a better job than corrected E[w], at least when we measure correlation? Check whether average absolute difference is smaller (might be better measure than correlation). E[w] does seem to produce fewer outliers than xb. ***

Appendix A – Variable Information

In addition to my measures of motivations for development assistance, I use 13 explanatory variables (as well as a lag of the dependent variable) in the regressions in this chapter. This appendix provides basic descriptive statistics for these variables. The dataset covers the 53 years from 1946 to 1998. Information is included for all 187 countries on the current list of eligible DAC recipients.[75] The total number of observations in the dataset, then, is 9911. No regression includes all these observations, however, as countries or years are missing for every variable. In particular, the smaller (island) states — quite a few of which still have not attained independence — are missing from nearly every dataset used in compiling my data.

ODA data is available for 182 countries, for the years 1960-1997. The data on voting agreement at the United Nations is available for 159 of these countries, from 1946-1996. The IMF Direction of Trade statistics cover the years 1948-1996. Information about exports from Belgium, Italy, and the Netherlands is available for 170 countries; data on imports is available for 166 countries. As for Norway, export data are available for 165 countries, and import data for 150 countries. The data from the *World Development Indicators* CD-ROM is available from 1960 through 1997. Population data is available for 172 countries, information about a state's surface area for 167, mortality rates for 166, GDP (and the derived GDP per capita information) for 162, and literacy rates for only 112 states. Democracy values from the Polity III dataset cover 172 states from 1946 through 1994. The Freedom House data on political and civil rights, finally, is available

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[75] The DAC does not provide information (even of a historical nature) about aid flows to countries that no longer exist (e.g. South Yemen or South Vietnam) or are no longer eligible for aid (e.g. Greece).

for 183 countries, but does not start until 1972. Since the regressions can include only observations for which all data are available, the two variables that cause the greatest loss of data are the rights variable (which eliminates all data from before 1972) and the illiteracy variable (which eliminates 75 countries), and, to a lesser degree, the democracy variable (which eliminates a number of recipients included in most other datasets). As noted in the footnotes, all regressions were also run without these three variables, and the results were substantially similar.

Most of the variables in the dataset are rescaled in order to generate a more even distribution and to allow pooling. In particular, variables that are distributed with geometrically decreasing densities (i.e. their histogram resembles a graph of e^{-x}) are transformed by taking their natural logarithm. This is done to the variables for trade, GDP, population, GDP/capita, and area. Moreover, the moments of most explanatory variables change over time independently from the total amounts of aid disbursed. To allow pooling, therefore, I standardize these variables on a year-by-year basis. The variables affected here are UN voting agreement, trade, GDP, population, GDP/capita, mortality, illiteracy, democracy, and rights.[76]

Finally, the World Bank indicators of infant mortality and illiteracy rates suffer from another problem: for many countries only a couple of observations are available over a 20-year period. Since I am concerned with the data available to by decision-makers, not the (unknown) actual values of these variables, it is not problematic to fill in missing data based on the available information. Two options suggest themselves: using the most recent available figure, or extrapolating from the available values. I chose to do the latter,

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76 Standardization is performed for all the data available in a given year, i.e. not just for the subset of countries for which all explanatory variables are present.

on the assumption that decision-makers are likely to impute continued progress (or deterioration, during crises) in these even when no new data is available.

Table 5A.1-2 display basic information for the dependent variables. Table 5A.1 shows the percentages of observations that were recorded as no aid, token aid, and substantial aid, for each of the four donors, with the threshold for a token contribution taken to be a relative aid share of 0.025% of total bilateral aid flows. To obtain the relative aid share, aid flows were divided by the total amount of bilateral aid the donor in question provided that particular year. This allows pooling without introducing problems of inflation or of increasing or decreasing real aid budgets. Unfortunately, negative data distort the aid share information, by reducing the apparent amount of aid provided.[77] To solve this problem, I add the sum of aid 'income' received by the donor (i.e. all the negative aid flows) each year to the official net ODA data. In addition, since donors cannot choose to 'give' negative aid,[78] the relative aid share of net payers is censored at 0. Table 5.2 shows descriptive statistics for relative aid share, the subset of relative aid payments that exceed the threshold, and the log of the latter value, which is used as the dependent variable in the regressions.

	Belgium	Italy	Netherlands	Norway
No aid	3940	4095	3702	4715
Token aid	730	584	716	369
Substantial aid	2204	2195	2454	1787

TABLE 5A.1. Eligibility statistics, by donor.

	Obs	Mean	Std. Dev.	Min	Max

77 In the extreme case of Italy in 1974, only $310,000 of total net ODA was provided, even though two countries received net ODA of over $10m and several others received more than the total net ODA sum. Clearly, division by the official sum will give very odd results here.

78 Although they *can* choose not to give sufficient positive aid to balance out the repayments, which is how negative values occur.

rel. B oda	6874	0.5081849	3.915328	0	101.788
rel. B oda > T	2204	1.581089	6.791998	0.0252075	101.788
log rel. B oda > T	2204	-1.261012	1.625363	-3.680613	4.622892
rel. I oda	6874	0.5279316	2.655909	0	87.77906
rel. I oda > T	2195	1.650273	4.49952	0.0251509	87.77906
log rel. I oda > T	2195	-0.9535598	1.661098	-3.682861	4.474823
rel. NL oda	6872	0.4579714	2.52942	0	78.20757
rel. NL oda > T	2454	1.27964	4.107367	0.0250052	78.20757
log rel. NL oda > T	2454	-1.126201	1.562345	-3.688672	4.359366
rel. N oda	6871	0.4827366	2.531685	0	69.53124
rel. N oda > T	1787	1.853896	4.702345	0.025048	69.53124
log rel. N oda > T	1787	-0.8741113	1.706473	-3.686961	4.241776

TABLE 5A.2. Summary statistics for dependent variables.

Summary statistics for UN voting agreement are shown in table 5A.3, before and after standardization.[79] Similarly, data for exports and imports are shown in table 5A.4, in current US$ million.[80]

	Obs	Mean	Std. Dev.	Min	Max
B S-UN	4976	.271	.235	-.75	1
Ibid., std.	4976	6.77e-11	.995	-5.285	5.822
I S-UN	4567	.328	.210	-.625	1
Ibid., std.	4567	-9.11e-11	.996	-5.775	5.551
NL S-UN	4976	.314	.227	-.875	1
Ibid., std.	4976	1.15e-10	.995	-5.509	5.247
N S-UN	4976	.410	.182	-.75	1
Ibid., std.	4976	2.49e-10	.995	-5.970	4.974

TABLE 5A.3. Summary statistics for UN voting agreement.

	Obs.	Mean	Std. Dev.	Min	Max
Belgium Exports	6134	73.984	194.864	0	3094
Ibid., log	5357	3.149	1.650	0	8.037
Ibid., std.log.	5357	8.93e-11	.996	-2.822	3.457
Italy Exports	5870	231.343	964.018	0	29767
Ibid., log	5281	3.880	1.840	0	10.301
Ibid., std.log.	5281	-6.61e-10	.995	-3.277	4.045
Netherlands Exports	6264	78.487	203.021	0	4851
Ibid., log	5448	3.351	1.586	0	8.487
Ibid., std.log.	5448	2.14e-10	.996	-3.379	3.265
Norway Exports	5443	65.187	338.633	0	12240
Ibid., log	4296	2.539	1.829	0	9.412
Ibid., std.log.	4296	7.50e-10	.994	-1.945	3.439
Belgium Imports	5746	89.202	289.979	0	7602

79 Remember that S values can range over the interval [-1,1]. Since standardization is done on a year-by-year basis, the overall values for mean and standard deviation are expected to diverge somewhat from 0 and 1 respectively.

80 Note: observations where exports or imports are 0 are being dropped (since one cannot take the log of 0). A better approach might be to add a minimal sum (e.g. $1) to each value to prevent this.

Ibid., log	4743	3.180	1.803	0	8.936
Ibid., std.log.	4743	3.24e-10	.995	-2.636	2.755
Italy Imports	5782	223.046	1009.087	0	30007
Ibid., log	5001	3.780	1.965	0	10.309
Ibid., std.log.	5001	1.79e-10	.995	-2.578	3.279
Netherlands Imports	5844	109.942	295.536	0	4545
Ibid., log	4867	3.312	1.863	0	8.422
Ibid., std.log.	4867	1.20e-09	.995	-2.339	3.157
Norway Imports	4805	108.225	746.024	0	21732
Ibid., log	3308	2.582	2.009	0	9.987
Ibid., std.log.	3308	5.88e-11	.993	-1.749	3.228

TABLE 5A.4. Summary statistics for trade flows to recipients.

Finally, data for the remaining independent variables, which do not vary across donors, are shown in table 5A.5.[81] This leaves only the dummy variables undiscussed. The colony dummies are set to 0, except for Zaire, Rwanda and Burundi in the case of Belgium, Somalia in the case of Italy,[82] and Indonesia, Suriname, the Netherlands Antilles, and Aruba for the Netherlands. Norway has no colonial background. The final dummy variable records a contiguous border with a Communist state. Table 5A.6 shows the states considered to be Communist at some time or another, and their neighbours.[83]

	Obs.	Mean	Std. Dev.	Min	Max
GDP (market prices)	4477	1.91e+10	5.87e+10	704928.6	9.02e+11
Ibid., log	4477	21.591	2.177	13.466	27.528
Ibid., std.log.	4477	2.55e-10	.996	-3.396	2.599
Population	6329	2.15e+07	9.34e+07	12170	1.23e+09
Ibid., log	6329	14.917	2.057	9.407	20.928
Ibid., std.log.	6329	1.12e-10	.997	-2.657	2.860
GDP/capita	4461	1853.421	3518.588	.2777	34731.69
Ibid., log	4461	6.563	1.341	-1.281	10.455
Ibid., std.log.	4461	-4.82e-10	.996	-6.040	3.244
Infant mortality	5445	81.9717	52.255	0	263
Ibid., std.	5445	-9.78e-11	.997	-1.911	3.60609
Illiteracy rate	3945	40.6931	27.359	.3	99.8
Ibid., std.	3945	4.45e-10	.9953	-1.842	2.673
Surface area	5264	553552.5	1291	20	1.70e+07
Ibid., log.	5264	11.140	2.798	2.996	16.649
rel. DAC oda	6552	.473	1.213	0	19.852
Ibid., log.	6552	-5.874	7.268186	-18.42068	2.988322
Democracy	4410	2.392	3.531	0	10
Ibid., std.	4410	2.02e-09	.9945	-1.170	2.688

81 The relevant units are: GDP - US$, infant mortality - /1000 live births, surface area - km^2.

82 Italy's case is somewhat ambiguous as there are also strong historical ties with Libya and Ethiopia.

83 Cuba has no contiguous neighbours. Communist states that are neighbours are not included in the dummy variable. Some countries border on more than one Communist state.

Rights	4210	8.567	3.753	2	14
Ibid., std.	4210	3.88e-10	.997	-2.433	1.726

TABLE 5A.5. Summary statistics for non-donor-specific explanatory variables.

State	Period	Neighbours
Afghanistan	1979-1992	Iran, Pakistan
Angola	1976-1991	Namibia, Zaire, Zambia
Cambodia	1973-1992	Laos, Thailand, Vietnam
China	1949-	Bhutan, India, Myanmar, Nepal, Pakistan, Taiwan
Laos	1975-	Cambodia, Myanmar, Thailand, Vietnam
Mozambique	1975-1989	Malawi, South Africa, Tanzania, Zambia, Zimbabwe
Nicaragua	1979-1989	Costa Rica, Honduras
North Korea	1948-	South Korea
North Vietnam	1954-	Cambodia, Laos
USSR	1945-1991	Afghanistan, Iran, Turkey

TABLE 5A.6. Data used to generate Communist-border variable.

In addition to the summary descriptive statistics presented above, we need to consider the possibility of multicollinearity in the data, which will reduce the significance of the estimates obtained. A common test is to see whether any bivariate correlations exceed 0.8 (cf. Kennedy 1992:180). There are a few such high correlations in the data. In particular, the correlation between the GDP and population variables is on the order of 0.75, and that between population and area about 0.7. GDP per capita is negatively correlated with mortality at about 0.73, and mortality is positively correlated with illiteracy at a level of about 0.8. Finally, the highest (and most surprising) correlation in the uninteracted dataset is between rights and democracy, a *negative* correlation of 0.85.[84]

In the interacted datasets some of these same patterns recur, since some of the variables just listed represent the same type of motivation. Thus humanitarianism*GDP/capita is negatively correlated (0.75) with humanitarianism*mortality rate, and the latter's correlation with humanitarianism*illiteracy is about 0.8. Similarly, the correlation power*GDP -

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84 The figures vary a little depending on how many observations are dropped due to missing values for other variables (i.e. there is some variation in the correlation from one regression to the next).

power*population is about 0.8, and in the Dutch case, power*GDP is also closely related to wealth * GDP (0.75). That same regression also features a very high correlation between two of the population interactions, power * population and prestige * population (0.89).[85]

No adjustment has been made for the potential impact of these high correlations in the regressions reported here. Simply dropping one of the affected variable pair will lead to misspecification (and all the shared variation would be attributed solely to the remaining variable) but is worth testing nonetheless, as are more sophisticated ways of allocating parts of the shared variance to each of the variables. Although several of these variables have statistically significant effects in the regressions as it is, others might well become significant if the collinearity is reduced or eliminated.

85 Full correlation matrices available upon request.

Appendix B – Regression results

In this appendix, I present more detailed results for the 8 regressions in the chapter. For each regression, I report the mean and standard deviation of each variable within the regression (i.e. excluding observations that were dropped due to missing variables), the estimated coefficient, its standard error, and the p-value of the coefficient estimate.[86] In addition, the last three columns report fitted values, along the same lines as in the overview tables in the main text. For the eligibility decision, I show the change (in percentage points) in the probability of receiving token aid or substantial aid, respectively, if the variable in question increases by a single standard deviation, holding all others at their mean (except for dummy variables, where the change is from one discrete value to another). For the amount decision, I show an adjusted coefficient estimate, calculated by taking the smallest change in the variable that produces a change in the expected value for the amount decision, and seeing how much that decision is changed. In addition, I show an adjusted coefficient for the more substantial change described in the last column (usually a single standard deviation, but from 0 to 1 for dummies). The latter is also presented in the main text table.

Finally, estimates for τ (the ordered probit threshold), σ (the standard deviation of the amount variable) and ρ (the correlation coefficient between the error terms of the two equations) are shown at the bottom. For the purposes of maximum likelihood estimation, we would prefer parameters to be estimated to range from $-\infty$ to $+\infty$. However, σ and

[86] For the variable names, s. stands for standardized, and l. for logged. Lags are as described in the text.

τ are bounded below by 0,[87] and ρ must be between -1 and 1. To get the desired bounds, I actually estimated ln(τ), ln(σ), and –ln(2/(ρ+1) –1). The estimates for these values and their standard errors are shown in the 4^{th} through 6^{th} columns of the table. The converted values — i.e. the actual ρ, σ, and τ — are shown in the second column.

Variable	Mean	Std. Dev.	Coefficient	Std. Err.	P>|z|	dP(0)	dP(1)	dP(2)	Change
Eligible, lag.	0.747	0.911	1.241	0.055	0.000	-18.57	-25.37	43.94	1->2
UN votes, s.	6.77E-11	0.995	0.112	0.042	0.008	-3.77	-0.09	3.87	1 s.d.
Comm. Bord.	0.072	0.259	-0.759	0.124	0.000	29.08	-8.98	-20.10	0->1
GDP, s.l.	3.61E-10	0.996	0.840	0.759	0.269	-21.60	-10.44	32.04	1 s.d.
Popul., s.l.	1.52E-10	0.997	-0.591	0.755	0.434	22.66	-6.62	-16.05	1 s.d.
Colony	0.016	0.127	3.435	206.378	0.987	-32.50	-40.86	73.36	0->1
Exports, s.l.	8.93E-11	0.996	-0.005	0.064	0.934	0.18	-0.01	-0.18	1 s.d.
Imports, s.l.	3.24E-10	0.995	-0.050	0.055	0.363	1.75	-0.11	-1.65	1 s.d.
Democracy, s	2.02E-09	0.995	-0.119	0.071	0.092	4.26	-0.40	-3.86	1 s.d.
Area, l.	11.140	2.798	0.092	0.032	0.004	-8.35	-0.91	9.25	1 s.d.
DAC share, l.	-5.874	7.278	0.039	0.010	0.000	-9.15	-1.14	10.30	1 s.d.
GDP/cap, s.l.	-3.55E-10	0.996	-0.667	0.436	0.126	25.62	-8.13	-17.49	1 s.d.
Mortality, s.	-7.00E-11	0.997	0.028	0.091	0.761	-0.95	0.02	0.94	1 s.d.
Illiteracy, s.	5.34E-10	0.995	0.005	0.072	0.943	-0.18	0.01	0.17	1 s.d.
Rights, s.	-2.85E-10	0.997	-0.242	0.086	0.005	8.91	-1.36	-7.55	1 s.d.
constant			-1.212	0.363	0.001				
						Adj. Coef.	*•E[]/•x*	*•E[]*	
Share, lag	-2.114	2.080	-0.00107	0.000	0.002	-0.00052	-0.00056	-0.001	1 s.d.
UN votes, s.	6.77E-11	0.995	0.09825	0.054	0.068	0.17700	0.02417	0.024	1 s.d.
Comm. Bord.	0.072	0.259	-0.13763	0.162	0.394		0.32701	0.327	0->1
GDP, s.l.	3.61E-10	0.996	1.84795	1.040	0.076	0.88000	1.34589	1.340	1 s.d.
Popul., s.l.	1.52E-10	0.997	-0.94863	1.029	0.356	-0.16600	-0.03907	-0.039	1 s.d.
Colony	0.016	0.127	3.71425	0.258	0.000		3.23670	3.237	0->1
Exports, s.l.	8.93E-11	0.996	-0.08919	0.079	0.257	0.11300	-0.04464	-0.044	1 s.d.
Imports, s.l.	3.24E-10	0.995	-0.25936	0.067	0.000	0.03600	-0.11259	-0.112	1 s.d.
Democracy, s	2.02E-09	0.995	-0.02530	0.085	0.766	0.18000	0.02633	0.026	1 s.d.
Area, l.	11.140	2.798	0.11990	0.048	0.013	0.03581	0.05012	0.140	1 s.d.
DAC share, l.	-5.874	7.278	0.05141	0.019	0.008	0.01542	0.02219	0.161	1 s.d.
GDP/cap, s.l.	-3.55E-10	0.996	-0.93483	0.604	0.122	-0.13600	0.02736	0.027	1 s.d.
Mortality, s.	-7.00E-11	0.997	0.16173	0.114	0.155	0.23500	0.08057	0.080	1 s.d.
Illiteracy, s.	5.34E-10	0.995	0.27738	0.086	0.001	0.30300	0.15219	0.151	1 s.d.
Rights, s.	-2.85E-10	0.997	-0.00220	0.106	0.983	0.22900	0.08582	0.086	1 s.d.
constant			-3.22269	0.581	0.000				
tau	1.085		0.082	0.056	0.143				
sigma	1.364		0.310	0.034	0.000				
rho	0.585		1.340	0.280	0.000				

TABLE 5B.1. Regression results: Belgium, basic regression.

Variable	Mean	Std. Dev.	Coefficient	Std. Err.	P>|z|	dP(0)	dP(1)	dP(2)	Change

87 In the case of τ, this is because the ordered probit estimation assumes that the lower of the two thresholds is fixed at 0.

Eligible, lag.	0.724	0.916	0.947	0.045	0.000	-1.40	-3.59	4.99	1->2
UN votes, s.	-9.11E-11	0.996	0.036	0.041	0.383	-0.22	-0.35	0.57	1 s.d.
Comm. Bord.	0.072	0.259	-0.371	0.128	0.004	3.23	4.21	-7.45	0->1
GDP, s.l.	3.61E-10	0.996	-1.156	0.719	0.108	19.60	14.07	-33.67	1 s.d.
Popul., s.l.	1.52E-10	0.997	1.016	0.715	0.155	-2.64	-5.55	8.18	1 s.d.
Exports, s.l.	-6.61E-10	0.995	0.217	0.071	0.002	-1.13	-1.93	3.06	1 s.d.
Imports, s.l.	1.79E-10	0.995	0.078	0.062	0.205	-0.47	-0.75	1.21	1 s.d.
Democracy, s	2.02E-09	0.995	0.113	0.067	0.090	-0.65	-1.06	1.71	1 s.d.
Area, l.	11.140	2.798	0.128	0.030	0.000	-1.64	-2.94	4.58	1 s.d.
DAC share, l.	-5.874	7.278	0.029	0.010	0.004	-1.12	-1.90	3.02	1 s.d.
GDP/cap, s.l.	-3.55E-10	0.996	0.361	0.414	0.384	-1.65	-2.95	4.60	1 s.d.
Mortality, s.	-7.00E-11	0.997	-0.049	0.089	0.583	0.33	0.50	-0.83	1 s.d.
Illiteracy, s.	5.34E-10	0.995	0.014	0.071	0.839	-0.09	-0.14	0.23	1 s.d.
Rights, s.	-2.85E-10	0.997	0.032	0.082	0.691	-0.20	-0.32	0.52	1 s.d.
constant			-1.757	0.342	0.000				
						Adj. Coef.	*•E[]/•x*	*•E[]*	
Share, lag	-1.761	2.199	-0.00062	0.000	0.041	-0.00023	-0.00029	-0.001	1 s.d.
UN votes, s.	-9.11E-11	0.996	-0.11190	0.061	0.066	-0.06700	-0.06548	-0.065	1 s.d.
Comm. Bord.	0.072	0.259	0.23079	0.171	0.178		0.27291	0.273	0->1
GDP, s.l.	3.61E-10	0.996	0.64994	1.223	0.595	0.76000	0.87324	0.870	1 s.d.
Popul., s.l.	1.52E-10	0.997	-0.70011	1.210	0.563	-0.72900	-0.56725	-0.566	1 s.d.
Exports, s.l.	-6.61E-10	0.995	0.74457	0.102	0.000	0.25700	0.34505	0.343	1 s.d.
Imports, s.l.	1.79E-10	0.995	-0.26991	0.097	0.006	-0.15600	-0.15246	-0.152	1 s.d.
Democracy, s	2.02E-09	0.995	-0.12801	0.101	0.206	-0.10500	-0.10252	-0.102	1 s.d.
Area, l.	11.140	2.798	0.41766	0.055	0.000	0.14241	0.22061	0.617	1 s.d.
DAC share, l.	-5.874	7.278	0.05977	0.021	0.004	0.01599	0.02201	0.160	1 s.d.
GDP/cap, s.l.	-3.55E-10	0.996	-0.84841	0.696	0.223	-0.53600	-0.49681	-0.495	1 s.d.
Mortality, s.	-7.00E-11	0.997	0.11195	0.127	0.378	0.07100	0.07171	0.071	1 s.d.
Illiteracy, s.	5.34E-10	0.995	-0.09192	0.098	0.346	-0.04900	-0.04768	-0.047	1 s.d.
Rights, s.	-2.85E-10	0.997	-0.42080	0.121	0.001	-0.20800	-0.19562	-0.195	1 s.d.
constant			-6.57113	0.685	0.000				
tau	*0.577*		-0.550	0.068	0.000				
sigma	*1.499*		0.405	0.038	0.000				
rho	*0.454*		0.978	0.289	0.001				

TABLE 5B.2. Regression results: Italy, basic regression.

Variable	Mean	Std. Dev.	Coefficient	Std. Err.	P>|z|	dP(0)	dP(1)	dP(2)	Change
Eligible, lag.	0.818	0.929	1.285	0.065	0.000	-16.26	-26.38	42.64	1->2
UN votes, s.	1.15E-10	0.995	0.029	0.046	0.538	-0.88	-0.19	1.07	1 s.d.
Comm. Bord.	0.072	0.259	-0.194	0.172	0.259	6.41	0.62	-7.02	0->1
GDP, s.l.	3.61E-10	0.996	0.068	0.812	0.933	-2.08	-0.50	2.58	1 s.d.
Popul., s.l.	1.52E-10	0.997	0.261	0.812	0.748	-7.37	-2.73	10.10	1 s.d.
Colony	0.021	0.145	-0.886	0.406	0.029	33.03	-7.32	-25.71	0->1
Exports, s.l.	2.14E-10	0.996	-0.138	0.074	0.064	4.50	0.51	-5.01	1 s.d.
Imports, s.l.	1.20E-09	0.995	0.040	0.060	0.506	-1.22	-0.27	1.49	1 s.d.
Democracy, s	2.02E-09	0.995	-0.069	0.078	0.381	2.18	0.34	-2.52	1 s.d.
Area, l.	11.140	2.798	-0.002	0.032	0.951	0.17	0.03	-0.20	1 s.d.
DAC share, l.	-5.874	7.278	0.038	0.012	0.001	-7.84	-3.01	10.85	1 s.d.
GDP/cap, s.l.	-3.55E-10	0.996	-0.344	0.465	0.459	11.86	-0.01	-11.85	1 s.d.
Mortality, s.	-7.00E-11	0.997	0.235	0.112	0.036	-6.69	-2.35	9.04	1 s.d.
Illiteracy, s.	5.34E-10	0.995	-0.156	0.087	0.072	5.13	0.52	-5.65	1 s.d.
Rights, s.	-2.85E-10	0.997	-0.305	0.097	0.002	10.44	0.20	-10.64	1 s.d.
constant			-0.074	0.383	0.847				
						Adj. Coef.	*•E[]/•x*	*•E[]*	
Share, lag	-2.006	2.187	0.00013	0.000	0.750	0.00005	0.00007	0.000	1 s.d.
UN votes, s.	1.15E-10	0.995	-0.20810	0.051	0.000	-0.12300	-0.11942	-0.119	1 s.d.
Comm. Bord.	0.072	0.259	0.12045	0.117	0.305		0.14564	0.146	0->1
GDP, s.l.	3.61E-10	0.996	2.33291	0.910	0.010	1.24200	1.74817	1.741	1 s.d.

Popul., s.l.	1.52E-10	0.997	-1.72349	0.892	0.053	-1.03300	-0.76143	-0.759	1 s.d.
Colony	0.021	0.145	1.36267	0.292	0.000		1.17385	1.174	0->1
Exports, s.l.	2.14E-10	0.996	0.13461	0.066	0.041	0.12600	0.12885	0.128	1 s.d.
Imports, s.l.	1.20E-09	0.995	-0.26455	0.057	0.000	-0.15800	-0.15165	-0.151	1 s.d.
Democracy, s	2.02E-09	0.995	-0.00028	0.070	0.997	0.02600	0.02671	0.027	1 s.d.
Area, l.	11.140	2.798	0.21340	0.037	0.000	0.11659	0.13036	0.365	1 s.d.
DAC share, l.	-5.874	7.278	0.10973	0.021	0.000	0.04515	0.06107	0.444	1 s.d.
GDP/cap, s.l.	-3.55E-10	0.996	-2.25599	0.524	0.000	-1.09400	-0.51498	-0.513	1 s.d.
Mortality, s.	-7.00E-11	0.997	0.07216	0.091	0.426	-0.04700	-0.03323	-0.033	1 s.d.
Illiteracy, s.	5.34E-10	0.995	-0.31115	0.072	0.000	-0.10900	-0.08689	-0.086	1 s.d.
Rights, s.	-2.85E-10	0.997	-0.30574	0.090	0.001	-0.05100	-0.00376	-0.004	1 s.d.
constant			-4.25830	0.451	0.000				
tau	*1.054*		0.053	0.064	0.407				
sigma	*1.187*		0.172	0.025	0.000				
rho	*0.234*		0.477	0.258	0.065				

TABLE 5B.3. Regression results: Netherlands, basic regression.

Variable	Mean	Std. Dev.	Coefficient	Std. Err.	P>|z|	dP(0)	dP(1)	dP(2)	Change
Eligible, lag.	0.574	0.875	1.075	0.053	0.000	-31.17	-9.54	40.71	1->2
UN votes, s.	2.49E-10	0.995	-0.029	0.045	0.519	1.13	-0.36	-0.77	1 s.d.
Comm. Bord.	0.072	0.259	-0.004	0.151	0.980	0.15	-0.05	-0.10	0->1
GDP, s.l.	3.61E-10	0.996	2.477	0.946	0.009	-57.54	-18.11	75.65	1 s.d.
Popul., s.l.	1.52E-10	0.997	-2.190	0.935	0.019	40.42	-21.97	-18.45	1 s.d.
Exports, s.l.	7.50E-10	0.994	0.045	0.052	0.394	-1.74	0.53	1.21	1 s.d.
Imports, s.l.	5.88E-11	0.993	-0.163	0.054	0.003	6.16	-2.15	-4.01	1 s.d.
Democracy, s	2.02E-09	0.995	0.017	0.078	0.826	-0.67	0.21	0.46	1 s.d.
Area, l.	11.140	2.798	0.002	0.037	0.954	-0.23	0.07	0.16	1 s.d.
DAC share, l.	-5.874	7.278	0.022	0.012	0.063	-6.35	1.74	4.61	1 s.d.
GDP/cap, s.l.	-3.55E-10	0.996	-2.017	0.554	0.000	39.94	-21.57	-18.37	1 s.d.
Mortality, s.	-7.00E-11	0.997	-0.006	0.113	0.960	0.22	-0.07	-0.15	1 s.d.
Illiteracy, s.	5.34E-10	0.995	-0.053	0.091	0.558	2.05	-0.67	-1.38	1 s.d.
Rights, s.	-2.85E-10	0.997	-0.218	0.099	0.028	8.20	-2.96	-5.25	1 s.d.
constant			-0.732	0.430	0.088				
						Adj. Coef.	*•E[]/•x*	*•E[]*	
Share, lag	-1.551	2.182	0.00070	0.001	0.235	0.00032	0.00027	0.001	1 s.d.
UN votes, s.	2.49E-10	0.995	-0.45148	0.105	0.000	-0.15500	-0.13851	-0.138	1 s.d.
Comm. Bord.	0.072	0.259	0.77289	0.198	0.000		0.33752	0.338	0->1
GDP, s.l.	3.61E-10	0.996	-0.55113	1.820	0.762	-1.71600	-0.72367	-0.721	1 s.d.
Popul., s.l.	1.52E-10	0.997	0.54977	1.792	0.759	1.54000	1.40647	1.402	1 s.d.
Exports, s.l.	7.50E-10	0.994	0.44134	0.086	0.000	0.14000	0.15837	0.157	1 s.d.
Imports, s.l.	5.88E-11	0.993	-0.19428	0.101	0.054	0.02400	0.03901	0.039	1 s.d.
Democracy, s	2.02E-09	0.995	0.15578	0.142	0.273	0.04800	0.05107	0.051	1 s.d.
Area, l.	11.140	2.798	0.12975	0.080	0.106	0.04812	0.05149	0.144	1 s.d.
DAC share, l.	-5.874	7.278	0.13020	0.044	0.003	0.03614	0.04970	0.362	1 s.d.
GDP/cap, s.l.	-3.55E-10	0.996	-1.27707	1.081	0.238	0.74000	1.29614	1.291	1 s.d.
Mortality, s.	-7.00E-11	0.997	-0.70341	0.184	0.000	-0.26500	-0.23232	-0.232	1 s.d.
Illiteracy, s.	5.34E-10	0.995	0.11691	0.149	0.433	0.07600	0.07720	0.077	1 s.d.
Rights, s.	-2.85E-10	0.997	-0.00958	0.182	0.958	0.12900	0.13954	0.139	1 s.d.
constant			-3.33660	0.973	0.001				
tau	*0.673*		-0.396	0.073	0.000				
sigma	*1.560*		0.445	0.038	0.000				
rho	*0.170*		0.343	0.302	0.256				

TABLE 5B.4. Regression results: Norway, basic regression.

Variable	Mean	Std. Dev.	Coefficient	Std. Err.	P>|z|	dP(0)	dP(1)	dP(2)	Change

Eligible lag	0.747	0.911	1.363	0.087	0.000	-16.33	-27.64	43.97	1->2
secUN	0.000	0.516	-0.123	0.154	0.422	4.25	0.03	-4.28	0->1sdu
secComm	0.021	0.167	-0.741	0.370	0.045	28.13	-7.06	-21.07	0->1
weaGDP	0.009	1.734	-0.092	0.059	0.120	3.14	0.08	-3.21	0->1sdu
weaEx	0.003	1.847	-0.035	0.061	0.570	1.16	0.06	-1.23	0->1sdu
weaIm	0.003	1.846	0.026	0.055	0.640	-0.85	-0.07	0.92	0->1sdu
esiPop	0.011	1.449	-0.092	0.060	0.125	3.13	0.08	-3.21	0->1sdu
esiDemoc	-0.009	1.497	0.034	0.033	0.313	-1.11	-0.10	1.21	0->1sdu
esiArea	10.744	14.095	0.009	0.004	0.046	-4.06	-0.15	4.22	0->1sdu
gloPop	0.012	1.414	0.242	0.073	0.001	-7.47	-1.61	9.08	0->1sdu
gloUN	-0.005	1.378	0.082	0.048	0.090	-2.65	-0.32	2.97	0->1sdu
gloODA	-6.967	12.198	0.023	0.010	0.022	-0.94	-0.27	1.21	0->1sdu
dutCol	0.030	0.267	2.098	28.318	0.941	-29.34	-34.83	64.17	0->1
dutODA	-10.153	15.238	-0.010	0.009	0.251	0.51	-0.02	-0.49	0->1sdu
dutEx	0.002	2.011	0.009	0.044	0.836	-0.30	-0.02	0.33	0->1sdu
humCap	-0.036	2.411	-0.096	0.042	0.023	3.27	0.06	-3.33	0->1sdu
humMort	0.007	2.367	-0.008	0.055	0.880	0.28	0.02	-0.30	0->1sdu
humLit	0.000	2.363	-0.052	0.043	0.233	1.75	0.08	-1.83	0->1sdu
humRight	0.012	2.459	-0.041	0.036	0.244	1.40	0.07	-1.47	0->1sdu
constant			-0.514	0.150	0.001				
						Adj. Coef.	*•E[]/•x*	*•E[]*	
Share lag	-2.114	2.080	-0.00243	0.001	0.000	-0.00200	-0.00137	-0.00284	1 s.d.
secUN	0.000	0.516	0.43470	0.277	0.117	0.24000	0.24846	0.24722	0->1sdu
secComm	0.021	0.167	-0.18526	0.660	0.779	-0.12900	-0.00100	-0.00100	0->1
weaGDP	0.009	1.734	0.01466	0.086	0.864	0.00500	0.00598	0.00595	0->1sdu
weaEx	0.003	1.847	0.02632	0.088	0.765	0.01300	0.01371	0.01365	0->1sdu
weaIm	0.003	1.846	-0.13906	0.079	0.080	-0.07800	-0.07634	-0.07595	0->1sdu
esiPop	0.011	1.449	0.18816	0.097	0.053	0.10200	0.10386	0.10355	0->1sdu
esiDemoc	-0.009	1.497	-0.05543	0.048	0.249	-0.03100	-0.02999	-0.02983	0->1sdu
esiArea	10.744	14.095	0.00345	0.007	0.630	0.00200	0.00212	0.02948	0->1sdu
gloPop	0.012	1.414	0.28368	0.092	0.002	0.16800	0.18792	0.18737	0->1sdu
gloUN	-0.005	1.378	-0.14473	0.081	0.073	-0.07900	-0.07808	-0.07769	0->1sdu
gloODA	-6.967	12.198	0.06004	0.025	0.016	0.03400	0.04243	0.05958	0->1sdu
dutCol	0.030	0.267	1.25482	0.241	0.000	0.77500	1.02917	1.02917	0->1
dutODA	-10.153	15.238	-0.01265	0.021	0.539	-0.00800	-0.00642	-0.00902	0->1sdu
dutEx	0.002	2.011	0.00827	0.075	0.912	0.00500	0.00498	0.00496	0->1sdu
humCap	-0.036	2.411	0.00415	0.079	0.958	-0.00100	0.00025	0.00025	0->1sdu
humMort	0.007	2.367	0.11956	0.097	0.220	0.06700	0.06800	0.06777	0->1sdu
humLit	0.000	2.363	0.05659	0.073	0.436	0.03000	0.03024	0.03010	0->1sdu
humRight	0.012	2.459	0.02646	0.059	0.655	0.01300	0.01360	0.01356	0->1sdu
constant			-1.62903	0.171	0.000				
lntau	1.053		0.052	0.090	0.564				
lnsigma	1.710		0.537	0.066	0.000				
xrho	0.867		2.642	0.541	0.000				

TABLE 5B.5. Regression results: Belgium, interacted regression.

Variable	Mean	Std. Dev.	Coefficient	Std. Err.	P>|z|	dP(0)	dP(1)	dP(2)	Change
Eligible lag	0.724	0.916	1.051	0.074	0.000	-25.76	-10.39	36.15	1->2
secUN	-0.016	1.255	0.338	0.242	0.162	-12.63	-0.57	13.20	0->1sdu
secComm	0.037	0.265	-0.594	0.541	0.272	23.24	-3.80	-19.44	0->1
powUN	-0.016	1.216	0.070	0.100	0.481	-2.73	0.07	2.66	0->1sdu
powGDP	0.000	1.268	-0.348	0.236	0.140	13.77	-1.69	-12.08	0->1sdu
powPop	0.007	1.167	0.238	0.223	0.287	-9.07	-0.14	9.21	0->1sdu
weaGDP	0.006	1.985	0.016	0.066	0.805	-0.64	0.02	0.61	0->1sdu
weaEx	-0.006	2.220	0.030	0.064	0.635	-1.19	0.04	1.14	0->1sdu
weaIm	-0.005	2.228	0.044	0.052	0.393	-1.73	0.06	1.68	0->1sdu
esiPop	0.014	1.663	0.008	0.073	0.908	-0.33	0.01	0.31	0->1sdu
esiDemoc	-0.003	1.269	-0.009	0.040	0.830	0.34	-0.02	-0.32	0->1sdu
esiArea	10.382	11.305	-0.001	0.006	0.895	0.41	-0.02	-0.40	0->1sdu
gloPop	0.018	2.042	0.189	0.057	0.001	-7.25	-0.02	7.26	0->1sdu

gloUN	-0.021	2.058	-0.011	0.034	0.756	0.42	-0.02	-0.40	0->1sdu
gloODA	-7.314	14.674	-0.007	0.010	0.498	0.37	-0.03	-0.35	0->1sdu
dutODA	-7.033	12.168	0.020	0.022	0.365	-1.08	-0.04	1.11	0->1sdu
dutEx	-0.006	1.633	0.056	0.106	0.596	-2.20	0.06	2.14	0->1sdu
humCap	-0.031	2.233	-0.031	0.056	0.578	1.22	-0.06	-1.16	0->1sdu
humMort	0.007	2.132	0.018	0.065	0.777	-0.72	0.03	0.69	0->1sdu
humLit	0.000	2.124	-0.021	0.049	0.670	0.81	-0.04	-0.77	0->1sdu
humRight	0.013	2.432	-0.066	0.039	0.091	2.58	-0.15	-2.43	0->1sdu
constant			-0.468	0.141	0.001				
						Adj. Coef.	*•E[]/•x*	*•E[]*	
Share lag	-1.761	2.199	-0.00185	0.000	0.000	-0.00100	-0.00089	-0.00196	1 s.d.
secUN	-0.016	1.255	-0.58333	0.412	0.157	-0.42600	-0.29577	-0.29447	0->1sdu
secComm	0.037	0.265	1.22154	0.856	0.154	0.63900	0.65181	0.65181	0->1
powUN	-0.016	1.216	0.01152	0.155	0.941	-0.11600	0.00063	0.00063	0->1sdu
powGDP	0.000	1.268	0.05823	0.421	0.890	0.05800	0.08181	0.08147	0->1sdu
powPop	0.007	1.167	0.59585	0.397	0.133	0.26600	0.32592	0.32496	0->1sdu
weaGDP	0.006	1.985	0.05858	0.106	0.581	0.02700	0.02725	0.02714	0->1sdu
weaEx	-0.006	2.220	0.04707	0.105	0.653	-0.09500	0.02064	0.02055	0->1sdu
weaIm	-0.005	2.228	-0.03605	0.093	0.698	-0.13700	-0.02099	-0.02089	0->1sdu
esiPop	0.014	1.663	0.16975	0.120	0.157	0.08100	0.08327	0.08303	0->1sdu
esiDemoc	-0.003	1.269	-0.02858	0.069	0.678	-0.01300	-0.01289	-0.01282	0->1sdu
esiArea	10.382	11.305	0.00048	0.010	0.963	0.00030	0.00029	0.00410	0->1sdu
gloPop	0.018	2.042	0.10107	0.073	0.164	0.03200	0.04239	0.04226	0->1sdu
gloUN	-0.021	2.058	-0.07009	0.053	0.189	-0.03200	-0.03227	-0.03213	0->1sdu
gloODA	-7.314	14.674	0.00089	0.022	0.967	0.00100	0.00114	0.00160	0->1sdu
dutODA	-7.033	12.168	0.06773	0.053	0.198	0.03500	0.04095	0.05750	0->1sdu
dutEx	-0.006	1.633	0.43075	0.179	0.016	0.09600	0.22140	0.22039	0->1sdu
humCap	-0.031	2.233	-0.03162	0.090	0.727	0.91300	-0.01205	-0.01200	0->1sdu
humMort	0.007	2.132	0.18687	0.107	0.079	-0.02000	0.09155	0.09124	0->1sdu
humLit	0.000	2.124	-0.06365	0.081	0.430	-0.14700	-0.02822	-0.02809	0->1sdu
humRight	0.013	2.432	-0.03671	0.063	0.558	-0.01100	-0.01063	-0.01059	0->1sdu
constant			-1.61976	0.208	0.000				
tau	0.509		-0.675	0.118	0.000				
sigma	1.781		0.577	0.070	0.000				
rho	0.789		2.139	0.462	0.000				

TABLE 5B.6. Regression results: Italy, interacted regression.

Variable	Mean	Std. Dev.	Coefficient	Std. Err.	P>|z|	dP(0)	dP(1)	dP(2)	Change
Eligible lag	0.818	0.929	1.360	0.106	0.000	-12.42	-32.24	44.66	1->2
powUN	-0.007	0.668	0.766	0.292	0.009	-13.90	-15.80	29.69	0->1sdu
powGDP	0.001	0.650	0.015	0.295	0.960	-0.40	-0.15	0.55	0->1sdu
powPop	0.005	0.635	-0.229	0.462	0.621	6.79	1.18	-7.97	0->1sdu
powCol	0.010	0.098	-3.510	77.043	0.964	81.40	-45.59	-35.81	0->1
weaGDP	0.003	0.771	-0.052	0.224	0.816	1.45	0.45	-1.90	0->1sdu
weaEx	0.000	0.812	-0.217	0.140	0.123	6.40	1.16	-7.56	0->1sdu
weaIm	0.001	0.812	0.031	0.111	0.782	-0.82	-0.31	1.14	0->1sdu
esiPop	0.007	0.860	0.085	0.125	0.499	-2.22	-0.95	3.17	0->1sdu
esiDemoc	-0.002	0.923	0.012	0.091	0.893	-0.33	-0.12	0.45	0->1sdu
esiArea	7.345	7.416	0.020	0.010	0.037	-7.79	-2.65	10.44	0->1sdu
gloPop	0.011	1.154	0.349	0.264	0.187	-8.03	-5.43	13.46	0->1sdu
gloUN	-0.007	1.151	-0.276	0.185	0.136	8.33	1.13	-9.45	0->1sdu
gloODA	-6.057	9.908	0.038	0.019	0.040	-1.13	-1.00	2.13	0->1sdu
dutCol	0.024	0.183	2.424	77.037	0.975	-20.64	-44.51	65.15	0->1
dutODA	-7.745	11.142	0.019	0.015	0.204	-0.63	-0.42	1.05	0->1sdu
dutEx	0.000	1.230	0.171	0.119	0.150	-4.28	-2.18	6.46	0->1sdu
humCap	-0.051	3.227	-0.126	0.037	0.001	3.62	0.87	-4.49	0->1sdu
humMort	0.007	3.158	0.082	0.049	0.095	-2.14	-0.92	3.06	0->1sdu
humLit	0.000	3.152	-0.072	0.039	0.066	2.01	0.59	-2.61	0->1sdu
humRight	0.022	3.603	-0.085	0.034	0.012	2.38	0.69	-3.07	0->1sdu
constant			-0.035	0.202	0.862				

						Adj. Coef.	*•E[]/•x*	*•E[]*	
Share lag	-2.006	2.187	0.00009	0.001	0.865	0.00005	0.00005	0.00010	1 s.d.
powUN	-0.007	0.668	-0.11250	0.329	0.733	-0.34900	-0.23454	-0.23335	0->1sdu
powGDP	0.001	0.650	0.34832	0.278	0.210	0.17900	0.19264	0.19184	0->1sdu
powPop	0.005	0.635	-0.68473	0.370	0.064	-0.27600	-0.19663	-0.19606	0->1sdu
powCol	0.010	0.098	0.92302	0.896	0.303	1.86700	1.95748	1.95748	0->1
weaGDP	0.003	0.771	-0.17723	0.194	0.362	-0.07400	-0.06911	-0.06882	0->1sdu
weaEx	0.000	0.812	-0.00415	0.115	0.971	0.08000	0.09166	0.09125	0->1sdu
weaIm	0.001	0.812	-0.13664	0.103	0.185	-0.08400	-0.08240	-0.08199	0->1sdu
esiPop	0.007	0.860	0.64001	0.107	0.000	0.30600	0.35885	0.35780	0->1sdu
esiDemoc	-0.002	0.923	0.03516	0.076	0.645	0.01500	0.01427	0.01419	0->1sdu
esiArea	7.345	7.416	-0.01903	0.010	0.062	-0.01800	-0.01787	-0.24905	0->1sdu
gloPop	0.011	1.154	0.58816	0.219	0.007	0.18100	0.26516	0.26438	0->1sdu
gloUN	-0.007	1.151	-0.31597	0.216	0.144	-0.06200	-0.02131	-0.02120	0->1sdu
gloODA	-6.057	9.908	0.08064	0.037	0.030	0.02900	0.04672	0.06560	0->1sdu
dutCol	0.024	0.183	0.85153	0.495	0.086	-0.51600	0.35704	0.35704	0->1
dutODA	-7.745	11.142	0.07043	0.034	0.040	0.01600	0.04321	0.06067	0->1sdu
dutEx	0.000	1.230	0.02697	0.087	0.756	-0.78800	-0.04281	-0.04262	0->1sdu
humCap	-0.051	3.227	-0.26385	0.040	0.000	-2.51300	-0.07518	-0.07487	0->1sdu
humMort	0.007	3.158	0.03308	0.038	0.388	-0.01300	-0.01141	-0.01137	0->1sdu
humLit	0.000	3.152	-0.08396	0.031	0.007	-0.05100	-0.01445	-0.01438	0->1sdu
humRight	0.022	3.603	-0.05523	0.029	0.059	0.00300	0.00537	0.00535	0->1sdu
constant			-1.44175	0.136	0.000				
tau	1.274		0.242	0.102	0.018				
sigma	1.229		0.207	0.039	0.000				
rho	0.171		0.345	0.370	0.352				

TABLE 5B.7. Regression results: Netherlands, interacted regression.

Variable	Mean	Std. Dev.	Coefficient	Std. Err.	P>|z|	dP(0)	dP(1)	dP(2)	Change
Eligible lag	0.574	0.875	1.242	0.094	0.000	-27.10	-15.96	43.06	1->2
secUN	0.000	0.335	0.419	0.311	0.178	-16.27	1.85	14.42	0->1sdu
secComm	0.014	0.116	-0.086	0.561	0.878	3.41	-0.87	-2.54	0->1
powUN	0.000	0.367	0.325	0.171	0.058	-12.75	1.81	10.94	0->1sdu
powGDP	0.001	0.382	-0.005	0.405	0.989	0.22	-0.05	-0.16	0->1sdu
powPop	0.002	0.368	0.043	0.466	0.927	-1.71	0.38	1.33	0->1sdu
weaGDP	0.001	0.360	-0.448	0.200	0.025	17.05	-5.76	-11.29	0->1sdu
weaEx	0.000	0.358	0.292	0.184	0.112	-11.49	1.74	9.75	0->1sdu
weaIm	0.000	0.354	-0.165	0.193	0.393	6.49	-1.78	-4.70	0->1sdu
esiPop	0.011	1.265	0.048	0.169	0.775	-1.93	0.43	1.50	0->1sdu
esiDemoc	-0.004	1.159	0.002	0.091	0.982	-0.08	0.02	0.06	0->1sdu
esiArea	9.592	9.836	-0.007	0.011	0.538	3.80	-0.85	-2.95	0->1sdu
gloPop	0.015	1.575	0.209	0.086	0.015	-8.30	1.47	6.82	0->1sdu
gloUN	-0.006	1.690	-0.086	0.039	0.029	3.38	-0.86	-2.52	0->1sdu
gloODA	-7.623	12.790	-0.023	0.012	0.064	1.25	-0.41	-0.84	0->1sdu
dutODA	-6.488	11.049	-0.001	0.016	0.952	0.06	-0.01	-0.04	0->1sdu
dutEx	0.000	1.241	-0.130	0.070	0.066	5.11	-1.36	-3.75	0->1sdu
humCap	-0.054	3.161	-0.164	0.045	0.000	6.47	-1.81	-4.66	0->1sdu
humMort	0.007	3.122	-0.035	0.051	0.488	1.41	-0.34	-1.07	0->1sdu
humLit	0.000	3.117	0.055	0.043	0.201	-2.18	0.48	1.70	0->1sdu
humRight	0.019	3.334	-0.108	0.034	0.001	4.28	-1.11	-3.17	0->1sdu
constant			-0.878	0.140	0.000				
						Adj. Coef.	*•E[]/•x*	*•E[]*	
Share lag	-1.551	2.182	-0.00092	0.001	0.300	-0.00100	-0.00051	-0.00111	1 s.d.
secUN	0.000	0.335	-0.28848	1.251	0.818	-0.20800	-0.20538	-0.20434	0->1sdu
secComm	0.014	0.116	2.20442	0.827	0.008	1.23500	1.51857	1.51857	0->1
powUN	0.000	0.367	-1.09720	0.432	0.011	-0.64300	-0.59333	-0.59034	0->1sdu
powGDP	0.001	0.382	-1.23216	0.843	0.144	-0.68300	-0.56216	-0.55983	0->1sdu
powPop	0.002	0.368	0.51580	0.681	0.449	0.27900	0.30550	0.30461	0->1sdu
weaGDP	0.001	0.360	0.66813	0.336	0.046	0.43500	0.44066	0.43883	0->1sdu

weaEx	0.000	0.358	-0.24690	0.287	0.390	-0.16700	-0.17201	-0.17105	0->1sdu
weaIm	0.000	0.354	-0.80902	0.319	0.011	-0.41400	-0.34384	-0.34133	0->1sdu
esiPop	0.011	1.265	-0.09252	0.238	0.697	-0.05900	-0.05799	-0.05782	0->1sdu
esiDemoc	-0.004	1.159	0.10159	0.141	0.472	0.05600	0.05694	0.05663	0->1sdu
esiArea	9.592	9.836	0.02156	0.019	0.267	0.01300	0.01283	0.17888	0->1sdu
gloPop	0.015	1.575	0.11755	0.125	0.346	0.03500	0.04707	0.04693	0->1sdu
gloUN	-0.006	1.690	-0.14420	0.092	0.116	-0.06800	-0.06238	-0.06206	0->1sdu
gloODA	-7.623	12.790	0.03023	0.037	0.413	0.02000	0.02047	0.02874	0->1sdu
dutODA	-6.488	11.049	0.02973	0.051	0.561	0.02700	0.01757	0.02468	0->1sdu
dutEx	0.000	1.241	0.35037	0.121	0.004	-0.09700	0.21674	0.21553	0->1sdu
humCap	-0.054	3.161	-0.44766	0.084	0.000	0.11600	-0.18599	-0.18521	0->1sdu
humMort	0.007	3.122	-0.13790	0.079	0.082	-0.06000	-0.06881	-0.06857	0->1sdu
humLit	0.000	3.117	-0.00327	0.068	0.962	0.05900	-0.00921	-0.00917	0->1sdu
humRight	0.019	3.334	-0.07411	0.055	0.176	-0.02600	-0.02164	-0.02157	0->1sdu
constant			-1.65136	0.274	0.000				
tau	0.689		-0.373	0.115	0.001				
sigma	1.614		0.478	0.082	0.000				
rho	0.590		1.355	0.666	0.042				

TABLE 5B.8. Regression results: Norway, interacted regression.

Appendix C – Expected Values

As discussed in the text, the expected value of the amount decision is not simply equal to xβ as would be the case for a normal OLS regression. Instead, both the selection and the truncation processes introduce complications. Individually, these are not too hard to model. For example, starting with E[w*]=μ=xβ, and truncating at T, we get:

$$E[w_i] = E[w_i^* | truncation] = x_i\beta + \sigma\lambda^t(\alpha_u)$$

where $\alpha_u = \dfrac{T - x_i\beta}{\sigma}$ and $\lambda^t(\alpha) = \dfrac{\phi(\alpha_u)}{\Phi(-\alpha_u)} = \dfrac{\phi\left(\dfrac{T - x_i\beta}{\sigma}\right)}{\Phi\left(\dfrac{x_i\beta - T}{\sigma}\right)}$

Analogously, starting with the same E[w*]=μ=xβ, and selecting conditional on y = 2:[88]

$$\begin{aligned} E[w^* | y_i = 2] &= E[w^* | y^* > \tau] \\ &= E[w^* | \varepsilon_i > \tau - z_i\gamma] \\ &= E[w^*] + E[\sigma u_i | \varepsilon_i > \tau - z_i\gamma] \\ &= E[w^*] + \rho\sigma\lambda^c(\alpha_\varepsilon) \end{aligned}$$

where $\alpha_\varepsilon = \tau - z_i\gamma$ and $\lambda^c(\alpha) = \dfrac{\phi(\alpha)}{\Phi(-\alpha)} = \dfrac{\varphi(\tau - z_i\gamma)}{\Phi(z_i\gamma - \tau)}$

Although these two expressions give an indication of the type and direction of the changes in the expected value for the amount decision, it is not possible to combine them in a straightforward way. Instead, we must go back to the definition for the expectation of a random variable:

$$E[x] = \int_x x f(x) dx$$

where f(x) is the density function for the variable x. We have an expression for the density function of our model, as derived in the text:

$$\psi(w,2|x,z)=\frac{1}{\sigma}\Phi\left(\frac{z\gamma-\tau-\rho J(u)}{\sqrt{(1-\rho^2)}}\right)*\frac{\varphi(u)}{\Phi\left(\frac{x\beta-T}{\sigma}\right)}$$

What we need to do then, is evaluate the integral of this expression multiplied by w over the full range of w, i.e. from T to infinity:[89]

$$\int_T^\infty \frac{w}{\sigma}\Phi\left(\frac{z\gamma-\tau-\rho J(u)}{\sqrt{(1-\rho^2)}}\right)*\frac{\varphi(u)}{\Phi\left(\frac{x\beta-T}{\sigma}\right)}dw$$

The error term *u* can be expressed in terms of w, i.e. *u* = (w-xβ)/σ, and it is necessary to make that substitution in order to be able to evaluate this expression:[90]

$$\int_T^\infty \frac{w}{\sigma}\Phi\left(\frac{z\gamma-\tau-\rho J\left(\frac{w-x\beta}{\sigma}\right)}{\sqrt{(1-\rho^2)}}\right)*\frac{\varphi\left(\frac{w-x\beta}{\sigma}\right)}{\Phi\left(\frac{x\beta-T}{\sigma}\right)}dw$$

No straightforward expression for this integral suggests itself, so it needs to be tackled by numerical integration. I use the Simpson's rule method, which provides a quadratic approximation to the area under a curve:

$$Simpson(x,\Delta x,f())=\left(2*f(x)+0.5*\left(f\left(x-\tfrac{\Delta x}{2}\right)+f\left(x+\tfrac{\Delta x}{2}\right)\right)\right)/3$$

---

88 Note the error in Greene (1993:709): the minus-sign is missing inside the parentheses in the dividend of the expression for λ. Cf. also Greene (1993:707).

89 Strictly speaking, the aid share w can only go as high as ln(100) • 4.6, but since the model assumes truncated OLS, the theoretical range is indeed up to infinity. In practice, I stop the numerical approximation process at w•10. It is easy enough to calculate the maximum possible loss from this truncation by noting that the complicated expression Φ(zγ-τ…) is bounded above by 1. Replacing it by 1 in the equation renders the latter integrable. Calculating the integral from the cut-off point to infinity shows that a cut-off around 10 leaves a maximum cut-off error size on the order of 10^{-9}.

90 Note that neither xβ nor zγ are functions of w and both can thus be treated as constants in this context

where x is the midpoint of an interval of width Δx and f(x) is the function whose integral is to be approximated. In approximating E[w], I use a step-size of $\Delta x = 0.005$, which appears to provide a reasonable compromise between accuracy and real-time computability. The values given for adjusted coefficients in the text are calculated by taking

$$\frac{E_{Simpson}[x_2] - E_{Simpson}[x_1]}{x_2 - x_1}.$$

On a final note, recall that J(u) = Φ^{-1}(G(u)). The function Φ^{-1} is apt to generate values of -• or +• as G(u) approaches its limits of 0 and 1. Since such results cannot be carried through the rest of the computation, I replace G(u) by $1*10^{-308}$ (or $1-1*10^{-308}$), which is the smallest (or largest) value Stata's Φ^{-1} function can handle.[91]

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[91] Stata code used to compute E[w] available upon request.