Barcelona GSE
Graduate School of Economics

Where Does the Money Flow?
Understanding Allocations of Post-Epidemic Foreign Aid

Ashley Do Nicolas Legrain Nadine Schüttler María Soares de Lima

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Abstract

The purpose of this paper is to examine aggregate and cross-sector allocations of foreign aid flows in the aftermath of epidemics and to determine whether latent effects can be observed in the following year. Using data from the Organization for Economic Cooperation and Development (OECD) on Bilateral commitments of Official Development Assistance (ODA) from 2005-2019, we employ an Ordinary Least Squares (OLS) model based on the structural gravity framework to account for spatial interactions between donor and recipient countries. Our results show that epidemics have a positive and significant effect on bilateral foreign aid across all sectors and that aid to the Humanitarian sector is less conditional on pre-existing relationships than others. Results for latent effects on aid vary by sector. We further find that isolating epidemics in our analysis suggests that certain diseases prompt a different aid response wherein aid to non-health sectors falls.

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1 Introduction

Health crises are affecting individuals' daily lives now more than ever. COVID-19 has lasted more than eighteen months, infected upwards of 175 million people, and caused almost 4 million deaths (WHO, 2020). OECD data shows that over USD 12 billion has been spent on COVID-related activities by DAC countries since the first official case was registered in Wuhan, China in January 2020 ("COVID-19 Spending", n.d.). Developing and emerging markets are most vulnerable to crises in general, with health crises having particularly dire consequences. The World Bank estimates that the current crisis is estimated to push an additional 17 to 26 million people in fragile and conflict-affected countries into extreme poverty in the coming year (Nishio, 2021). The main channel through which developed countries help poor countries cope with the consequences of such crises is through Official Development Assistance (ODA). The European Commission has increased its annual humanitarian budget by 60% in the past year in response to the COVID-19 pandemic ("EU Boosts", n.d.). However, not all health crises are as deadly, widespread, and consistently covered by the media as the current pandemic. The foreign aid response of donor countries is therefore rarely, if ever, as extensive as in the case of COVID-19.

This raises the following question: Do epidemics really drive changes in foreign aid? More specifically, do we see a reallocation between sectors, and if so, are the effects persistent in the immediate aftermath of said epidemics? This is a particularly relevant issue considering countless sources which argue that in the future, health crises will increase in frequency and severity unless there is a drastic change in human activity ("Pandemics to", n.d.). In this paper, we, therefore, examine whether epidemics lead to surges in foreign aid. We use the OECD database on Bilateral ODA commitments which is broken down into different sectors and includes data on 29 donor countries and 155 recipient countries. Our base model includes seven control variables to absorb variation outside of the desired causal relationship. We then build on this model by introducing two new regressions which incorporate lags. After estimating these using OLS, our results indicate a positive and significant relationship between epidemics and bilateral ODA commitments. We also find that ODA to all sectors increases not only in epidemic years but also in the year following an epidemic. These results are not only robust to changing the sample, but also to the placebo tests which imply that our models are reliable.

The remainder of the paper is structured as follows. Section 2 reviews the key strands of existing relevant literature and our main contribution. In Section 3, we describe our data. Section 4 introduces our methodological framework and our choice of models. Section 5 describes our main results, complemented by the robustness checks in Section 6. Finally, in Section 7 we conclude with a brief discussion of key takeaways and policy implications.

2 Literature Review

The study presented here relates to discourse regarding three main strands of literature on foreign aid: the effects of foreign aid on recipient countries, the determinants of foreign aid flows and allocations, and how foreign aid responds to various shocks.

Literature examining the broad effects of foreign aid on recipient countries is expansive, yet largely divided. Proponents argue that foreign aid is indeed an effective agent for promoting growth in developing countries given certain characteristics, though there is no clear consensus on their relative importance. Aid has been shown to be useful for poverty reduction (Collier and Dollar, 2002) and Svensson (1999) finds that aid has a positive effect on growth in democratic countries. Moreover, in a seminal work, Burnside and Dollar (2000) show that aid is an effective tool for poverty reduction conditional on the implementation of stable and effective recipient-country policies. Guillaumont and Chauvet (2019) further argue that the economic vulnerability of a recipient (i.e.,climactic shocks) is also a stronger pre-condition for effective aid allocation such that aid may act as insurance in “poor” environments with greater risk of experiencing negative shocks. Other research, however, pushes back against the so-called “pro-aid” paradigm. Jepma (1997) shows that foreign aid crowds out private saving with no positive effect on growth or policies. This supports the well-known argument that foreign aid hinders growth by promoting consumption (rather than investment) which is not beneficial to the poorest and most vulnerable populations in recipient countries (Boone, 1996; Easterly, 2003,2008). Pack and Pack (1993) along with Feyzioglu et al. (1998) have shown that foreign aid is limited in its ability to affect income distribution in recipient nations due to issues of fungibility.

Another relevant strand focuses on the determinants of aid allocations. A seminal work in this field is Alesina and Dollar (2000) who examine donor-recipient relationships and determine that the direction of aid depends far more on the political and strategic needs of the donor country rather than the actual immediate need or policy performance of the recipient. Olsen, Cartensen, and Høyen (2003) show that there are significant demand factors at play in determining aid flows – particularly depending upon whether a recipient country is prepared to absorb aid via NGO channels. Younas (2008) also finds that OECD countries allocate more aid to countries that import goods in which donors have a comparative advantage. Given this, there is also much research on the volatility of aid. Chong and Gradstein (2008) find that aid is negatively affected by inefficiencies within the donor government while Pallage and Robe (2001), through an analysis of development aid flows to Africa, find that it is both volatile and highly procyclical.

Emergency international assistance in the aftermath of crises in developing countries has been the subject of extensive empirical study in recent years; in this category, papers focus mainly on aid flows in the event of natural disasters or violent conflict. However, conclusions about the responsiveness of aid to these types of crises are not unified. Notably, through an analysis of hurricane intensity, Yang (2008) concludes that developing countries which are more exposed to hurricanes receive increased foreign aid. Becerra et al. (2014) extends that conclusion using an event-study approach to estimate surges in ODA flows following natural disasters; this paper finds that such influxes are correlated with the occurrence of natural disasters but only cover a small share of the cost of damages. In contrast, David (2011) argues that, in general, natural disasters in recipient countries do not elicit an increased aid response. Examinations of aid after conflict are less disjointed. Kang and Meernik (2004) focus on the post-conflict determinants and allocations of foreign aid by studying data on OECD donors. Here, they find that aid not only increases to conflict-affected countries but is also sustained in the following years. Importantly, they find that the characteristics of the conflict itself (i.e., regime change/transition) are useful in predicting allocations of foreign aid in the OECD context. Balla and Reinhardt (2008) also argue that donor perceptions of conflict influence how useful it expects aid will be in achieving donor interests. Literature in this category also considers both the supply and demand-side factors which influence the allocation of foreign aid. From the perspective of donors, Olsen, Cartensen, and Høyen (2003) posit that recipient characteristics are critical in determining where aid goes and that their decision-making process is critically guided by the extent of media coverage in the recipient country. Dreher and Fuchs (2011) analyze the U.S.' War on Terror and conclude that while countries in which terrorism originates do not receive more aid as a result, if they do receive foreign aid, they are indeed more likely to receive larger sum commitments. However, they do not find that when disaggregating aid, money is reallocated to sectors associated with preventing terror.

Our Contribution: Divisions in the literature represent a continuing need for related research and suggest that extending similar questions of foreign aid to other applications can be useful. With respect to our paper, we suppose that health crises may present a set of circumstances in which economic and humanitarian needs are inextricably tied, such that aid allocations may behave differently (as compared to other shocks). As such, our contribution seeks to apply similar analyses of aid flow behavior in the aftermath of exogenous shocks similar to Dreher and Fuchs (2011) and Becerra et al. (2014) while using a gravity framework following Yotov et al. (2016) in the context of biological disasters. Specifically, the goal of our argument is to clarify not only changes in overall foreign aid for epidemic relief but also in the dis-aggregation of aid commitments. To the best of our knowledge, the mechanism through which epidemics affect foreign aid has not been studied yet. Moreover, we provide an extensive analysis of aid behavior in different sectors and under different model specifications.

3 Data

As is standard in the literature involving foreign aid flows, we use foreign aid data on Official Development Assistance (ODA) from the Organization for Economic Cooperation and Development's (OECD) statistical database. Our sample includes data on the bilateral commitments of 29 donor countries to 155 recipient countries between 2005 and 2019. The aid data is measured in million USD constant prices. Our analysis is centered on Bilateral ODA because it represents a large majority of total aid flows disbursed by bilateral, multilateral, and private donors combined (88% in 2019). Furthermore, foreign aid values are log-transformed for ease of analysis and to reduce skewness in the data distribution (Lundsgaarde et al., 2010). We also consider aid commitments rather than disbursements - following the standard established by other aid allocation discourse. This is well-suited to our purposes for two reasons. First, aid commitments are, by nature, more flexible to changes in recipient characteristics (Bermeo, 2008). Secondly, because commitments are less dependent upon the capacity of the recipient to absorb donor funding, they arguably better represent the intentions of the donor government (Dudley and Montmarquette, 1976).

The OECD's ODA database also decomposes aid provided into sectors, which allows for a more detailed analysis of both overall flows and the detailed composition of ODA. The table below provides a breakdown of the sectors contained within Bilateral ODA. Note that we do not analyze the Unallo-

Table 1: Sector overview

Sector	Sector Code	Share of bilateral aid (2019)	Explanation
Social Infrastructure and Services	100	37%	Efforts to improve human living conditions
Economic Infrastructure and Services	200	17%	Assistance for networks, utilities and services
Production Sectors	300	7%	Contribution to all directly productive sectors
Multisector	400	9%	Projects which focus on several sectors
Programme Assistance	500	1%	Budget support and commodity assistance
Action Relating to Debt	600	0%	Debt forgiveness, rescheduling, refinancing, etc.
Humanitarian Aid	700	14%	Emergency and distress relief
Unallocated / Unspecified	998	15%	Aid which cannot be assigned to another sector
Bilateral ODA	1000	100%	Aid directly sent from one country to another

cated/Unspecified sector because it encompasses a wide and unclear portion of aid and it would thus be inaccurate to make conclusions about the drivers of aid flows allocated to it. We also do not make comprehensive conclusions regarding Action Relating to Debt in our main specification as it only represents 0.034% of Bilateral ODA commitments and does not undergo any significant variation.

A prominent issue in the literature involving trade and aid flows is how to handle values of zero flows between countries. Because the norm in these models is to use the logged specification to measure relative changes, this method leads to complications when a significant proportion of values are zeros. There is a lack of consensus about the best way to address those zeros. The method most suitable to our analysis is to simply run the models on all positive values of aid, thus excluding observations that include zero foreign aid flows between countries.

Our analysis takes into account seven diseases: Cholera, Dengue, Ebola, Japanese Encephalitis, Malaria, Measles, and Mumps. We obtain data on these diseases from the World Health Organization (WHO) and the Pan American Health Organization (PAHO). These databases provide the total number of cases for each disease, across all years of our analysis. We select these diseases based on two main criteria:

1. There must be at least one instance of the disease which the WHO classifies as a "Public Health Emergency of International Concern", and
2. Outbreaks must not be considered global pandemics (i.e. Influenza, COVID-19) - so as to avoid endogeneity such that aid disbursements are affected by a contemporaneous outbreak in the donor country

We use our sample to construct an epidemic dummy variable which takes a value of 1 if an outbreak's case-population ratio is greater than the median of case-to-population ratios for all outbreaks of a particular disease, and 0 otherwise. Note that following Becerra et al. (2014) we set the epidemic classification threshold as the median in order to avoid the effects of large outliers in the sample. Our regressions also include a measure of *severity*, represented by the interaction term between the epidemic dummy and the *fatality rate* of the disease (relevant to each respective outbreak). This variable accounts for both the size (by population) and the severity of each epidemic. This interaction is included in our model in order to capture the possibility that epidemics which are both more deadly and affect more people trigger a larger foreign aid response.

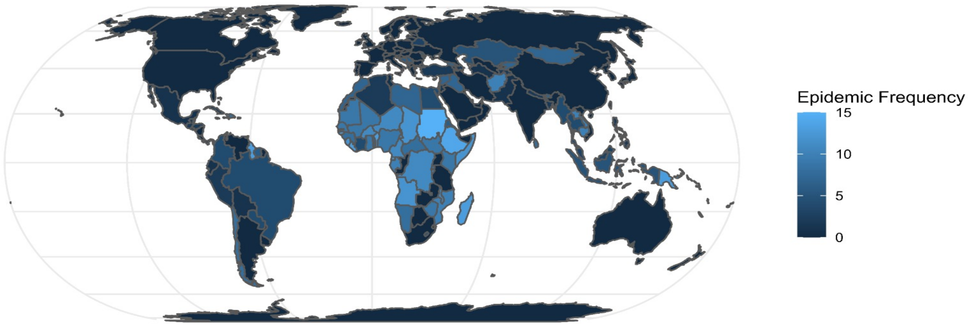

Figure 1: Number of epidemics in each country (2005-2019)

To identify the appropriate control variables, we consider other determinants of foreign aid. According to the Gravity Model (to be further explained in the following section) requisite of accounting for the economic size of both donors and recipients, we use Gross Domestic Product (GDP) values from the World Bank's national accounts data, measured in constant (2010) millions of US Dollars and spans from 2005-2019 account for the economic size of donor and recipient countries respectively. Here, constant USD are used instead of current USD to adjust for inflation and incorporate the trend of the variable in our regressions. The Democracy Index is constructed by The Economist's Intelligence Unit. This index is based on the ratings for 60 indicators, grouped into five categories: electoral process and pluralism, civil liberties, the functioning of government, political participation, and political culture. Each category has a rating on a 0 to 10 scale and the overall index is the simple average of the five category indexes. Life Expectancy data is gathered from a database created by Our World in Data and is measured in years. Finally, data on the distance between donor and recipient countries is drawn from a dataset published in Rose (2004). Distance in this database is measured in the log of kilometers. Colony data on whether a recipient country was a colony of a donor country is also obtained from a dataset published in this paper. In the appendix (Table 5) we provide summary statistics for all of our explanatory variables.

4 Empirical Strategy

This section describes the empirical strategy employed to estimate the effect of epidemics on foreign aid flows. We begin by introducing our main specification, which we extend to include time-lag effects. The Gravity equation is a well-regarded and highly robust economic workhorse model (Leamer and Levinsohn, 1995). The model itself is based on the assertion that bilateral trade between countries will be inversely affected by the geographic distance between them and positively proportional to economic size, proxied by GDP (Tinbergen, 1962). The main advantage in the context of trade is that the model is able to estimate the sensitivity of trade flows given different trade barriers/costs. As such, we rely on a structural gravity framework to account for spatial interactions between donor and recipient countries and apply the same logic to questions of foreign aid with respect to dyadic control factors.

$$T_{A,B} = \frac{GDP_A^{\alpha} GDP_B^{\beta}}{Dist_{AB}^{\zeta}}$$

Where:

- $T_{A,B}$: Trade between countries A and B
- GDP_A^{α}: GDP of country A
- GDP_B^{β}: GDP of country B
- $Dist_{AB}^{\zeta}$: Distance between countries A and B
- α, β: Role of economic size
- ζ: Role of distance

4.1 Identifying Assumptions

We begin by verifying that all of the basic assumptions underpinning OLS estimation hold (see Appendix A.2 for basic checks). Further, we run the models with robust standard errors. Given this, we also impose the following identifying assumptions on our model. Most importantly, our analysis is conditional on having positive aid through bilateral transactions. This serves to eliminate any problems that arise when taking the log of zero-values and facilitates inference by focusing the model on dyadic effects between the donor (origin) and recipient (destination) countries. We also assume that aid is donor-driven and that donors do not collude amongst themselves when allocating aid.

4.2 Base Regression

Our baseline specification is as follows:

$$\begin{aligned} \ln(X_{ijt}) =& \beta_0 + \beta_1 Epidemic_{jt} + + \beta_2 ln(Distance_{ij}) \\ & + \beta_3 ln(Y_{it}) + \beta_4 ln(Y_{jt}) + \beta_5 Colony_j + \beta_6 ln(Democracy_{jt}) \\ & + \beta_7 (Population_{jt}) + \epsilon_{ijst} \end{aligned} \tag{1}$$

We first estimate a simple OLS to determine the change in bilateral commitments when an epidemic affects a country. All the continuous variables are taken into account in the logarithm specification, as we are interested in measuring relative changes instead of absolute changes. The dependent variable is computed as the log of foreign aid flows of a donor country to a recipient country in a given year for each sector of ODA. The subscript i = 1,...,N indicates donor countries, j = 1,...,N refers to recipient countries, s indicates the nine different sectors of foreign aid, and t = 1,...,T is a given year. We control for time-invariant country-specific components (Distance, Colony) and for country-specific time-varying components.

4.3 Introduction of Lags

To extend the analysis of foreign aid's commitment-response to epidemics, we introduce lagged variables. The analysis is two-fold.

First, we introduce the lag of foreign aid as an explanatory variable. To motivate this extension we rely on a statement made in Eichengreen & Irwin (1998): "We will never run another gravity equation that excludes lagged trade flows. If our paper is successful (and widely read), neither will other investigators." Among their arguments, they indicate that the standard gravity model formulation neglects the role of historical factors and hence suffers from omitted variable bias. It is well understood that the amount of foreign aid a country received in a previous year is one of the main determinants of a given recipient's current foreign aid inflows, since a significant amount of foreign aid falls under the classification of so-called Country Programmable Aid (CPA), which is subject to multi-year planning at the country level. Since the explanatory power of the lag of foreign aid is generally high (Zimmerman, 2007), this improves the predictive power of the model itself. However, this also comes at a cost, to be discussed, together with our results.

$$\begin{aligned} ln(X_{ijst}) =& \beta_0 + \beta_1 Epidemic_{jt} + \boldsymbol{\beta_2 \ln(X_{ijst-1})} + \beta 3 Epidemic_{jt} * ln(Fatality_{jt}) \\ &+ \beta_4 ln(Distance_{ij}) + \beta_5 ln(Y_{it}) + \beta_6 ln(Y_{jt}) + \beta_7 Colony_{ij} \\ &+ \beta_8 ln(Democracy_{jt}) + \beta_9 (LifeExpectancy_{jt}) + \epsilon_{ijst} \end{aligned} \tag{2}$$

Secondly, we introduce the lag of the epidemic dummy variable to account for a possible latent response of foreign aid flows in our model. We posit that this delay could either be attributed to the fact that donors have latent reactions or, the increase in certain types of foreign aid is sustained in the year following an epidemic. The first argument addresses the issue that foreign aid commitments face bureaucratic barriers. The second argues that health outbreaks may take time to gain traction in terms of garnering attention from media and large health organizations. The intuition here is that when an epidemic occurs in a given country, the aid response of donors is very rarely immediate and may take several months or years to materialize as aid. We also lag the interaction between fatality, the measure of epidemic severity, and the epidemic variable lagged by one year to account for the severity of the epidemics occurring in the previous year.

$$\begin{aligned} ln(X_{ijst}) =& \beta_0 + \boldsymbol{\beta_1 \mathrm{Epidemic}_{jt-1}} + \boldsymbol{\beta_2 \mathrm{Epidemic}_{jt-1} * \ln(\mathrm{Fatality}_{jt-1})} + \beta_3 Epidemic_{jt} \\ &+ \beta_4 Epidemic_{jt} * ln(Fatality_j) + \beta_5 ln(Distance_{ij}) + \beta_6 ln(Y_{it}) + \beta_7 ln(Y_{jt}) \\ &+ \beta_8 Colony_{ij} + \beta_9 ln(Democracy_{jt}) + \beta_{10}(LifeExpectancy_{jt}) + \epsilon_{ijst} \end{aligned} \tag{3}$$

5 Results

5.1 Background[1]

Bilateral ODA is the aggregate measure of aid flows between donor governments and recipient countries, excluding aid which flows through multilateral channels. In general, it is the main route for development financing and an indicator of a donor's aid commitments. While many nations give substantial amounts of foreign aid, the top donors have been fairly consistent. Over the selected time period, the top donors of Bilateral ODA, the U.S. Japan and Germany, have remained so (Figure 3). The top recipients of bilateral aid have been subject to variation. However, they can be broadly characterized by the fact that they are mostly countries, which were hit by military conflicts and/or humanitarian crises like Iraq, Yemen, Indonesia among others, that received the most aid in the past years. Of the eight sectors of foreign aid, we posit that three are directly related to health: Humanitarian, Programme Assistance, and Social Infrastructure; together, they make up 52% of total aid. Since the focus of our analysis is health crises, we group our results into two subsections.

Health-Related Sectors:

In this context, **Humanitarian Aid** and Programme Assistance are best understood jointly. Humanitarian programming seeks to "save lives, alleviate suffering and maintain human dignity" throughout cycles of crises, both man-made and natural (Collinson and Buchanan-Smith, 2009). This sector includes support for emergency response, reconstruction relief and rehabilitation, and disaster prevention and preparedness - all of which can be considered short-term (need-based) by nature. From 2005-2019, the top donors were on average the United States (U.S.), United Kingdom, and Germany, which made up 77% of total Humanitarian Aid in 2019. The top recipients were less consistent but at the regional level, the South of Sahara and Middle East received the most. Aid to this sector has increased over the last 15 years, from 9% of total Bilateral Aid to 14% and by 2019 reached a historic peak of USD 17.8 billion.

Programme Assistance, also known as Commodity Aid, is closely related to Humanitarian Aid, but has a more mid-to-long-term orientation. It can be disaggregated into general budget support, development food assistance and other commodity assistance. Importantly, it does not contain emergency food assistance, which is allocated under Humanitarian Aid. Aid for Programme Assistance, as a share of total Bilateral Aid, has generally decreased over the last 15 years and in 2019 only constituted 1.8% of Bilateral Aid. The dissimilar behavior of aid to the two aforementioned sectors represents the increasing global demand for humanitarian assistance. The UN Office for the Coordination of Humanitarian Affairs (UNOCHA) reported a 61% increase in people in need, translating to USD 8.5 billion of additional funding required.

Furthermore, **Social Infrastructure and Services** supports human resources such as education, health and population, water supply, sanitation, and sewage, among others. Importantly, the Health and Population category within this sector includes assistance to hospitals and clinics, disease and epidemic control, vaccination programs, public health administration among others. During our period of analysis, Social Infrastructure aid grew by 57%. In 2019, The U.S. was the biggest donor to this sector followed by Germany and France while Jordan, Afghanistan, and Indonesia were the top recip-

[1] See Figure 2 for summary of aid by sector

ients. In 2019, Social Infrastructure and Services constituted 37% of overall Bilateral Aid, and as such was the sector with the highest share.

Sectors Indirectly related to Health

As naming would suggest, the **Production Sector** supports productive industrial operations to include Agriculture, Forestry and Fishing, Industry, Mining, and Construction, as well as Trade and Tourism. During our period of analysis, aid to this sector grew by 57%. In 2019, Japan was the biggest donor followed by France and The U.S. whereas Iraq, Bangladesh, and Ethiopia were the top recipients. Production Sector aid constituted 7% of Bilateral aid in 2019.

Economic Infrastructure covers aid for communications, transportation, and storage services. Assistance in this sector provides support for planning, operations, management, and capacity building across industries such as information technology and public transport. Aid commitments to this sector have been relatively steady from 2005-2019 and in 2019, made up 17% of total Bilateral Aid. **Multisector** aid provides support for projects which intersect with several sectors and focus particularly on the environment, gender projects, as well as urban/rural development. Top recipient countries have shifted from Sudan, Indonesia, and China in 2005 to Mongolia, the Philippines, and Côte d'Ivoire in 2019, which is indicative of the evolution of emerging markets and developing economies over the last 15 years. **Action Relating to Debt** aid covers mainly debt forgiveness, rescheduling, refinancing.

5.2 Basic Regression Results - Model 1[2]

As a general trend, our results for all model specifications indicate that ceteris paribus, increases in *life expectancy*, and *distance* will decrease the average aid received across all sectors. In line with what we would expect from a gravity framework, the *GDP* of both donors and recipients is significant and positive for all sectors. Other recipient characteristics such as whether a recipient was a *colony* of a respective donor, as well as the *level of democracy*, have a positive impact on levels of aid in general. The importance of these explanatory variables aligns with existing literature on the determinants of aid flows, namely, Alesina and Dollar (2000) whose study shows that aid is motivated not only by altruism but also by political and strategic ties.

5.2.1 Bilateral ODA

Throughout our analysis, the explanatory variable of interest is epidemic years. Our main regression indicates that Bilateral ODA increases by 111.9%[3] = ($e^{0.751}$ −1) in a year that a recipient country was directly impacted by an epidemic. Ceteris paribus, our control regressors, including those that account for colonial ties and the level of democratization, are significant and therefore help explain how aid behaves, in agreement with Alesina and Dollar (2000). Overall, estimates for this sector align with our expectations of aid behavior in the aggregate and serve as a primer for the sector-level analyses to be presented in the following sections.

[2] All interpretations are ceteris paribus and only consider positive values of aid

[3] Given that we specify a log-log model, calculations of percentage changes vary between dummy and continuous variables. For dummies, the interpretation of the coefficient is ascertained using the following formula:(e^{B} −1) x 100

5.2.2 Sectors Directly Related to Health

Humanitarian Aid is, often by construction, volatile, since it should react to humanitarian emergencies (OECD). The results of our regression analysis confirm this behavioral pattern and suggest that Humanitarian Aid in particular reacts to the onset of an epidemic. In an epidemic year, Humanitarian Aid increases on average by 110.8% as compared to years with no epidemic events. Ceteris paribus, conditional on actually facing an epidemic, a 1% increase in the severity of the epidemic itself, increases Humanitarian Aid flows on average by 0.035%.

Interestingly, colonial ties and proximity between donor and recipient do not explain the change in the dependent variable for this sector. For this, we posit the explanation that the determinants of Humanitarian Aid are less conditional than other types of aid. Annen and Strickland (2017) argue that allocations of Humanitarian Aid are impacted by the domestic political agendas of donor countries. They show that Humanitarian Aid increases by 19% in the year before elections, which can be attributed to the fact that this type of aid spending is highly visible and therefore politically advantageous in terms of garnering voter support. Beyond that, this can further explain why other strategic interests like distance or colony, which are typically relevant in a gravity framework, lack significance for this sector. It is also plausible to argue that in some circumstances, the need for humanitarian relief may transcend other determinants of aid such that factors like distance or past linkages become secondary.

Regarding Programme Assistance, even though emergency food assistance is classified as Humanitarian Aid, epidemics have a positive and highly significant effect, increasing aid by 40.9%. However, even though this increase is relatively high, the relevance of this result is diminished by the relatively low share of total aid held by Programme Assistance, especially in comparison to Humanitarian Aid. Unlike other sectors, the estimates of many other explanatory variables for this sector (*severity, recipient GDP* and *democracy*) are insignificant. Even so, *life expectancy* still has a significant effect. Although the link between Programme Assistance and epidemics is not clear-cut, we posit that this sector may support the implementation of non-urgent relief efforts. This explanation hinges on the fact that Programme Assistance also includes aid for organizational infrastructures, such as covering costs related to the organization of food programs or the implementation of macroeconomic reforms (OECD).

An epidemic also has a positive significant effect on Social Infrastructure, increasing aid by 97.4%. However, ceteris paribus, when we control for epidemic severity, the coefficient of the interaction term is significantly smaller, with aid increasing by only 0.13%. Given that Social Infrastructure is directly related to health assistance, a priori we would expect an increase in this type of aid. This explanation is supported in practice, as the Social Infrastructure share of Bilateral Aid is often used as a progress indicator for the UN's Millennium Development Goals. Through our analysis, it is not possible to disaggregate the increase in Social infrastructure by purpose. However, we still anticipate aid flows to Sanitation and Education. First, investments in Water Supply, Sanitation, and Sewerage arguably play a critical role in mitigating epidemics given the direct relationship between sanitation, hygiene, and health. It is also well understood that social aid should affect economic growth through human capital. If we consider investments and improvements in human capital as bettering the coping mechanism for future shocks, it follows logically that support would increase for educational aid during epidemics. However, such a view has been heavily debated by policymakers.

Table 2: Sectors Directly Related to Health (Model 1)

	1000	700	500	100
Epidemic year	0.751***	0.746***	0.343**	0.680***
	(0.053)	(0.072)	(0.136)	(0.053)
Severity	0.133***	0.035**	0.057*	0.126***
	(0.010)	(0.016)	(0.033)	(0.010)
Life expectancy	−3.112***	−1.384***	−2.608***	−2.316***
	(0.162)	(0.237)	(0.522)	(0.166)
GDP donor	0.965***	0.416***	0.556***	0.846***
	(0.011)	(0.015)	(0.041)	(0.012)
GDP recipient	0.331***	0.236***	−0.017	0.253***
	(0.010)	(0.017)	(0.038)	(0.010)
Distance	−0.535***	−0.027	−0.205**	−0.463***
	(0.027)	(0.044)	(0.098)	(0.028)
Colony	1.946***	−0.118	0.471***	1.972***
	(0.059)	(0.107)	(0.145)	(0.058)
Democracy	0.260***	−1.145***	0.070	0.414***
	(0.043)	(0.061)	(0.122)	(0.043)
Constant	0.975	−1.043	4.666**	−1.354*
	(0.718)	(1.033)	(2.244)	(0.731)

Robust standard errors in parentheses
*p<0.1; **p<0.05; ***p<0.01

When human capital in recipient countries is analyzed, Social Infrastructure Aid does not appear to play a role. One explanation is that although aid can increase the number of resources aimed at education, this will not necessarily target utilization or directly imply that educational attainment will improve (Akramov, 2012). Finally, we infer that once health-related aid has already been increased, donors subsequently consider indirect mechanisms for assistance in recipient countries.

5.2.3 Sectors Indirectly Related to Health

Notably, epidemics also increase aid to other sectors. In the case of epidemics, the results show that Production Sector aid increases. However, the magnitude is significantly lowered when we control for epidemic severity. As such, it can be inferred that in an epidemic year, Production Sector Aid will increase 70.7% on average in comparison to years when countries do not face an epidemic. When epidemics are controlled by *severity*, aid increases by 0.11%.

Although ex-ante, we would not expect this sector to react immediately, we consider several explanations for the observed increase. Over the past thirty years, there has been a downward sloping trend in aid to production sectors, primarily to agriculture; for instance, agriculture aid fell to less than 10% in the early 2000s. Akramov (2012) maintains that the main explanation for this is both political and economic. Politically, as issues of climate change have become increasingly important, Agricultural Aid itself has been negatively affected by the correlation between agriculture and environmental degradation. In addition, push-back from agricultural lobbies in donor countries against helping competitors in their main export markets has limited the economic attractiveness of allocating aid to this sector. Economically, variations in international commodity prices and past failure of some development projects focused on agriculture. Given this background, an influx of aid going to Production Sectors to revert this trend is expected. However, aid flowing to this sector is of critical importance for poor nations where agriculture constitutes a major part of the domestic economy. Thus, increases in Production Sector aid may not only boost agricultural productivity but also food production and security.

Table 3: Sectors Indirectly Related to Health (Model 1)

	200	300	400	600
Epidemic year	0.341***	0.535***	0.663***	−0.094
	(0.092)	(0.067)	(0.060)	(0.300)
Severity	0.067***	0.107***	0.134***	0.208**
	(0.018)	(0.014)	(0.012)	(0.085)
Life expectancy	−0.594**	−1.195***	−0.683***	−4.947***
	(0.291)	(0.215)	(0.189)	(1.007)
GDP donor	0.720***	0.446***	0.609***	−0.272***
	(0.020)	(0.015)	(0.013)	(0.100)
GDP recipient	0.191***	0.119***	0.191***	0.429***
	(0.019)	(0.014)	(0.012)	(0.068)
Distance	−0.652***	−0.182***	−0.313***	−0.253
	(0.051)	(0.040)	(0.031)	(0.169)
Colony	0.418***	0.589***	1.263***	−0.212
	(0.107)	(0.081)	(0.071)	(0.213)
Democracy	0.292***	0.309***	0.488***	−0.573**
	(0.078)	(0.060)	(0.049)	(0.273)
Constant	−5.504***	−2.120**	−6.946***	23.554***
	(1.266)	(0.931)	(0.821)	(4.162)

Robust standard errors in parentheses
*p<0.1; **p<0.05; ***p<0.01

Results from the base regression (Model 1) show that in an epidemic year, aid to Economic Infrastructure and Multisector increases by 40.6% and 94.1% respectively. The coefficients of all control regressors here are significant and thus we ascertain that the increase in epidemic-induced aid to this sector can be explained by both donor and recipient characteristics. Indeed, considering the significance of certain regressors such as *severity* and *life expectancy*, we infer that aid to this sector depends notably on the intensity of the epidemic and the standards of health in the recipient country. We also posit that aid to these sectors supports preventative measures which are implemented in the long run but are highly visible in media and therefore garner public support for donor governments.

5.3 Lagged Variable

5.3.1 Lagging the Dependent Variable - Model 2

As an extension, we include a new version of the model allowing for the presence of lagged foreign aid as a regressor. Based on arguments from existing literature, we check the explanatory power of the lag of foreign aid in our model. Depending on the sector, the R^2 ranges from 30% to 70%. Results yield a very high estimate for lagged foreign aid. In particular, the epidemic variable's coefficients are now smaller. This can be attributed to the fact that the lag of foreign aid has a disproportionately high R^2. Consequently, several variables in our model lose significance. For example, in table 8 the results for Bilateral Aid are similar to those of our base model but yield reduced coefficients. Irrespective of *severity*, an epidemic increases aid by 8.2%. When we control the epidemic using the interaction term, a 1% increase in *severity* will lead to an aid increase by 0.015%. Moreover, table 8 shows that if there is an epidemic, Humanitarian Aid will increase by 28.4% as opposed to when there is not. In contrast, this value is near 110.8% in Model 1 (Table 2). As expressed above, the lagged dependent variable explains a major part of the model, accounting for a 100% relative increase in the case of Humanitarian Aid.

However, these results should be interpreted with caution considering that a dynamic bias is expected (Olivero & Yotov, 2012). There is vast literature supporting the fact that gravity models should include the lagged dependent variable as an explanatory variable and that its omission may bias the estimation when dynamic phenomena are being analyzed. However, it has been argued that introducing this approach is not costless and may lead to well-known dynamic panel bias. Technically, the inclusion of the lagged dependent variable on the right-hand side of the equation may lead to a correlation with the error term. There are various solutions proposed in the literature to overcome this problem. Among the most popular ones, the GMM approach popularized by Arellano and Bond (1991). In line with this, we test for both normality and multicollinearity (Figure 4, 5; Table 7) . Under this model specification, the tests show that the normality assumption does not hold while the results of the collinearity test can be found in the appendix.

5.3.2 Lagged Epidemic Years - Model 3

We also run an extension of the model to account for time lag effects in foreign aid. Here, we address the sectors which produce noteworthy results. Broadly speaking, Bilateral ODA behaves in much the same way as in the previously presented models. This indicates that in general, Bilateral Aid reacts positively not only in the year of the outbreak of an epidemic, but also in the following year. Since Humanitarian Aid is unpredictable by nature and donors grant it more flexibility than other types of foreign aid, a priori we would expect the effect of a single period lag to be relatively small. We observe a significant 36.2% average increase in Humanitarian Aid in the year after an epidemic, which is smaller than the effect in an actual epidemic year (Table 4). Similarly, Economic Infrastructure aid increases to this sector by 38.4% one year later (Table 10). One explanation relies on the composition of the sector itself. We infer that in the year after an epidemic, donor countries may prioritize the need for more preventative measures (rather than curative) to promote economic recovery and ensure that recipients have the capacity to deal with health crises in the future. Aid for economic infrastructure is ultimately relevant as it supports the transport and communication capacities of the recipient country, thus affecting its ability to effectively absorb aid and implement future relief efforts.

Table 4: Sectors directly related to health (Model 3)

	1000	700	500	100
Epidemic year	0.493^{***}	0.660^{***}	0.298^{*}	0.428^{***}
	(0.060)	(0.087)	(0.165)	(0.061)
Severity	0.090^{***}	0.018	0.026	0.083^{***}
	(0.012)	(0.020)	(0.043)	(0.012)
Epidemic year t-1	0.417^{***}	0.309^{***}	0.145	0.416^{***}
	(0.059)	(0.088)	(0.173)	(0.060)
Severityt-1	0.073^{***}	0.041^{*}	−0.007	0.073^{***}
	(0.013)	(0.023)	(0.054)	(0.013)
Life expectancy	-2.789^{***}	-1.093^{***}	-3.041^{***}	-1.876^{***}
	(0.169)	(0.273)	(0.631)	(0.174)
GDP donor	0.948^{***}	0.441^{***}	0.446^{***}	0.824^{***}
	(0.012)	(0.017)	(0.050)	(0.012)
GDP recipient	0.309^{***}	0.280^{***}	0.038	0.226^{***}
	(0.010)	(0.020)	(0.045)	(0.010)
Distance	-0.486^{***}	−0.001	-0.243^{**}	-0.390^{***}
	(0.028)	(0.051)	(0.115)	(0.029)
Colony	1.908^{***}	−0.098	0.387^{**}	1.905^{***}
	(0.058)	(0.115)	(0.157)	(0.057)
Democracy	0.242^{***}	-1.195^{***}	0.068	0.380^{***}
	(0.044)	(0.066)	(0.134)	(0.045)
Constant	−0.238	-3.021^{**}	8.030^{***}	-3.069^{***}
	(0.748)	(1.177)	(2.727)	(0.765)

Robust standard errors in parentheses
*p<0.1; **p<0.05; ***p<0.01

Production Sector aid increases 41.1% in an epidemic year and 44.8% in the following year (Table 10). Note that when we control for severity, aid is increased by 0.07%. The intuition for this result follows that of economic infrastructure where it seems plausible that donors may hope to support production both as a curative measure in the short run and a preventative measure in the long run.

However, results for time lags greater than one period are insignificant. Therefore, it is not possible to identify an increasing trend that persists more than one year.

5.4 Isolating Epidemics

We have shown that epidemics do have an impact on the provision of foreign aid. In the case of epidemics overall, we do not observe a reallocation across sectors. Even so, our analysis explains that epidemics affect an increase in both health-related and non-related sectors. This result merits an analysis of each disease independently. For Mumps, Cholera (Tables 11; 12), Dengue Fever, and Japanese Encephalitis, the effect of epidemics on aid to health-related sectors is significant. Yet for most non-health-related sectors it is not. This suggests that analyzing these diseases individually cannot explain cross-sector changes in aid provided for Production, Economic Infrastructure, Multisector, and Action Relating to Debt.

However, an exception arises when we analyze Measles epidemics(Tables 13 and 14). Notably, the coefficient for Action relating to Debt becomes significant and negative. The epidemic estimate is also significant and positive for Bilateral ODA, Humanitarian, Social and Economic Infrastructure, and Production sectors. This indicates that when a country is affected by Measles, we should expect aid for Action Relating to Debt to fall by 66.3%. Hence, we infer that this reduction may imply a reallocation from non-health-related sectors to health-related sectors. Whether this constitutes a significant reallocation in terms of size, depends on the magnitude of Action Relating to Debt as a share of overall aid for each country. Despite the fact that we cannot comment on the magnitude given our results, this implication for Measles is of particular interest since, in 2019, reported cases surged worldwide (WHO), with the number of reported cases reaching highs unmatched since 1996. Considering the strength and persistence of this new Measles outbreak, we find the reallocation of aid mentioned above to be reasonable.

6 Robustness Checks

6.1 Changes in the Sample

Here, we check whether our results are still robust if we consider different samples. To do so, we run models 1 and 2 for all sectors, using the following criteria:

- i) excluding the top donor: the U.S.,
- ii) excluding the top recipient: India,
- iii) excluding the top regional recipient: Asia,
- iv) excluding the most vulnerable region: Africa.

As a separate exercise, we also run the models for the inclusion of Asia and Africa exclusively (but separately). All results signal that our specifications are robust to applications of the above criteria. Firstly, if we consider results obtained when the U.S. is excluded (Tables 15; 16), for Bilateral ODA, the distance coefficients are higher across both models in absolute value. When the main donor is removed from the full sample, an increase in distance between donor and recipient leads to a larger decrease in aid. As expected, this implies that while the coefficients remain significant and negative, the estimates still capture geopolitical and strategic considerations of donor countries. Interestingly the coefficients for Democracy remain unchanged, this suggests that the level of democracy in recipient countries remains an important determinant of aid, regardless of which donors are included in the sample. Next, when we exclude India (Tables 17; 18), the epidemic coefficients of Models 1 and 2 decrease for Humanitarian Aid. This means that in the event of an epidemic, when we exclude India, there will still be an increase in Humanitarian Aid but said increase will be smaller. Third, analysis of Asia and Africa is even more relevant as the majority of the epidemics in our sample are concentrated in these regions (Figure 1). When we exclude them (Tables 19, and 21), the coefficient of epidemic years for Model 1 drops by almost 10% for Bilateral ODA. This aligns with our expectations since, independently, both receive the highest proportions of overall aid. Finally, if we run our models to include only Africa (Table 23) and only Asia (Table 25) the coefficients of epidemics and epidemics controlled by severity become significantly higher for Bilateral ODA.

6.2 Placebo Test

We run a Placebo test to assess whether our estimator could be biased by confounders or the model is misspecified such that the estimated treatment effect is not reliably measuring the actual treatment effect (Eggers et al., 2021) . Therefore, we construct 10 placebo dummy variables which randomly take values of zero or one. We also generate a separate placebo dummy which randomly turns to zero or one, but in the exact same proportion as the actual treatment variable. Running the regression separately for each placebo treatment produces estimates that, for Humanitarian Aid, are insignificant - validating the specification of our model (Table 27). Placebo results are significant for some sectors (Table 28). We attribute this to the fact that around 40-50% of the randomly produced “treatment” ones are concurrent with the actual treatment. This is also in line with the fact that even though the coefficients of the placebo are significant, they are just half the size. However, we also run the placebo regression for model 2 and mainly all results are insignificant.

6.3 Testing for Persistence

The results of Model 3 show that when countries face an epidemic, aid increases in the year of the outbreak and, for some sectors, in the next year. However, it is possible that the positive and significant lagged coefficients do not stem from a persistent trend, but rather the existence of multiyear epidemics. To address this, we create an epidemic variable that turns to one in the final year of an epidemic for every country. In doing so, we test whether the lagged coefficients remain significant and positive using a variable that can identify the conclusion of an epidemic; the results show this to be true. Thus, we conclude that the lagged coefficient indeed partly explains a sustained trend in the provision of foreign aid. Here, a caveat is in order. This robustness check does not undermine the conclusion that when countries face multi-year epidemics, aid received can be sustained. This may vary depending on the sector and type of epidemic. Nevertheless, with this exercise, we show that regardless of the duration, once an epidemic is concluded there may still be a sustained trend in aid in the following year (Tables 29 and 30).

7 Limitations and Extensions

We recognize that there are some limitations to this analysis. First, data limitations: as explained in the data section, for the construction of the epidemic variable, we assume: i) for each disease, fatality is the overall case-fatality rate, ii) that an outbreak is defined as an epidemic by meeting or surpassing the median of case/population ratio per disease. These assumptions limit our analysis because the number of cases is generally under-reported and the case-fatality rate for each disease is not standardized. In fact, case-fatality can vary with age groups, country characteristics, among other factors. Therefore, depending on the actual fatality rate (unique to each epidemic outbreak individually) our results may be over/underestimates. While we include *life expectancy* to account for the health status in the recipient country, we acknowledge that this may not fully capture the capacity of the health system itself, which could be highly indicative of how resilient a country is to the pressure an epidemic places on existing health infrastructure. The main challenge we face here is acquiring consistent and comparable data for all recipient countries Our model may also suffer from omitted variable bias as some variables that we cannot control for may bias our estimates. These include variables that account for the actual awareness of the donor countries (e.g. epidemic media coverage), the status of donor-recipient relations (political biases), donor perceptions of recipient development status (stereotyping), and the disproportionate vulnerability of recipient countries to climate crises or other types of shocks.

Moreover, countries such as China and India are regarded as recipients in our sample, while in reality, they both receive and donate foreign aid. In 2019, China ranked as the sixth-largest provider of ODA (Johnson, Zühr, 2021), and will continue growing in its role as a global development actor (China's State Council Information Office, 2021). In line with this, it is possible to expect a distortion in some explanatory variables, e.g. in terms of GDP China is an outlier. To address this as part of our robustness checks, we run the regression excluding Asia from the sample and results remain robust. It would be insightful to perform the analysis considering China as a donor to test whether our results hold. Furthermore, while other research has not found evidence of cross-country reallocation (Becerra et al., 2014), it would be relevant to test this conclusion in the context of public health emergencies.

8 Conclusion

To conclude, we find that epidemics do indeed engender changes in foreign aid behavior. To be specific, epidemics have a positive and significant effect on foreign aid committed to all sectors. Our results are unable to shed light on the question of reallocation between sectors. However, they do illustrate that aid to both health-related and non-health-related sectors increases. Aid in this context is also persistent. That is, our results, robust to numerous checks, show that the positive effects of epidemics may be observed not only in the year of the outbreak but also in the following year.

Having expanded on the epidemic-aid dynamic through this thesis, we posit that targeting aid to health-related sectors may be a more effective mechanism for combating epidemics through aid and that overall, aid as a tool is being underutilized. However, our study does not measure the effectiveness of aid and this is necessary for the construction of productive policy that may save countless lives. Naturally, this presents new opportunities for research and raises important questions regarding optimal allocations of aid given shocks to global health. That is, does increasing aid to all sectors serve as an effective one-size-fits-all solution? Or is it more efficient that donors reallocate aid across sectors to account for short and long-term changes in the demand for healthcare caused by an epidemic?

A potential approach may be able to answer such questions by drawing on prevalent literature from development economics and applying the known advantages of Randomized Control Trials (RCTs) to sector-level analyses of aid utilization in countries that depend heavily on aid. This is of particular need for sectors where the health benefit is not clear-cut. Furthermore, the benefits of this research would be bolstered by an increase in public support for development aid (Kobayashi et al., 2021), maximize returns on donor investments, and the efficacy of health expenditure in recipient countries - all of which would critically support public health policy for the prevention of future pandemics.

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A Appendix

A.1 Descriptive

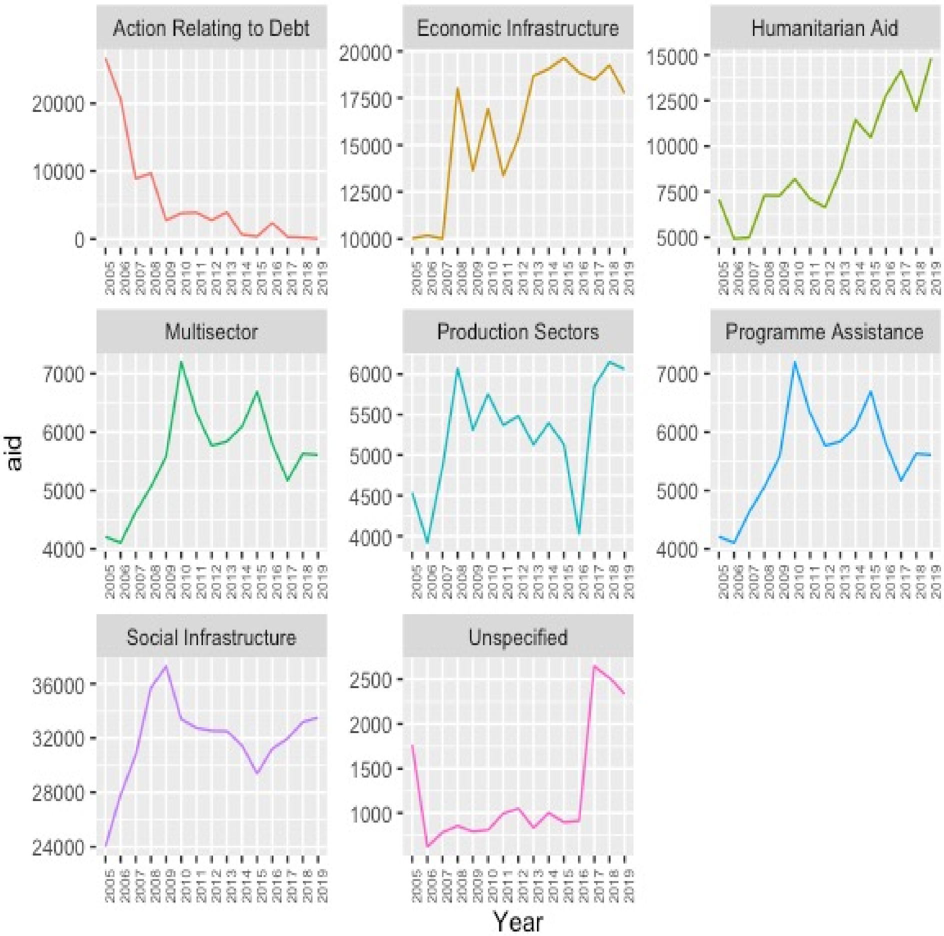


Figure 2: Aid by sectors

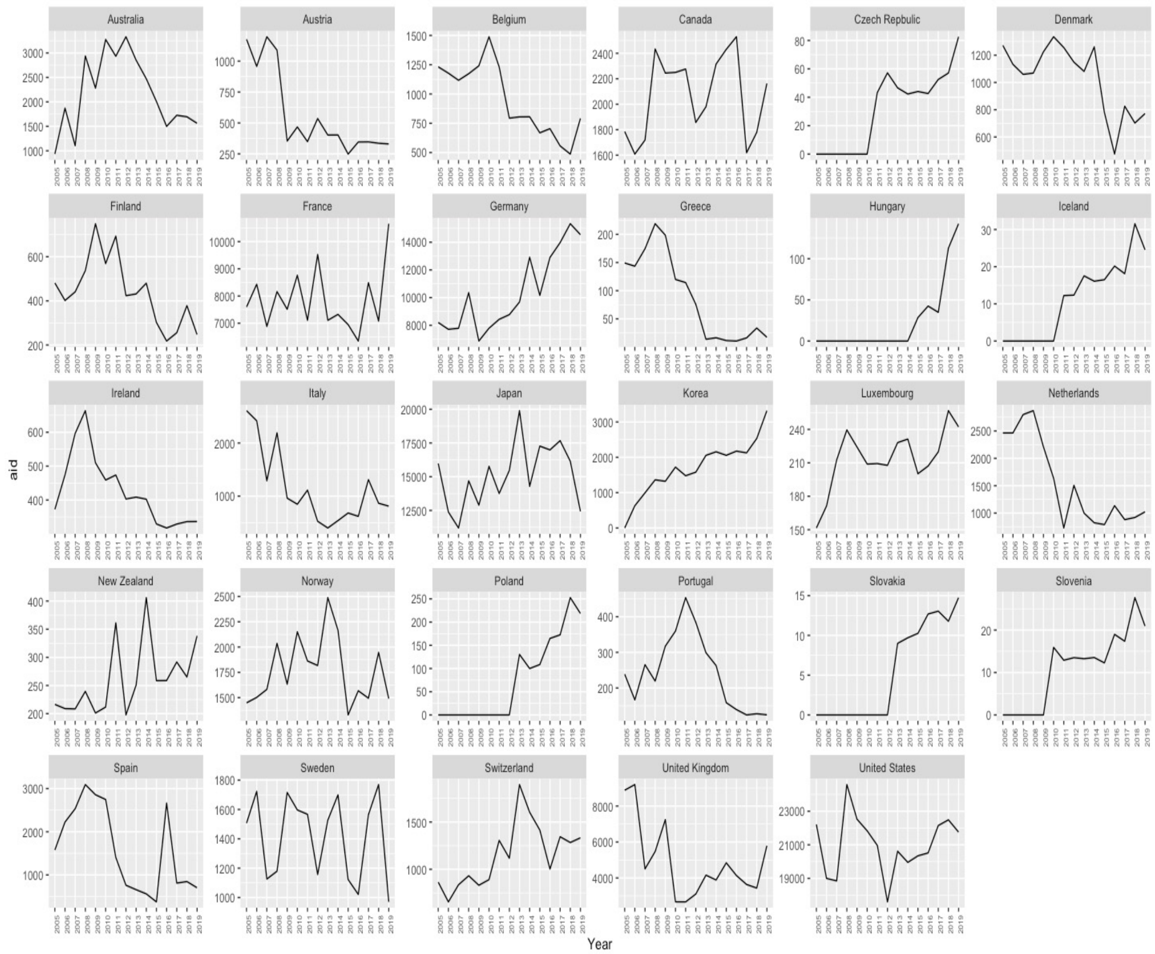


Figure 3: Donors provision of ODA

A.2 Data & Model Specification

Table 5: Summary statistics (non-dummy variables)

Variables	Observations	Mean	Median	Min	Max	St. Dev
GDP Donor	174,538	2,555,482	1,311,782.5	13,941.17	18,300,386	3,886,987.11
GDP Recipient	167,384	217,787.73	22,322.52	29.19	11,520,043	871,249.79
Democracy Index	128,476	4.79	4.95	0.86	9.28	1.72
Fatality Rate	174,538	11.65%	10.15%	0.027%	50%	10.94%
Life Expectancy	170,061	67.08	68.85	42.52	81.86	7.97
lnDistance	148,248	8.31	8.44	5.16	9.38	0.57

Heteroskedasticity

For the constant variance assumption, we tested whether or not the variance of the error term is homoskedastic using the Breusch-Pagan/Cook-Weisberg test for heteroskedasticity. The test rejects for most of the sectors that the variance of the error term is constant. The only exception is the sector of Multisector aid (400), where the null hypothesis of constant variance can not be rejected at chi2(1)=1.92 with a p-value of 0.1660. To account for the heteroskedasticity in our samples we use robust standard errors to correct the error term.

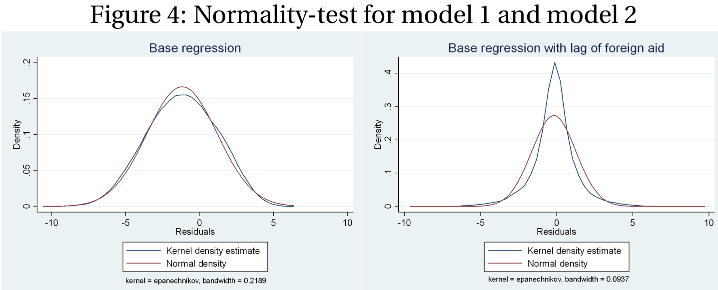
Table 6: Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Sector:	1000	100	200	300	400	500	600	700
chi2(1)	97.63	52.66	110.28	15.85	1.92	48.00	13.51	175.33
Prob > chi2	0.0000	0.0000	0.0000	0.0001	0.1660	0.0000	0.0002	0.0000

Normality:

To test for the assumption that error terms should be normally distributed, we use the Kernel density estimation. This assumption holds for all base regressions, whereas in the regression model with the lag of foreign aid, error terms are not normal. While this means, that for this particular model, OLS does not possess the desirable property of being the best linear unbiased estimator (BLUE) and the standard errors of the OLS estimate are not reliable, it does not erode the validity of the OLS method itself. By assessing the standardized normal probability plot and the quantile-normal plot it becomes evident that in the regression with the lag of foreign aid there is non-normality in the middle-range as well as near the tails of the distribution.

Figure 4: Normality-test for model 1 and model 2



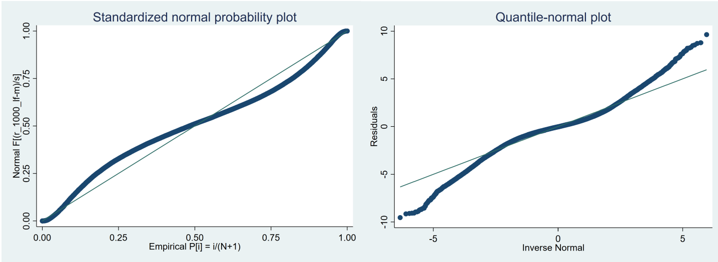


Figure 5: Standardized normal probability plot and the quantile-normal plot

Multicollinearity:

Furthermore, we test for multicollinearity by using the variance inflation factor. In all our samples for each sector we found that the mean value of the Variance Inflation Factor (VIF) for all explanatory variables is between 1.82 and 2.16, which indicates there is no multicollinearity among explanatory variables. However, the correlation matrix reveals that the correlation between the dependent variable foreign aid and the independent variable lag of foreign aid is between 0.60 and 0.86. This indicates a high correlation, such that the regression with this explanatory variable must be taken carefully.

Figure 6: *Correlation Sector 1000*

	lnFore~d	epi_~ian	lag1_f~d	lag1_e~n	severi~n	lag1_s~n	lnLife~y	lnGDP_~r	lnGDP_~t	LogDis~e	Colony~N	lndemo~y
lnForeignaid	1.0000											
epi_ally~ian	0.0443	1.0000										
lag1_forei~d	0.8742	0.0453	1.0000									
lag1_epi_a~n	0.0421	0.4904	0.0496	1.0000								
severity_a~n	0.0239	-0.7326	0.0272	-0.2874	1.0000							
lag1_sever~n	0.0241	-0.3368	0.0231	-0.7236	0.4656	1.0000						
lnLifeexpe~y	-0.0742	-0.3178	-0.0728	-0.3542	-0.0329	0.0111	1.0000					
lnGDP_donor	0.4606	0.0066	0.4532	0.0039	-0.0172	-0.0094	0.0063	1.0000				
lnGDP_reci~t	0.0882	-0.2508	0.0925	-0.2762	0.0853	0.1137	0.4556	-0.0491	1.0000			
LogDistance	0.0156	-0.0103	0.0191	0.0259	0.0860	0.0542	-0.0803	0.1737	0.0803	1.0000		
Colony_YN	0.2025	0.0090	0.2027	0.0141	0.0126	0.0097	-0.0303	0.0946	-0.0140	-0.0359	1.0000	
lndemocracy	-0.0142	-0.2070	-0.0067	-0.1971	0.0487	0.0420	0.3935	-0.0284	0.2969	0.1597	-0.0033	1.0000

Figure 7: *Correlation Sector 700*

	lnFore~d	epi_~ian	lag1_f~d	lag1_e~n	severi~n	lag1_s~n	lnLife~y	lnGDP_~r	lnGDP_~t	LogDis~e	Colony~N	lndemo~y
lnForeignaid	1.0000											
epi_ally~ian	0.1686	1.0000										
lag1_forei~d	0.7310	0.1715	1.0000									
lag1_epi_a~n	0.1189	0.4924	0.1515	1.0000								
severity_a~n	-0.1031	-0.7063	-0.1069	-0.2960	1.0000							
lag1_sever~n	-0.0605	-0.3395	-0.0900	-0.7103	0.4822	1.0000						
lnLifeexpe~y	-0.0992	-0.3333	-0.0956	-0.3382	-0.0045	0.0148	1.0000					
lnGDP_donor	0.2633	-0.0454	0.2531	-0.0376	0.0004	0.0076	0.0808	1.0000				
lnGDP_reci~t	0.0416	-0.2793	0.0529	-0.2738	0.0809	0.0840	0.5254	0.0190	1.0000			
LogDistance	0.0892	-0.0210	0.1104	0.0245	0.1125	0.0706	-0.0955	0.3181	0.0424	1.0000		
Colony_YN	0.0038	-0.0157	0.0170	-0.0041	0.0298	0.0188	-0.0086	0.0616	-0.0332	-0.0523	1.0000	
lndemocracy	-0.2071	-0.2612	-0.1971	-0.2366	0.1255	0.1040	0.4450	0.0771	0.3798	0.0824	0.0108	1.0000

Table 7: VIF

	1000	100	200	300	400	500	600	700
Bilateral ODA t-1	1.39	1.33	1.16	1.09	1.19	1.12	1.17	1.20
Epidemic year	3.75	3.73	3.57	3.39	3.62	2.64	3.26	3.28
Severity	3.53	3.53	3.40	3.31	3.44	2.72	2.50	3.10
Epidemic year t-1	3.66	3.64	3.54	3.40	3.57	2.77	3.55	3.29
Severity t-1	3.33	3.33	3.22	3.19	3.27	2.80	2.84	3.08
Life expectancy	1.84	1.79	1.66	1.67	1.74	1.81	2.14	1.90
GDP donor	1.36	1.31	1.26	1.13	1.23	1.32	1.33	1.24
GDP recipient	1.40	1.37	1.30	1.36	1.34	1.34	1.74	1.54
Distance	1.14	1.14	1.18	1.10	1.14	1.24	1.13	1.19
Colony	1.05	1.05	1.01	1.02	1.03	1.09	1.21	1.01
Democracy	1.27	1.26	1.15	1.27	1.26	1.16	1.41	1.40
Mean VIF	2.16	2.14	2.04	2.00	2.08	1.82	2.02	2.02

A.3 Results

Table 8: Sectors directly related to health (Model 2)

	1000	700	500	100
Aid t-1	0.828***	0.693***	0.629***	0.807***
	(0.004)	(0.011)	(0.027)	(0.005)
Epidemic year	0.079**	0.250***	0.204*	0.019
	(0.031)	(0.057)	(0.123)	(0.032)
Severity	0.015**	0.021*	0.015	0.005
	(0.006)	(0.012)	(0.027)	(0.006)
Life expectancy	−0.542***	−0.391**	−1.054**	−0.701***
	(0.097)	(0.190)	(0.487)	(0.102)
GDP donor	0.179***	0.164***	0.148***	0.174***
	(0.007)	(0.013)	(0.040)	(0.007)
GDP recipient	0.050***	0.081***	0.016	0.038***
	(0.006)	(0.015)	(0.035)	(0.006)
Distance	−0.095***	−0.087**	−0.163*	−0.088***
	(0.016)	(0.038)	(0.099)	(0.016)
Colony	0.315***	−0.121	0.110	0.344***
	(0.035)	(0.087)	(0.130)	(0.033)
Democracy	−0.004	−0.410***	−0.037	0.069***
	(0.024)	(0.048)	(0.106)	(0.027)
Constant	0.209	−0.237	3.603*	0.835*
	(0.415)	(0.815)	(2.138)	(0.431)

Robust standard errors in parentheses
*p<0.1; **p<0.05; ***p<0.01

Table 9: Sectors not related to health (Model 2)

	200	300	400	600
Aid t-1	0.554***	0.622***	0.658***	0.709***
	(0.012)	(0.009)	(0.008)	(0.036)
Epidemic year	0.120	0.149***	0.197***	−0.130
	(0.089)	(0.056)	(0.048)	(0.262)
Severity	0.023	0.026**	0.044***	0.086
	(0.018)	(0.012)	(0.009)	(0.053)
Life expectancy	−0.732***	−0.729***	−0.301*	−2.576***
	(0.279)	(0.177)	(0.160)	(0.829)
GDP donor	0.323***	0.166***	0.221***	−0.047
	(0.019)	(0.013)	(0.011)	(0.089)
GDP recipient	0.093***	0.042***	0.065***	0.146***
	(0.017)	(0.011)	(0.010)	(0.056)
Distance	−0.324***	−0.079**	−0.120***	−0.342**
	(0.050)	(0.035)	(0.025)	(0.140)
Colony	0.088	0.184***	0.476***	0.043
	(0.101)	(0.065)	(0.053)	(0.175)
Democracy	0.031	0.114**	0.140***	−0.177
	(0.073)	(0.051)	(0.039)	(0.226)
Constant	−0.021	0.629	−2.066***	12.735***
	(1.234)	(0.762)	(0.681)	(3.547)

Robust standard errors in parentheses
*p<0.1; **p<0.05; ***p<0.01

Table 10: Sectors not related to health (Model 3)

	200	300	400	600
Epidemic year	0.179	0.344^{***}	0.431^{***}	-0.522
	(0.115)	(0.077)	(0.068)	(0.371)
Severity	0.046^{*}	0.069^{***}	0.094^{***}	0.108
	(0.024)	(0.018)	(0.014)	(0.109)
Epidemic year t-1	0.325^{***}	0.370^{***}	0.368^{***}	0.278
	(0.115)	(0.078)	(0.067)	(0.409)
Severityt-1	0.032	0.074^{***}	0.069^{***}	0.202
	(0.027)	(0.019)	(0.015)	(0.127)
Life expectancy	-0.912^{***}	-0.996^{***}	-0.530^{**}	-6.904^{***}
	(0.341)	(0.234)	(0.210)	(1.228)
GDP donor	0.735^{***}	0.429^{***}	0.619^{***}	-0.280^{**}
	(0.022)	(0.016)	(0.014)	(0.123)
GDP recipient	0.198^{***}	0.095^{***}	0.185^{***}	0.577^{***}
	(0.021)	(0.015)	(0.013)	(0.082)
Distance	-0.717^{***}	-0.146^{***}	-0.330^{***}	-0.686^{***}
	(0.058)	(0.043)	(0.033)	(0.205)
Colony	0.221^{**}	0.440^{***}	1.203^{***}	0.345
	(0.111)	(0.081)	(0.070)	(0.232)
Democracy	0.224^{**}	0.322^{***}	0.472^{***}	-0.270
	(0.089)	(0.064)	(0.052)	(0.287)
Constant	-3.626^{**}	-2.607^{**}	-7.378^{***}	32.933^{***}
	(1.488)	(1.018)	(0.914)	(5.015)

Robust standard errors in parentheses
*p<0.1; **p<0.05; ***p<0.01

Table 11: Sectors Related to Health: Cholera

	1000	700	500	100
Epidemic year	0.267***	0.412***	0.302**	0.260***
	(0.064)	(0.083)	(0.144)	(0.065)
Life expectancy	−1.901***	1.280***	−0.093	−1.300***
	(0.311)	(0.420)	(0.822)	(0.309)
GDP donor	0.972***	0.455***	0.446***	0.845***
	(0.021)	(0.027)	(0.058)	(0.022)
GDP recipient	0.154***	0.046	−0.106*	0.101***
	(0.020)	(0.031)	(0.059)	(0.021)
Distance	−0.267***	0.123	0.321*	−0.085
	(0.070)	(0.095)	(0.169)	(0.072)
Colony	2.184***	−0.092	1.156***	2.254***
	(0.095)	(0.194)	(0.233)	(0.090)
Democracy	0.227***	−1.265***	0.481***	0.393***
	(0.083)	(0.097)	(0.186)	(0.084)
Constant	−4.114***	−11.363***	−8.028**	−6.783***
	(1.341)	(1.782)	(3.559)	(1.334)

Robust standard errors in parentheses
*p<0.1; **p<0.05; ***p<0.01

Table 12: Sectors Not Related to Health: Cholera

	200	300	400	600
Epidemic year	−0.054	0.065	0.079	0.033
	(0.111)	(0.079)	(0.070)	(0.286)
Life expectancy	0.132	−0.051	0.973***	−5.657***
	(0.550)	(0.403)	(0.342)	(1.627)
GDP donor	0.719***	0.425***	0.581***	0.325**
	(0.039)	(0.029)	(0.025)	(0.161)
GDP recipient	0.118***	−0.014	0.021	0.583***
	(0.038)	(0.028)	(0.024)	(0.109)
Distance	−0.695***	0.003	−0.325***	−0.904**
	(0.125)	(0.089)	(0.075)	(0.391)
Colony	0.685***	0.720***	1.416***	−0.607*
	(0.181)	(0.134)	(0.122)	(0.343)
Democracy	0.612***	0.435***	0.485***	−0.839*
	(0.148)	(0.106)	(0.092)	(0.428)
Constant	−7.538***	−6.645***	−11.217***	22.240***
	(2.403)	(1.721)	(1.475)	(6.835)

Robust standard errors in parentheses
*p<0.1; **p<0.05; ***p<0.01

Table 13: Sectors Related to Health: Measles

	1000	700	500	100
Epidemic year	0.302***	0.810***	0.149	0.204***
	(0.058)	(0.097)	(0.246)	(0.059)
Life expectancy	−3.207***	−0.747	−1.205	−2.322***
	(0.331)	(0.490)	(1.251)	(0.356)
GDP donor	1.076***	0.410***	0.647***	0.963***
	(0.021)	(0.033)	(0.150)	(0.023)
GDP recipient	0.301***	0.255***	−0.012	0.200***
	(0.019)	(0.034)	(0.100)	(0.020)
Distance	−0.595***	0.001	−0.389	−0.538***
	(0.043)	(0.079)	(0.250)	(0.045)
Colony	1.832***	−0.458*	0.657*	1.788***
	(0.125)	(0.246)	(0.371)	(0.132)
Democracy	0.338***	−0.963***	−0.169	0.552***
	(0.081)	(0.139)	(0.331)	(0.083)
Constant	0.340	−4.385**	−0.803	−2.145
	(1.446)	(2.175)	(5.303)	(1.556)

Robust standard errors in parentheses
*p<0.1; **p<0.05; ***p<0.01

Table 14: Sectors Not Related to Health: Measles

	200	300	400	600
Epidemic year	0.233^{**}	0.190^{**}	0.096	-1.088^{**}
	(0.108)	(0.090)	(0.070)	(0.526)
Life expectancy	-1.903^{***}	-2.205^{***}	-1.830^{***}	-2.381
	(0.654)	(0.544)	(0.410)	(2.914)
GDP donor	0.895^{***}	0.513^{***}	0.725^{***}	-0.256
	(0.037)	(0.036)	(0.030)	(0.279)
GDP recipient	0.141^{***}	0.091^{***}	0.139^{***}	0.482^{*}
	(0.037)	(0.031)	(0.026)	(0.247)
Distance	-0.739^{***}	-0.184^{***}	-0.351^{***}	-0.886^{**}
	(0.081)	(0.068)	(0.050)	(0.414)
Colony	0.354	0.669^{***}	1.546^{***}	-0.772
	(0.255)	(0.189)	(0.167)	(0.567)
Democracy	0.260	0.412^{***}	0.760^{***}	-1.540^{**}
	(0.162)	(0.137)	(0.100)	(0.588)
Constant	-1.360	1.119	-3.551^{**}	18.383
	(2.810)	(2.316)	(1.740)	(11.592)

Robust standard errors in parentheses
*p<0.1; **p<0.05; ***p<0.01

A.4 Robustness

Table 15: Robustness Check Excluding USA (Model 1)

	1000	100	200	300	400	500	600	700
Epidemic year	0.770***	0.701***	0.416***	0.518***	0.653***	0.233	−0.051	0.721***
	(0.055)	(0.055)	(0.099)	(0.069)	(0.063)	(0.150)	(0.309)	(0.073)
Severity	0.139***	0.130***	0.091***	0.101***	0.129***	0.041	0.309***	0.037**
	(0.010)	(0.010)	(0.020)	(0.015)	(0.012)	(0.037)	(0.094)	(0.016)
Life expectancy	−2.947***	−2.096***	−0.580*	−1.051***	−0.692***	−2.674***	−4.157***	−1.217***
	(0.168)	(0.170)	(0.311)	(0.220)	(0.199)	(0.557)	(1.020)	(0.240)
GDP donor	0.887***	0.735***	0.763***	0.370***	0.535***	0.611***	0.045	0.258***
	(0.013)	(0.013)	(0.025)	(0.018)	(0.017)	(0.051)	(0.144)	(0.018)
GDP recipient	0.323***	0.246***	0.191***	0.118***	0.186***	−0.026	0.508***	0.206***
	(0.010)	(0.010)	(0.020)	(0.014)	(0.013)	(0.040)	(0.076)	(0.017)
Distance	−0.578***	−0.517***	−0.736***	−0.221***	−0.314***	−0.334***	−0.450**	−0.152***
	(0.028)	(0.029)	(0.055)	(0.042)	(0.032)	(0.109)	(0.205)	(0.046)
Colony	2.048***	2.107***	0.358***	0.663***	1.314***	0.389***	−0.244	0.019
	(0.060)	(0.059)	(0.109)	(0.083)	(0.073)	(0.149)	(0.241)	(0.110)
Democracy	0.267***	0.402***	0.361***	0.284***	0.453***	0.170	−0.155	−1.085***
	(0.045)	(0.045)	(0.085)	(0.063)	(0.053)	(0.135)	(0.278)	(0.061)
Constant	1.741**	−0.268	−5.542***	−1.315	−5.798***	5.227**	16.147***	1.633
	(0.748)	(0.754)	(1.367)	(0.961)	(0.867)	(2.397)	(4.427)	(1.052)

Robust standard errors in parentheses
*p<0.1; **p<0.05; ***p<0.01

Table 16: Robustness Check Excluding USA (Model 2)

	1000	100	200	300	400	500	600	700
Aid t-1	0.823***	0.800***	0.547***	0.599***	0.651***	0.618***	0.682***	0.656***
	(0.005)	(0.005)	(0.012)	(0.010)	(0.009)	(0.030)	(0.039)	(0.012)
Epidemic year	0.084***	0.026	0.159	0.141**	0.202***	0.160	−0.125	0.291***
	(0.032)	(0.034)	(0.097)	(0.059)	(0.052)	(0.133)	(0.268)	(0.060)
Severity	0.016***	0.006	0.038*	0.022*	0.042***	0.021	0.130**	0.029**
	(0.006)	(0.006)	(0.020)	(0.013)	(0.010)	(0.028)	(0.061)	(0.013)
Life expectancy	−0.528***	−0.681***	−0.728**	−0.682***	−0.324*	−1.507***	−2.655***	−0.366*
	(0.101)	(0.107)	(0.304)	(0.185)	(0.172)	(0.537)	(0.869)	(0.203)
GDP donor	0.170***	0.159***	0.365***	0.150***	0.220***	0.162***	−0.005	0.102***
	(0.008)	(0.008)	(0.025)	(0.015)	(0.014)	(0.049)	(0.150)	(0.017)
GDP recipient	0.050***	0.039***	0.098***	0.043***	0.065***	0.040	0.189**	0.079***
	(0.006)	(0.006)	(0.019)	(0.012)	(0.010)	(0.037)	(0.073)	(0.016)
Distance	−0.106***	−0.103***	−0.390***	−0.100***	−0.117***	−0.264**	−0.427**	−0.135***
	(0.016)	(0.017)	(0.055)	(0.038)	(0.027)	(0.114)	(0.205)	(0.041)
Colony	0.341***	0.383***	0.050	0.216***	0.484***	0.081	0.063	−0.051
	(0.036)	(0.035)	(0.103)	(0.066)	(0.055)	(0.135)	(0.206)	(0.090)
Democracy	−0.001	0.071**	0.085	0.110**	0.127***	0.005	−0.087	−0.433***
	(0.026)	(0.028)	(0.082)	(0.055)	(0.043)	(0.120)	(0.240)	(0.051)
Constant	0.356	1.053**	−0.218	0.803	−1.966***	5.856**	12.655***	0.921
	(0.439)	(0.458)	(1.358)	(0.798)	(0.727)	(2.423)	(4.084)	(0.886)

Robust standard errors in parentheses
*p<0.1; **p<0.05; ***p<0.01

Table 17: Robustness Check Excluding India (Model 1)

	1000	100	200	300	400	500	600	700
Epidemic year	0.756***	0.686***	0.347***	0.536***	0.669***	0.328**	−0.094	0.719***
	(0.053)	(0.053)	(0.093)	(0.067)	(0.060)	(0.136)	(0.300)	(0.072)
Severity	0.133***	0.126***	0.067***	0.106***	0.134***	0.055*	0.208**	0.035**
	(0.010)	(0.010)	(0.018)	(0.014)	(0.012)	(0.033)	(0.085)	(0.016)
Life expectancy	−3.045***	−2.240***	−0.472	−1.154***	−0.610***	−2.698***	−4.947***	−1.696***
	(0.165)	(0.168)	(0.292)	(0.217)	(0.191)	(0.526)	(1.007)	(0.243)
GDP donor	0.959***	0.841***	0.699***	0.434***	0.601***	0.546***	−0.272***	0.414***
	(0.011)	(0.012)	(0.020)	(0.015)	(0.014)	(0.041)	(0.100)	(0.016)
GDP recipient	0.325***	0.246***	0.178***	0.117***	0.183***	0.004	0.429***	0.275***
	(0.010)	(0.011)	(0.019)	(0.015)	(0.013)	(0.039)	(0.068)	(0.018)
Distance	−0.529***	−0.457***	−0.631***	−0.175***	−0.310***	−0.188*	−0.253	−0.033
	(0.027)	(0.028)	(0.051)	(0.040)	(0.031)	(0.098)	(0.169)	(0.044)
Colony	1.946***	1.972***	0.372***	0.565***	1.240***	0.461***	−0.212	−0.125
	(0.060)	(0.058)	(0.107)	(0.082)	(0.071)	(0.146)	(0.213)	(0.107)
Democracy	0.247***	0.400***	0.268***	0.300***	0.473***	0.087	−0.573**	−1.094***
	(0.043)	(0.044)	(0.078)	(0.060)	(0.049)	(0.122)	(0.273)	(0.061)
Constant	0.805	−1.558**	−5.714***	−2.140**	−7.067***	4.828**	23.554***	−0.114
	(0.724)	(0.737)	(1.270)	(0.939)	(0.826)	(2.253)	(4.162)	(1.045)

Robust standard errors in parentheses
*p<0.1; **p<0.05; ***p<0.01

Table 18: Robustness Check Excluding India (Model 2)

	1000	100	200	300	400	500	600	700
Aid t-1	0.828^{***}	0.808^{***}	0.541^{***}	0.623^{***}	0.655^{***}	0.629^{***}	0.709^{***}	0.693^{***}
	(0.004)	(0.005)	(0.012)	(0.010)	(0.008)	(0.027)	(0.036)	(0.011)
Epidemic year	0.079^{***}	0.019	0.130	0.151^{***}	0.200^{***}	0.201	−0.130	0.242^{***}
	(0.031)	(0.032)	(0.089)	(0.056)	(0.049)	(0.123)	(0.262)	(0.057)
Severity	0.015^{**}	0.005	0.024	0.026^{**}	0.044^{***}	0.015	0.086	0.021^{*}
	(0.006)	(0.006)	(0.018)	(0.012)	(0.009)	(0.027)	(0.053)	(0.012)
Life expectancy	-0.536^{***}	-0.692^{***}	-0.652^{**}	-0.691^{***}	-0.279^{*}	-1.072^{**}	-2.576^{***}	-0.485^{**}
	(0.098)	(0.103)	(0.283)	(0.179)	(0.163)	(0.491)	(0.829)	(0.194)
GDP donor	0.178^{***}	0.173^{***}	0.320^{***}	0.160^{***}	0.220^{***}	0.145^{***}	−0.047	0.164^{***}
	(0.007)	(0.007)	(0.020)	(0.013)	(0.012)	(0.041)	(0.089)	(0.013)
GDP recipient	0.049^{***}	0.038^{***}	0.085^{***}	0.039^{***}	0.064^{***}	0.020	0.146^{***}	0.092^{***}
	(0.006)	(0.006)	(0.018)	(0.012)	(0.010)	(0.036)	(0.056)	(0.015)
Distance	-0.093^{***}	-0.087^{***}	-0.320^{***}	-0.075^{**}	-0.120^{***}	−0.160	-0.342^{**}	-0.089^{**}
	(0.016)	(0.016)	(0.050)	(0.035)	(0.025)	(0.099)	(0.140)	(0.038)
Colony	0.317^{***}	0.345^{***}	0.070	0.174^{***}	0.471^{***}	0.109	0.043	−0.126
	(0.035)	(0.034)	(0.102)	(0.065)	(0.054)	(0.130)	(0.175)	(0.087)
Democracy	−0.006	0.067^{**}	0.018	0.108^{**}	0.136^{***}	−0.035	−0.177	-0.395^{***}
	(0.024)	(0.027)	(0.074)	(0.051)	(0.040)	(0.107)	(0.226)	(0.048)
Constant	0.194	0.814^{*}	−0.266	0.548	-2.122^{***}	3.661^{*}	12.735^{***}	0.055
	(0.419)	(0.434)	(1.243)	(0.770)	(0.690)	(2.143)	(3.547)	(0.821)

Robust standard errors in parentheses
$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 19: Robustness Check Excluding Asia (Model 1)

	1000	100	200	300	400	500	600	700
Epidemic year	0.662***	0.646***	0.271***	0.477***	0.539***	0.395***	0.085	0.866***
	(0.060)	(0.061)	(0.105)	(0.076)	(0.065)	(0.147)	(0.316)	(0.080)
Severity	0.122***	0.120***	0.053**	0.089***	0.112***	0.021	0.240**	0.071***
	(0.011)	(0.011)	(0.021)	(0.016)	(0.013)	(0.038)	(0.098)	(0.017)
Life expectancy	−3.664***	−2.910***	−1.747***	−1.576***	−1.266***	−2.795***	−5.300***	−1.834***
	(0.187)	(0.193)	(0.328)	(0.246)	(0.210)	(0.568)	(1.081)	(0.274)
GDP donor	0.934***	0.801***	0.615***	0.403***	0.567***	0.464***	−0.203*	0.418***
	(0.013)	(0.014)	(0.022)	(0.018)	(0.015)	(0.045)	(0.108)	(0.018)
GDP recipient	0.336***	0.260***	0.164***	0.095***	0.163***	−0.105**	0.446***	0.229***
	(0.012)	(0.012)	(0.022)	(0.017)	(0.014)	(0.043)	(0.085)	(0.022)
Distance	−0.526***	−0.476***	−0.561***	−0.121***	−0.352***	0.102	0.092	0.016
	(0.030)	(0.031)	(0.055)	(0.044)	(0.033)	(0.107)	(0.200)	(0.049)
Colony	2.095***	2.122***	0.564***	0.646***	1.314***	0.641***	−0.088	−0.196*
	(0.068)	(0.067)	(0.116)	(0.090)	(0.078)	(0.156)	(0.233)	(0.113)
Democracy	0.232***	0.470***	0.802***	0.525***	0.605***	0.169	−0.461	−1.300***
	(0.054)	(0.056)	(0.099)	(0.075)	(0.061)	(0.138)	(0.301)	(0.069)
Constant	3.503***	1.579*	−0.687	−0.595	−3.576***	4.746**	20.722***	0.602
	(0.815)	(0.838)	(1.419)	(1.057)	(0.905)	(2.384)	(4.643)	(1.154)

Robust standard errors in parentheses
*p<0.1; **p<0.05; ***p<0.01

Table 20: Robustness Check Excluding Asia (Model 2)

	1000	100	200	300	400	500	600	700
Aid t-1	0.824***	0.809***	0.507***	0.628***	0.651***	0.595***	0.691***	0.687***
	(0.005)	(0.006)	(0.015)	(0.011)	(0.010)	(0.030)	(0.043)	(0.014)
Epidemic year	0.089**	0.015	0.090	0.133**	0.147***	0.247*	−0.047	0.324***
	(0.035)	(0.037)	(0.105)	(0.064)	(0.054)	(0.133)	(0.282)	(0.067)
Severity	0.014**	−0.00001	0.014	0.015	0.035***	0.013	0.104*	0.040***
	(0.007)	(0.007)	(0.021)	(0.014)	(0.011)	(0.031)	(0.061)	(0.014)
Life expectancy	−0.718***	−0.860***	−1.408***	−0.906***	−0.623***	−1.351**	−2.721***	−0.606***
	(0.113)	(0.117)	(0.328)	(0.202)	(0.184)	(0.554)	(0.920)	(0.227)
GDP donor	0.175***	0.166***	0.312***	0.142***	0.217***	0.125***	−0.021	0.166***
	(0.008)	(0.008)	(0.023)	(0.014)	(0.013)	(0.044)	(0.109)	(0.017)
GDP recipient	0.058***	0.042***	0.088***	0.037***	0.054***	−0.015	0.128*	0.102***
	(0.007)	(0.007)	(0.022)	(0.014)	(0.011)	(0.041)	(0.074)	(0.018)
Distance	−0.097***	−0.093***	−0.304***	−0.025	−0.149***	−0.094	−0.321*	−0.054
	(0.017)	(0.018)	(0.055)	(0.039)	(0.027)	(0.109)	(0.181)	(0.044)
Colony	0.348***	0.364***	0.199*	0.214***	0.479***	0.188	0.064	−0.189**
	(0.040)	(0.038)	(0.107)	(0.071)	(0.056)	(0.138)	(0.201)	(0.096)
Democracy	0.024	0.092***	0.330***	0.204***	0.211***	−0.049	−0.155	−0.384***
	(0.031)	(0.034)	(0.100)	(0.065)	(0.050)	(0.123)	(0.254)	(0.057)
Constant	0.856*	1.549***	2.212	1.109	−0.453	4.864**	12.866***	0.085
	(0.478)	(0.493)	(1.422)	(0.865)	(0.769)	(2.389)	(3.993)	(0.952)

Robust standard errors in parentheses
*p<0.1; **p<0.05; ***p<0.01

Table 21: Robustness Check Excluding Africa (Model 1)

	1000	100	200	300	400	500	600	700
Epidemic year	0.659***	0.509***	0.554***	0.501***	0.831***	0.336	−2.085***	0.831***
	(0.092)	(0.090)	(0.156)	(0.110)	(0.110)	(0.275)	(0.676)	(0.130)
Severity	0.133***	0.114***	0.089***	0.128***	0.168***	0.076	−0.236*	0.040
	(0.015)	(0.015)	(0.027)	(0.020)	(0.018)	(0.059)	(0.128)	(0.026)
Life expectancy	−8.195***	−6.741***	−8.000***	−5.775***	−4.471***	−5.059***	−6.774**	−3.771***
	(0.415)	(0.409)	(0.749)	(0.528)	(0.499)	(1.559)	(3.421)	(0.625)
GDP donor	0.988***	0.901***	0.802***	0.506***	0.696***	0.735***	−0.921***	0.390***
	(0.014)	(0.014)	(0.025)	(0.019)	(0.018)	(0.072)	(0.150)	(0.021)
GDP recipient	0.314***	0.228***	0.203***	0.102***	0.223***	0.184***	0.121	0.299***
	(0.013)	(0.012)	(0.024)	(0.018)	(0.016)	(0.061)	(0.100)	(0.022)
Distance	−0.681***	−0.612***	−0.672***	−0.270***	−0.337***	−0.882***	−0.273	−0.348***
	(0.034)	(0.035)	(0.062)	(0.052)	(0.038)	(0.164)	(0.275)	(0.059)
Colony	1.622***	1.621***	−0.102	0.791***	0.930***	−0.329	0.448	0.398***
	(0.078)	(0.080)	(0.148)	(0.109)	(0.101)	(0.224)	(0.492)	(0.140)
Democracy	0.335***	0.397***	−0.194*	0.048	0.424***	−0.568**	0.342	−1.086***
	(0.065)	(0.063)	(0.117)	(0.093)	(0.077)	(0.253)	(0.692)	(0.110)
Constant	23.732***	18.408***	25.839***	17.965***	8.005***	16.861***	43.506***	11.363***
	(1.765)	(1.738)	(3.101)	(2.193)	(2.102)	(6.515)	(14.384)	(2.699)

Robust standard errors in parentheses
*p<0.1; **p<0.05; ***p<0.01

Table 22: Robustness Check Excluding Africa (Model 2)

	1000	100	200	300	400	500	600	700
Aid t-1	0.832***	0.813***	0.566***	0.622***	0.678***	0.651***	0.789***	0.683***
	(0.006)	(0.006)	(0.016)	(0.013)	(0.011)	(0.048)	(0.051)	(0.015)
Epidemic year	0.010	0.002	0.316**	0.127	0.261***	0.253	−0.903*	0.230**
	(0.050)	(0.054)	(0.141)	(0.089)	(0.083)	(0.292)	(0.535)	(0.098)
Severity	0.008	0.008	0.053**	0.040**	0.057***	0.014	−0.090	0.006
	(0.008)	(0.009)	(0.025)	(0.016)	(0.014)	(0.054)	(0.085)	(0.020)
Life expectancy	−1.499***	−1.644***	−4.404***	−2.723***	−1.512***	−1.674	−1.759	−0.953*
	(0.240)	(0.249)	(0.690)	(0.446)	(0.391)	(1.511)	(2.578)	(0.502)
GDP donor	0.180***	0.177***	0.334***	0.185***	0.231***	0.263***	−0.166	0.173***
	(0.009)	(0.009)	(0.025)	(0.017)	(0.015)	(0.079)	(0.118)	(0.018)
GDP recipient	0.044***	0.033***	0.100***	0.041***	0.070***	0.131**	0.069	0.103***
	(0.007)	(0.007)	(0.021)	(0.014)	(0.012)	(0.064)	(0.067)	(0.021)
Distance	−0.113***	−0.111***	−0.344***	−0.154***	−0.107***	−0.325*	−0.238	−0.231***
	(0.019)	(0.019)	(0.059)	(0.047)	(0.031)	(0.174)	(0.169)	(0.049)
Colony	0.230***	0.245***	−0.193	0.289***	0.269***	−0.244	0.063	0.009
	(0.047)	(0.050)	(0.142)	(0.082)	(0.079)	(0.244)	(0.411)	(0.118)
Democracy	−0.024	0.064*	−0.137	−0.003	0.099*	−0.179	0.001	−0.513***
	(0.035)	(0.037)	(0.101)	(0.078)	(0.058)	(0.221)	(0.621)	(0.086)
Constant	4.560***	5.111***	15.889***	9.734***	2.927*	4.787	10.909	3.139
	(1.008)	(1.047)	(2.877)	(1.831)	(1.634)	(6.343)	(10.889)	(2.147)

Robust standard errors in parentheses
*p<0.1; **p<0.05; ***p<0.01

Table 23: Robustness Check Only Africa (Model 1)

	1000	100	200	300	400	500	600	700
Epidemic year	0.755***	0.747***	0.245**	0.472***	0.515***	0.190	0.472	0.676***
	(0.065)	(0.066)	(0.113)	(0.083)	(0.070)	(0.153)	(0.333)	(0.086)
Severity	0.097***	0.100***	0.029	0.039*	0.067***	0.026	0.401***	0.023
	(0.015)	(0.015)	(0.028)	(0.021)	(0.017)	(0.041)	(0.114)	(0.020)
Life expectancy	−1.900***	−0.900***	1.547***	0.481	0.173	0.105	−6.665***	−0.629*
	(0.232)	(0.245)	(0.420)	(0.324)	(0.268)	(0.617)	(1.151)	(0.330)
GDP donor	0.904***	0.742***	0.573***	0.362***	0.481***	0.348***	0.199	0.421***
	(0.018)	(0.018)	(0.031)	(0.024)	(0.020)	(0.051)	(0.149)	(0.022)
GDP recipient	0.403***	0.345***	0.272***	0.204***	0.166***	−0.059	0.582***	0.154***
	(0.016)	(0.017)	(0.030)	(0.023)	(0.018)	(0.047)	(0.092)	(0.027)
Distance	−0.178***	−0.020	−0.244***	0.081	−0.165***	0.581***	−0.549**	0.359***
	(0.047)	(0.049)	(0.089)	(0.064)	(0.053)	(0.134)	(0.269)	(0.070)
Colony	2.368***	2.474***	1.188***	0.637***	1.639***	1.385***	−0.255	−0.411***
	(0.085)	(0.082)	(0.141)	(0.111)	(0.096)	(0.173)	(0.260)	(0.152)
Democracy	0.353***	0.575***	1.177***	0.723***	0.700***	0.191	−0.440	−1.182***
	(0.060)	(0.062)	(0.105)	(0.080)	(0.066)	(0.140)	(0.309)	(0.073)
Constant	−7.054***	−10.636***	−17.854***	−11.493***	−10.025***	−9.705***	24.285***	−6.542***
	(1.088)	(1.152)	(1.935)	(1.450)	(1.224)	(2.631)	(5.501)	(1.435)

Robust standard errors in parentheses
*p<0.1; **p<0.05; ***p<0.01

Table 24: Robustness Check Only Africa (Model 2)

	1000	100	200	300	400	500	600	700
Aid t-1	0.816***	0.793***	0.488***	0.598***	0.615***	0.574***	0.645***	0.695***
	(0.007)	(0.007)	(0.018)	(0.014)	(0.013)	(0.034)	(0.051)	(0.017)
Epidemic year	0.121***	0.040	0.037	0.139*	0.161***	0.161	0.103	0.233***
	(0.039)	(0.041)	(0.116)	(0.072)	(0.060)	(0.135)	(0.293)	(0.071)
Severity	0.011	−0.007	−0.011	−0.011	0.018	0.011	0.164**	0.036**
	(0.009)	(0.010)	(0.029)	(0.019)	(0.015)	(0.033)	(0.073)	(0.015)
Life expectancy	−0.433***	−0.566***	0.536	−0.090	−0.227	−0.213	−3.729***	−0.146
	(0.145)	(0.155)	(0.443)	(0.279)	(0.239)	(0.590)	(1.044)	(0.264)
GDP donor	0.179***	0.169***	0.300***	0.138***	0.206***	0.083*	0.082	0.134***
	(0.011)	(0.011)	(0.033)	(0.020)	(0.018)	(0.047)	(0.158)	(0.021)
GDP recipient	0.068***	0.057***	0.147***	0.072***	0.060***	−0.020	0.218**	0.077***
	(0.010)	(0.011)	(0.031)	(0.019)	(0.016)	(0.044)	(0.097)	(0.021)
Distance	−0.038	−0.017	−0.074	0.069	−0.101**	0.132	−0.490*	0.154**
	(0.029)	(0.030)	(0.095)	(0.057)	(0.046)	(0.136)	(0.254)	(0.064)
Colony	0.441***	0.493***	0.587***	0.227**	0.725***	0.500***	0.114	−0.126
	(0.052)	(0.047)	(0.142)	(0.094)	(0.074)	(0.162)	(0.231)	(0.128)
Democracy	0.049	0.121***	0.569***	0.297***	0.258***	−0.066	−0.167	−0.365***
	(0.034)	(0.039)	(0.111)	(0.071)	(0.055)	(0.122)	(0.264)	(0.060)
Constant	−0.983	−0.540	−8.482***	−3.470***	−2.520**	−0.935	15.965***	−2.792**
	(0.663)	(0.718)	(2.108)	(1.243)	(1.068)	(2.661)	(4.989)	(1.149)

Robust standard errors in parentheses
*p<0.1; **p<0.05; ***p<0.01

Table 25: Robustness Check Only Asia (Model 1)

	1000	100	200	300	400	500	600	700
Epidemic year	1.587***	1.164***	1.261***	1.141***	1.385***	0.308	−2.322***	0.585***
	(0.113)	(0.113)	(0.192)	(0.142)	(0.144)	(0.338)	(0.878)	(0.163)
Severity	0.261***	0.203***	0.182***	0.196***	0.244***	0.134*	−0.275	−0.014
	(0.021)	(0.021)	(0.036)	(0.028)	(0.026)	(0.070)	(0.179)	(0.034)
Life expectancy	−7.696***	−5.230***	−6.909***	−5.897***	−3.213***	1.167	−0.278	−1.958**
	(0.570)	(0.557)	(1.060)	(0.787)	(0.694)	(2.184)	(5.669)	(0.830)
GDP donor	1.086***	1.001***	1.026***	0.590***	0.741***	0.978***	0.067	0.447***
	(0.021)	(0.020)	(0.038)	(0.030)	(0.029)	(0.089)	(0.305)	(0.028)
GDP recipient	0.238***	0.171***	0.178***	0.152***	0.175***	0.240***	0.656***	0.163***
	(0.019)	(0.018)	(0.035)	(0.026)	(0.023)	(0.078)	(0.172)	(0.032)
Distance	−0.759***	−0.554***	−1.275***	−0.614***	−0.260***	−1.669***	−2.418***	−0.244***
	(0.067)	(0.065)	(0.118)	(0.093)	(0.080)	(0.224)	(0.606)	(0.094)
Colony	1.431***	1.440***	0.249	0.604***	1.085***	−0.093	0.686	0.657**
	(0.111)	(0.110)	(0.267)	(0.170)	(0.168)	(0.382)	(0.648)	(0.269)
Democracy	1.096***	0.960***	0.495***	0.293**	0.827***	−0.462	−1.991**	−0.398***
	(0.078)	(0.077)	(0.147)	(0.117)	(0.094)	(0.301)	(0.972)	(0.134)
Constant	20.824***	10.077***	22.448***	19.256***	1.408	−7.091	16.626	2.726
	(2.561)	(2.492)	(4.479)	(3.433)	(3.044)	(9.527)	(23.926)	(3.742)

Robust standard errors in parentheses
*p<0.1; **p<0.05; ***p<0.01

Table 26: Robustness Check Only Asia (Model 2)

	1000	100	200	300	400	500	600	700
Aid t-1	0.824***	0.789***	0.592***	0.583***	0.651***	0.655***	0.738***	0.698***
	(0.008)	(0.009)	(0.020)	(0.019)	(0.016)	(0.062)	(0.076)	(0.019)
Epidemic year	0.164**	0.138*	0.504***	0.438***	0.443***	0.191	−1.010	0.058
	(0.064)	(0.072)	(0.177)	(0.124)	(0.111)	(0.316)	(0.644)	(0.110)
Severity	0.033***	0.034***	0.077**	0.083***	0.082***	0.041	−0.087	−0.018
	(0.012)	(0.013)	(0.033)	(0.025)	(0.020)	(0.060)	(0.115)	(0.024)
Life expectancy	−1.470***	−1.377***	−3.602***	−2.908***	−0.887	1.619	0.290	−0.423
	(0.325)	(0.347)	(0.963)	(0.695)	(0.576)	(2.013)	(4.087)	(0.626)
GDP donor	0.212***	0.218***	0.398***	0.255***	0.245***	0.359***	0.038	0.162***
	(0.014)	(0.015)	(0.039)	(0.027)	(0.025)	(0.103)	(0.228)	(0.024)
GDP recipient	0.017	0.014	0.065**	0.047**	0.058***	0.082	0.270***	0.060**
	(0.011)	(0.012)	(0.031)	(0.023)	(0.018)	(0.075)	(0.100)	(0.029)
Distance	−0.126***	−0.109***	−0.529***	−0.395***	−0.051	−0.539**	−0.760	−0.168**
	(0.037)	(0.039)	(0.114)	(0.081)	(0.064)	(0.247)	(0.546)	(0.076)
Colony	0.255***	0.303***	−0.084	0.242	0.553***	−0.494	0.216	0.217
	(0.073)	(0.076)	(0.291)	(0.157)	(0.149)	(0.470)	(0.569)	(0.201)
Democracy	0.115**	0.204***	0.144	0.144	0.253***	0.009	−0.762	−0.434***
	(0.046)	(0.049)	(0.130)	(0.100)	(0.076)	(0.243)	(0.626)	(0.103)
Constant	4.241***	3.451**	13.164***	11.264***	−0.468	−8.421	2.430	0.895
	(1.418)	(1.510)	(4.072)	(2.964)	(2.491)	(8.647)	(16.779)	(2.796)

Robust standard errors in parentheses
*p<0.1; **p<0.05; ***p<0.01

A.5 Placebo

Table 27: Placebo-Test for Humanitarian Aid

	Humanitarian Aid
Epidemic year	0.746***
Placebo dummy 1	0.377***
Placebo dummy 2	-0.00303
Placebo dummy 3	0.0415
Placebo dummy 4	0.0427
Placebo dummy 5	0.0247
Placebo dummy 6	0.0326
Placebo dummy 7	0.0539
Placebo dummy 8	0.0135*
Placebo dummy 9	0.0466
Placebo dummy 10	0.05
Placebo dummy prop	0.0849

Table 28: Placebo-Test: model 1

	1000	100	200	300	400	500	600	700
Placebo dummy 1	0.377***	0.335***	0.270***	0.305***	0.364***	0.174	0.163	0.052
Placebo dummy 2	0.375**	0.300***	0.144	0.319***	0.347***	0.127	0.133	-0.003
Placebo dummy 3	0.352***	0.303***	0.102	0.317***	0.341***	0.653	0.235	0.042
Placebo dummy 4	0.381***	0.289***	0.303***	0.283***	0.304***	-0.173	0.002	0.043
Placebo dummy 5	0.322***	0.300***	0.381***	0.328***	0.385***	0.171	0.167	0.025
Placebo dummy 6	0.314***	0.342***	0.211**	0.299***	0.370***	0.187	-0.029	0.033
Placebo dummy 7	0.385***	0.371***	0.356***	0.270***	0.329***	0.217	0.408	0.054
Placebo dummy 8	0.303***	0.202***	0.201*	0.371***	0.388***	0.201	0.903***	0.013*
Placebo dummy 9	0.399***	0.282***	0.238*	0.349***	0.358***	-0.003	0.166	0.046
Placebo dummy 10	0.342***	0.399***	0.330***	0.339***	0.414***	-0.121	0.311	0.055
Placebo dummy prop	0.317***	0.348***	0.305***	0.287***	0.315***	-0.342	0.0438	0.0849

A.6 Persistence

Table 29: Robustness Check 1: Persistence

	1000	700	500	100
Epidemic year	0.416**	0.847***	−0.346	0.422***
	(0.162)	(0.269)	(0.496)	(0.158)
Severity	0.147***	0.211***	−0.240*	0.131***
	(0.031)	(0.062)	(0.145)	(0.031)
Epidemic year t-1	0.256*	−0.697***	−0.993*	0.451***
	(0.152)	(0.268)	(0.523)	(0.158)
Severityt-1	0.105***	−0.056	−0.363**	0.126***
	(0.031)	(0.063)	(0.156)	(0.032)
Life expectancy	−3.825***	−1.987***	−3.771***	−2.857***
	(0.155)	(0.260)	(0.603)	(0.159)
GDP donor	0.943***	0.439***	0.441***	0.818***
	(0.012)	(0.018)	(0.049)	(0.012)
GDP recipient	0.301***	0.251***	0.026	0.219***
	(0.010)	(0.020)	(0.045)	(0.010)
Distance	−0.454***	−0.001	−0.240**	−0.361***
	(0.028)	(0.052)	(0.114)	(0.029)
Colony	1.933***	−0.119	0.383**	1.929***
	(0.059)	(0.117)	(0.158)	(0.057)
Democracy	0.186***	−1.298***	0.035	0.324***
	(0.044)	(0.067)	(0.134)	(0.045)
Constant	4.252***	1.603	11.492***	1.188*
	(0.687)	(1.115)	(2.619)	(0.701)

Robust standard errors in parentheses
*p<0.1; **p<0.05; ***p<0.01

Table 30: Robustness Check 2: Persistence

	200	300	400	600
Epidemic year	0.296	0.142	0.424^{**}	1.080
	(0.315)	(0.192)	(0.180)	(1.081)
Severity	0.095	0.058	0.124^{***}	0.496^{*}
	(0.066)	(0.046)	(0.037)	(0.267)
Epidemic year t-1	−0.027	0.331^{*}	0.584^{***}	0.705
	(0.300)	(0.190)	(0.160)	(0.736)
Severityt-1	−0.034	0.108^{**}	0.133^{***}	−0.039
	(0.067)	(0.047)	(0.036)	(0.213)
Life expectancy	-1.588^{***}	-1.866^{***}	-1.514^{***}	-6.597^{***}
	(0.301)	(0.211)	(0.188)	(1.240)
GDP donor	0.727^{***}	0.419^{***}	0.606^{***}	-0.239^{**}
	(0.022)	(0.016)	(0.014)	(0.120)
GDP recipient	0.192^{***}	0.092^{***}	0.181^{***}	0.595^{***}
	(0.021)	(0.015)	(0.013)	(0.085)
Distance	-0.696^{***}	-0.117^{***}	-0.297^{***}	-0.760^{***}
	(0.058)	(0.043)	(0.033)	(0.207)
Colony	0.224^{**}	0.446^{***}	1.213^{***}	0.149
	(0.111)	(0.082)	(0.071)	(0.230)
Democracy	0.182^{**}	0.249^{***}	0.407^{***}	−0.176
	(0.088)	(0.064)	(0.053)	(0.298)
Constant	−0.625	1.214	-3.083^{***}	30.972^{***}
	(1.309)	(0.910)	(0.815)	(4.909)

Robust standard errors in parentheses
*p<0.1; **p<0.05; ***p<0.01